Hedge funds: Influence of Autocorrelation on Risk Underestimation and Relationship with Hedge Fund Features

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1 author:

Aleksandar Petreski
Jönköping University

ICMA CENTRE
THE BUSINESS SCHOOL FOR FINANCIAL MARKETS

The University of Reading

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Aleksandar Petreski

Supervisor: Dr. Jacque Pezier

I. Abstract

Hedge funds tend to invest in illiquid assets, which are difficult to mark-to-market on daily basis, and hence, hedge fund managers are forced to mark-to-model the assets. More freedom in appraising asset values gives an incentive for hedge fund managers to smooth the performance of their funds. A likely consequence of the marking-to-model, due to illiquidity, is autocorrelation exhibited in hedge fund returns. A traditional risk measure, which does not take autocorrelation into account, is underestimating the true risk and overestimating true performance. Only when observed asset returns are corrected for the autocorrelation, they could be regarded as appropriate input in traditional risk estimation methods.

In this paper, first of all, the presence of the autocorrelation in the hedge fund returns was confirmed, next, the relationship between VaR underestimation and autocorrelation coefficient was quantified and finally it was examined whether separate features (attributes) of the hedge funds, displayed in the hedge fund reports are connected with autocorrelation.

Research showed that, for a given confidence level, VaR underestimation increases with the increase of the autocorrelation coefficient. Autocorrelation is related to hedge fund strategy and development of the market, but not with the continent domicile of the investment. Autocorrelation increases with the size of the fund up to some level and then starts to decrease. Redemption, notification, and subscription frequency and lock-up period have significant influence on autocorrelation. Management fees are related to the autocorrelation, while performance fees are not. Also, results showed that other factors like high watermark, hurdle rate, leverage, listing on the exchange and penalty provisions have insignificant effect on autocorrelation.

II. Acknowledgements

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‘ I certify that all material in this research project which is not my own work, has been properly identified through the use of appropriate academic conventions of citation and referencing ’

Name: Aleksandar Petreski *Date: 23/04/2007*

Signed:

III. Table of Contents

1. Introduction

After the LTCM (Long Term Capital Management) crisis in August 1998, initiated by the default on Russian government debt, the importance of liquidity as a risk factor was more emphasized. From the crisis onwards, existing methods of risk estimation have been reinvented and traditional risk measures were adjusted to capture liquidity risk.

One of the methods, proposed by the practitioners, for estimating the liquidity risk was to use the degree of autocorrelation[1] in asset returns as a proxy for the magnitude of market illiquidity. A traditional risk measure, which does not take autocorrelation into account, is underestimating the true risk and overestimating true performance. Only when observed asset returns are corrected for the autocorrelation, they could be regarded as appropriate input in traditional risk estimation methods.

Particularly, hedge funds[2] exhibited significant autocorrelation compared to traditional funds. Brooks and Kat (2002) have shown that monthly return distributions display negative skewnes and highly unusual kurtosis as well significant first-order autocorrelation.

Since hedge funds tend to invest in illiquid assets, which are difficult to daily mark-to market on daily basis, hedge fund managers are forced to mark-to-model the assets. Enabling more freedom in appraising asset values gives incentive for hedge fund managers to smooth the performance of their funds. Moreover, the fact that hedge funds are not required to be transparent regarding the return reporting leads to even more space for smoothing and even stronger autocorrelation in hedge fund returns.

Hedge funds are alternative investments very different from traditional mutual funds. According to Amenc et all (2004), hedge funds employ dynamic investment strategies and hedge fund managers have a great flexibility with reference to instruments that could be used, and leverage they can undertake. They can enter long and short positions and can freely use derivative securities. Main target of hedge fund mangers is absolute performance rather then relative performance. Position of managers and their remuneration system is different compared to mutual funds, as the fees they charge are performance related and have some specific targets such as high watermark[3] or hurdle rate[4]. Also, it is specific that hedge funds may follow consistently one particular investment strategy over some period of time. There are different classifications of these hedge fund strategies, but in this paper, which is examining the hedge funds in the

[1] The term ‘autocorrelation’ according to Gujarati (2003), may be defined as ‘correlation between members of series of observations ordered in time or space’.

[2] The term ‘hedge fund’, at first sight, leads to an impression that it is the fund that employs hedged portfolio, which performs invariant to the market direction. But, today’s hedge fund meaning deviates from this definition, as hedge fund’s strategies are more unhedged than hedged

[3] High watermark is a fund valuation level below which performance fees are not paid

[4] Hurdle rate is the return that a fund has to generate before a performance fee is payable

Eurekahedge database, the classification provided by Eurekahedge will be used. Definition of the hedge funds strategies used in this database will be provided additionally in the Appendix at the end of the paper. A separate class of funds called Fund-of Funds is worth mentioning, but these are not an object of interest in this paper. These funds represent an alternative to constructing a portfolio of different hedge fund strategies.

A lot of studies on hedge funds were done, in which the autocorrelation presence was tested and appropriate methodology to adjust traditional performance and risk estimates was suggested. It was shown that after the adjustment for the autocorrelation, performance of the funds has decreased and risk has increased, having strong impact on investment allocation decisions. Hence, this was the motivation to observe the phenomenon of autocorrelation exhibited in hedge fund returns.

In this paper, beside the usual autocorrelation test and the common method of return unsmoothing using autocorrelation, the relationship between risk underestimation and autocorrelation for separate hedge fund strategies was quantified. This quantification should provide a clearer picture of risk underestimation for a particular strategy and enable comparison between different strategies.

Furthermore, it is examined whether separate features (attributes) of the hedge funds displayed in the hedge fund reports are connected with autocorrelation. The hedge fund reports contain additional data that describe the remuneration policy, cash-flows dynamics of the hedge funds, whether the fund is listed on the stock exchange, subscription frequency, redemption frequency, redemption notification period, lock-up period, leverage, penalty, hurdle rate, high watermark, management fees and performance fees.

These features could give some indication on the aggressiveness of the fund to attract investors. For instance, new funds might try to attract investors by giving better investment conditions, such as easier entrance and exit from the fund, lower fees and lower risk (standard deviation). However, this marketing is costly, since the funds must forgo some part of their profit, by lowering fees or must undertake higher liquidity risk, by giving a chance to investors for faster withdrawal of their money. The only free way to improve their performance is by lowering standard deviation, for which they do not pay anything. Still, it could be assumed that a manager can smooth its returns, only if its cash-flow conditions allow it. That is, the manager can decrease the standard deviation, if the fund’s conditions are not generous to the investors and exit periods are longer. In addition, it might be assumed that exit and reporting periods are related, since hedge funds are not required to report regularly and it might be expected from them to report at least at the end of the maturity period of investment. Hence, as exit and reporting periods are related, with the increase of the exit period, the reporting period increases as a consequence. With the increase of both periods, the hedge fund manager has more opportunities to smooth the data, which leads to higher autocorrelation.

Therefore, this paper elaborates the relationships between strategy and autocorrelation, between fund size and autocorrelation and investment geography and autocorrelation. The assumption whether there is a relationship between autocorrelation and the cash-flows dynamics of the hedge funds is tested, approximated by subscription, redemption and notification frequency, lock-up period and penalty provisions. Also, the influence of the remuneration policy of the hedge funds is examined, approximated by hurdle rate, high watermark, management fees and performance fees. Answers on these questions could give full picture of the phenomenon of autocorrelation and might explain which factors are strongly influencing it.

At the beginning, Section 2 will portray different interpretations of the reasons for autocorrelation appearance. Theoretical description of the methodology applied along with reasons for choosing a particular methodology will be handled in Section 3. General findings will be presented in section 4 and finally, conclusions and some propositions for further research will be stated in Section 5.

2. Literature Review

An early consideration of the relationship between illiquidity, performance smoothing and autocorrelation could be found in real estate literature. According to Geltner et all (2003), in the real estate market, due to infrequent trading or confidentiality, there is a lack of price information. Therefore, appraisals are used for the purpose of market tracking and asset assessment. Smoothing appears (real estate market analogous to hedge fund mangers) during the assessment process, when appraisers are extracting the signal from noisy transaction prices. Furthermore, smoothing is reasonably believed to be related to liquidity. According to this author, as liquidity increases, more signal information is available on current transactions, so appraisers (hedge fund mangers) place more weight on current value relative to past valuations and there is less smoothing. Returns computed from the smoothed asset values exhibit lower volatility and higher autocorrelation than real returns. By contrast, more frequently traded assets are marked-to-market and autocorrelation is insignificant. Both appraisers and hedge fund mangers are involved in an important way in interpreting information and can have impact on the price. Moreover, the fact that hedge funds are not required to be transparent regarding the return reporting, leads to even more room for smoothing.

There is a slightly extended interpretation of the appearance of autocorrelation in the hedge fund returns. In accordance with Chan et al (2005), in an inefficient market, market frictions such as transaction costs, cost of gathering information, borrowing constraints, and institutional restrictions on short selling, all bring to autocorrelation in returns. Hence, autocorrelation could be regarded as a proxy for the extent of the market frictions and illiquidity as the most common form of market friction. Furthermore, it is argued by this author, that autocorrelation makes returns more predictable, but this predictability may not be arbitraged due to the presence of illiquidity.

Several papers have examined the method for adjusting the risk and performance due to autocorrelation in the hedge fund returns. According to used approach, they can be classified in two groups. The first group of authors are correcting the returns for autocorrelation, before returns are used for further examination. This approach was used by Brooks and Kat (2002) and it may be traced back to Blundell and Ward (1987) and Geltner (1991), which were the first to develop models to extract underlying market values from appraisal values. The other group of authors, such as Getmansky et all (2003) attempted to modify reported performance statistics rather than returns, which are considered as given.

By using the Blundell and Ward method, in most studies, only the first order autocorrelation is removed from the hedge fund returns. According to Okunev and White (2003), this approach is not sufficient, as there is an evidence of autocorrelation of second and higher order. They suggest a methodology for removing any order of the autocorrelation entirely by using a general filter. This approach is more complex compared to the simple Blundell-Ward filter and if one wants to carefully analyze hedge fund performance, rather than the autocorrelation itself, a simple method seems more useful.

In this paper, only the first order autocorrelation was removed by using the Blundell-Ward filter. Due to the purpose of paper, I find it more appealing to use this simple method. More specifically, the intention of this text is to observe the relationship between the VaR underestimation, hedge fund features and autocorrelation. Autocorrelation is appropriately and sufficiently represented by significant and pronounced first order coefficients. According to presented data in the paper of Okunev and White (2003), the autocorrelation coefficients of first order (at time lag 1), are greater and far more significant than coefficients of a higher order (at time lag 2, 3 or more).

3. Methodology

3.1. Autocorrelation and Unsmoothing Method

In efficient markets, since prices move in random and unpredictable way, autocorrelation coefficients are supposed to be zero. However, due to the appraising (smoothing) process, coefficients become different from zero. Therefore, at the beginning, time-series of hedge fund returns were tested for the presence of the first order autocorrelation. Afterwards, estimated autocorrelation coefficients were checked for their statistical significance by their standard error and T-statistics. If the computed coefficient was not significant, the null hypothesis that the autocorrelation coefficient is zero could not be rejected. Significant first order autocorrelation coefficients were used as an appraising factor *"α"* in a model, by which underlying market values were extracted from the appraisal values.

As presented by Clayton et al (2001) and Brooks and Kat (2002), smoothing is best described by the adaptive expectations model, similar to the models used in the real estate literature,

$$V^{*}=\alpha\ V_t+ (1-\alpha)\ Vt_{-1}^{*} \qquad (1)$$

where the observed (smoothed value) value V^* of a hedge fund indicator at time t is derived as the weighted average of the unobserved (true) value V_t and the smoothed value V_{t-1}^* at the period t-*1*.

Intuitively, if the hedge fund manager has more new information by which he could estimate the value of the assets, the appraising factor "α" could be set higher (he puts more weight on true value V_t). On the other hand, if the manager does not have new precise information, the best estimate for the period will be the previous period, so the difference $1-\alpha$ increases (he attributes more weight on previous already smoothed data V_{t-1}^*).

It could be shown that from equation (1), the expression for computing unsmoothed returns with zero first order autocorrelation could be derived:

$$r_t = r_t^* - \alpha\ \ r_{t-1}^* /\ (1-\alpha) \qquad (2)$$

with r_t as true underlying return and r_t^*, as smoothed observed return.

By using this method, from the original 4029 series, new unsmoothed 4029 series were created.

It might be expected, according to Brooks and Kat (2002), that computed unsmoothed series will have approximately zero first order lagged correlation or decreased lagged correlation, similar mean to smoothed series and different standard deviations. Standard deviation will be higher, if the appraising factor *"α"* is positive (if there is positive first order autocorrelation), and opposite, standard deviation will decrease, if the appraising factor *"α"* is negative (if the first order autocorrelation is negative).

3.2. Autocorrelation and Risk Underestimation

After computing the new series, this paper proceeds with Value-at-Risk analysis for both kinds of series of the hedge fund returns, smoothed and unsmoothed.

According to Alexander (2001), Value-at risk (in further text VaR) is an estimate of the loss from a fixed set of trading positions over a fixed time h that would be equalled or exceeded with a specified probability of 1-α%.

VaR has two parameters: holding period h and significance level $\alpha\%$. Hence, it is maximum loss that $1- \alpha\%$ portfolios would have out of 100 (100 * $\alpha\%$ portfolios would lose more than VaR) or it is maximum loss that a portfolio would have in 100*(1- α %) time periods h out of 100 (in 100 * $\alpha\%$ time periods one would loose more than VaR).

Usually, a confidence interval is chosen according to the purpose of risk estimation. If the risk measures are used for the purpose of capital requirements calculation, so as to decrease the probability of insolvency, VaR could be set at a very high significance level, close to 100%, but still less than it. In this paper, VaR is computed at a confidence level[5] of 95% and at a confidence level of 99%, for both smoothed and unsmoothed series.

There are several methods for calculating VaR: analytical (linear), historical and Monte Carlo VaR, but this paper will concentrate on the historical VaR. Linear VaR is not used since it requires strong assumption about the normality of the distribution of the returns in order to estimate VaR. As many authors, such as Brooks and Kat (2002), found non-normality (skewnes and kurtosis) in their empirical researches, the assumption of normality does not hold and it is more convenient to use historical method and percentile as risk statistic. Historical method is also more appealing compared to Monte Carlo VaR, since Monte Carlo VaR estimation for 4029 time-series is quite burdensome.

Although the historical method has its own disadvantages, according to Alexander (2001), that strongly depends on the assumption of identical historical and future distribution of the returns, I still find it as an optimum method for this project in terms of accuracy and speed.

Next, after computing the VaR for all smoothed and unsmoothed series, the difference in VaR is calculated for every time series,

$$VaR_{difference,\,1-\alpha,i} = VaR_{unsmoothed,\,1-\alpha,i} - VaR_{smoothed,\,1-\alpha,I} \qquad (3)$$

where $1-\alpha$ is the confidence level at which VaR is computed for the particular fund i (i=1, 2, 3…n).

In fact, a VaR difference is the level of underestimation (overestimation) of the risk, and it increases with the increase of the autocorrelation coefficient.

Next, funds are grouped according to strategy and a regression analysis is used. The difference in estimated VaR statistic is regressed on the autocorrelation coefficient of the original series for every fund:

$$Y_i = \beta_I + \beta_2 * X_i + u_i \qquad (4)$$

where Y_i is VaR difference (underestimation) and X_i is autocorrelation coefficient for the particular hedge fund. By using the autocorrelation coefficient, for a particular strategy and coefficients β_I and β_2, one should easily compute the level of risk underestimation.

[5] Confidence level is equal to 1—α, where α is significance level

3.3. Relationship between Autocorrelation and Hedge Fund Features

This research, apart from examining the existence of autocorrelation in the returns and how it affects estimated risk statistics, it examines also whether separate features (attributes) of the hedge funds displayed in the hedge fund reports are connected with autocorrelation.

In this paper, mean autocorrelation coefficients across different features are compared by using the dummy variable regression models. Dummy variable regression models, according to Gujarati (2003), are used when the dependant variable or regressand is influenced by the qualitative variable or dummy variables. These variables indicate presence or absence of a quality or an attribute, and could be quantified by creating artificial variables, that take on values of 1 or 0. If the attribute is present, the variable takes the value of 1, otherwise 0. The dummy variable method should help to quantify the relationship between autocorrelation coefficients, which is a quantitative dependant variable and some hedge fund feature, which is a qualitative (dummy) variable.

4. Data and Empirical Results

This research uses the Eurekahedge fund database. The database is analysed using 9 different hedge fund strategies:

- Arbitrage strategy
- CTA strategy
- Distressed debt strategy
- Event driven strategy
- Fixed income strategy
- Long short strategy
- Macro strategy
- Multi strategy and
- Relative value strategy

For each strategy there are different numbers of hedge funds, with different length of monthly data series, in the period between March 1989 and December 2006. Some monthly data series, which were too short, were removed, by taking 12 observations as the minimum length of a series. It was ambiguous to increase the criteria since the hedge fund history is rather short, so if the interval was increased, it could have reduced available data points for further examination. Finally, this paper examines 4029 time-series of particular hedge funds.

4.1. Investment Strategy and Autocorrelation

At the beginning, it is examined whether the investment strategy has any influence on the autocorrelation coefficient. As expected, hedge funds which are believed to invest in illiquid assets have higher autocorrelation coefficients. The dummy variables regression analysis was applied to the monthly data, where the strategy employed by the fund was a set as dummy variable. According to these criteria, the following was obtained:

Table 1. Hedge fund strategy and autocorrelation coefficients

Investment Style	Autocorrelation coefficient	Standard Error	t Stat	P-value
Intercept (Distressed debt)	0.19422	0.01724	11.26825	0.00000
Arbitrage	-0.00422	0.01965	-0.21487	0.82988
Multi-Strategy	-0.08015	0.01914	-4.18810	0.00003
Event Driven	-0.09324	0.02104	-4.43229	0.00001
Fixed Income	-0.12633	0.02012	-6.27988	0.00000
Relative Value	-0.14145	0.02156	-6.56081	0.00000
Long / Short Equities	-0.15240	0.01767	-8.62261	0.00000
Macro	-0.15585	0.02049	-7.60470	0.00000
CTA / Managed Futures	-0.18110	0.01889	-9.58690	0.00000

As illustrated by the computed data in Table 1, all strategies except Arbitrage have statistically different average autocorrelation coefficients. The Distressed Debt strategy has the highest autocorrelation coefficient (0.19422), while CTA/Managed Futures strategy has the lowest autocorrelation coefficient (0.01311=0.19422-0.18110). The Arbitrage strategy has very high p-value and therefore its autocorrelation coefficient is not significantly different from the coefficient of the Distressed Debt strategy.

It was identified that every hedge fund strategy has a different structure of positive, negative and zero autocorrelation coefficients, which is complementary with the level of average autocorrelation coefficient for a particular strategy. When counting the number of positive, negative and zero autocorrelation coefficients with reference to strategy, the following figures were obtained:

Table 2. Hedge fund strategy and structure of autocorrelation coefficients

Investment Style	autocorrelation coefficient	number of total coefficients	number of positive coefficients	%	number of negative coefficients	%	number of zero coefficients	%
Distressed Debt	0.19422	96	47	49%	0	0%	49	51%
Arbitrage	0.18999	320	134	42%	7	2%	179	56%
Multi-Strategy	0.11406	412	122	30%	5	1%	285	69%
Event Driven	0.10097	196	57	29%	3	2%	136	69%
Fixed Income	0.06789	265	69	26%	20	8%	176	66%
Relative Value	0.05277	170	26	15%	2	1%	142	84%
Long / Short Equities	0.04181	1,861	230	12%	16	1%	1,615	87%
Macro	0.03837	232	25	11%	2	1%	205	88%
CTA / Managed Futures	0.01311	477	30	6%	12	3%	435	91%
Total Average	0.06606	4,029	740	18%	67	2%	3,222	80%

The table shows that strategies with higher autocorrelation coefficients also have higher relative participation of the positive coefficients in its own total number of coefficients and lowest relative participation of zero and negative autocorrelation coefficients.
The Distressed Debt strategy has the highest autocorrelation coefficient and the highest percentage of positive autocorrelation coefficients (49%), while CTA/Managed Futures strategy has the lowest autocorrelation coefficient and the lowest percentage of positive autocorrelation coefficients (6%). Inversely, the CTA/Managed Futures strategy has the highest percentage of zero autocorrelation coefficients (91%), while the Distressed Debt strategy has the lowest percentage of zero autocorrelation coefficients (51%). Regarding the negative autocorrelation coefficients, the Distressed Debt strategy has the lowest percentage of zero autocorrelation coefficients (0%), while CTA/Managed Futures strategy has the second highest percentage of negative autocorrelation coefficients (3%), after the Fixed Income strategy, which has 8% negative autocorrelation coefficients in its own total number of coefficients.

Furthermore, for all these 8058 time-series, as many moment coefficients (mean, standard deviation, skewnes and kurtosis) were computed.

Table 3. Hedge fund strategy and moments of distribution

Investment style	autocorrelation coefficient (average)	mean (average)	standard deviation (average)	skewnes (average)	kurtosis (average)
Distressed Debt	0.19422	1.46948	2.42371	0.40921	2.36433
Arbitrage	0.18999	0.63713	1.60917	-0.04110	2.27582
Multi-Strategy	0.11406	1.14553	2.63058	0.25780	2.84355
Event Driven	0.10097	1.08313	2.45474	0.07976	2.37364
Fixed Income	0.06789	0.65418	1.38631	-0.01729	2.47304
Relative Value	0.05277	0.93798	2.55094	0.11903	1.83273
Long / Short Equities	0.04181	0.98188	3.18703	0.11293	1.47040
Macro	0.03837	0.64252	3.08818	0.11908	1.63757
CTA / Managed Futures	0.01311	0.79800	4.65919	0.25445	1.46006
Total Average	0.06606	0.92306	2.97432	0.12976	1.82966

Table 4. Equity indices and moments of distribution,
Source: Yahoo Finance, monthly data, 1996-2006

Equity index	autocorrelation coefficient (average)	mean (average)	standard deviation (average)	skewnes (average)	kurtosis (average)
NASDAQ Composite	-0.06764	-0.00290	0.08402	0.97064	1.81919
T stat	*(-0.76694)*				
S&P	0.07189	-0.00515	0.04411	0.86601	1.48876
T stat	*(0.81590)*				
DJIA	-0.01346	-0.00541	0.04449	0.91874	2.32062
T stat	*(-0.15224)*				

Tables 3 and 4 demonstrate that hedge funds compared with global equity indices, in average, have higher autocorrelation, higher mean, higher standard deviation, lower skewnes and higher kurtosis. Global equity indices have statistically insignificant autocorrelation and hence, null hypothesis that the autocorrelation coefficient is zero could not be rejected. Also, it could be observed that autocorrelation increases with the increase of the kurtosis, while there is no obvious relationship between autocorrelation for a particular strategy and skewnes.

Table 5. Change in standard deviation after unsmoothing

Investment Style	autocorrelation coefficient (average)	standard deviation (average) original	standard deviation (average) unsmoothed	standard deviation (average) difference
Distressed Debt	0.19422	2.42371	3.10973	0.68603
Arbitrage	0.18999	1.60917	2.08307	0.47390
Multi-Strategy	0.11406	2.63058	3.17292	0.54234
Event Driven	0.10097	2.45474	3.04146	0.58672
Fixed Income	0.06789	1.38631	1.64213	0.25581
Relative Value	0.05277	2.55094	2.94965	0.39870
Long / Short Equities	0.04181	3.18703	3.62892	0.44189
Macro	0.03837	3.08818	3.34817	0.25999
CTA / Managed Futures	0.01311	4.65919	4.79357	0.13438
Total Average	0.06606	2.97432	3.38094	0.40663

Table 5 supports the findings in other studies, for instance in Brooks and Kat (2002), that after unsmoothing, standard deviation has changed. In this case, since autocorrelation in average is positive, standard deviation has increased. Also, it is evident that with the increase in the autocorrelation coefficient, the difference between two standard deviations is increasing.

Next, for all the 8058 time-series, as many estimated VaR statistics at confidence level of 95% and 99% were computed. The percentile method was used to capture the non-normality of the return distribution. VaR figures obtained from the original series were subtracted from VaR figures resulting from unsmoothed series, applying the equation (3) from chapter 3.2 from this paper. The computed VaR difference is in fact VaR (risk) underestimation due to the autocorrelation (liquidity) effect. Then, by using a cross-strategy comparison, the difference in the VaR underestimation may be analyzed.

Figure 1. Autocorrelation coefficient and VaR underestimation at 95% confidence level

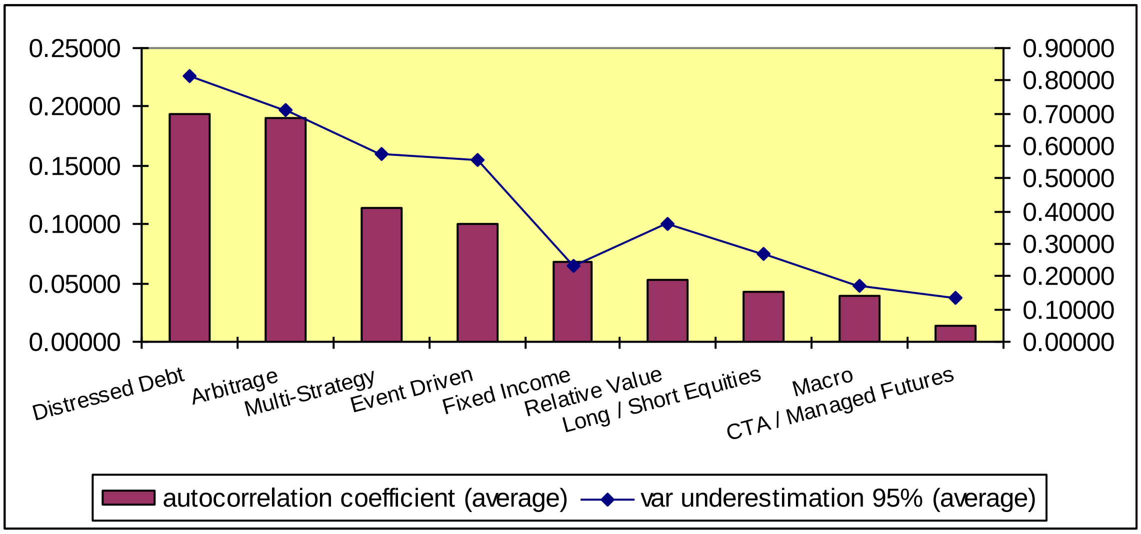


Figure 2. Autocorrelation coefficient and VaR underestimation at 99% confidence level

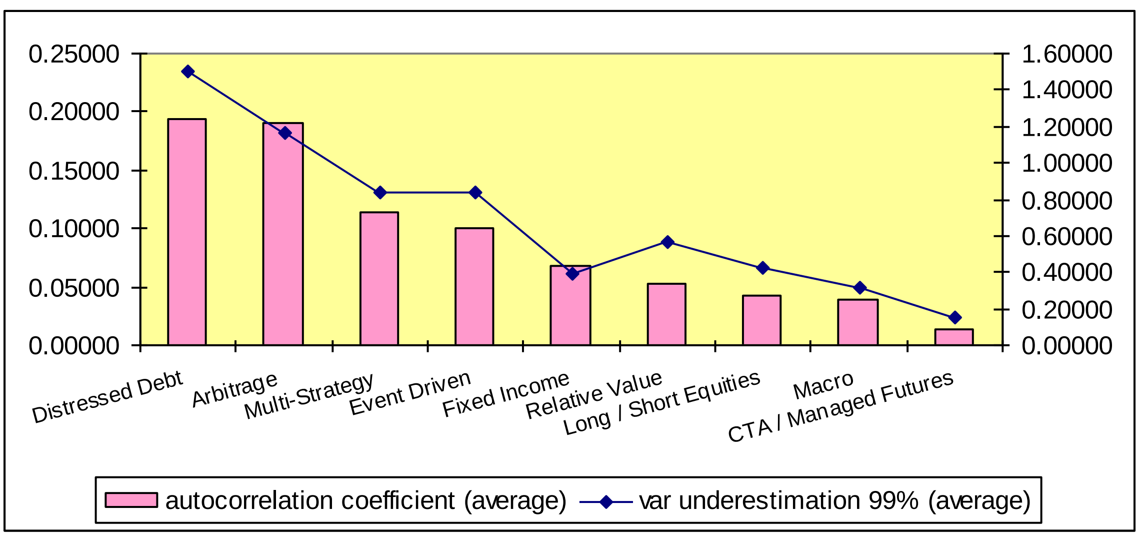
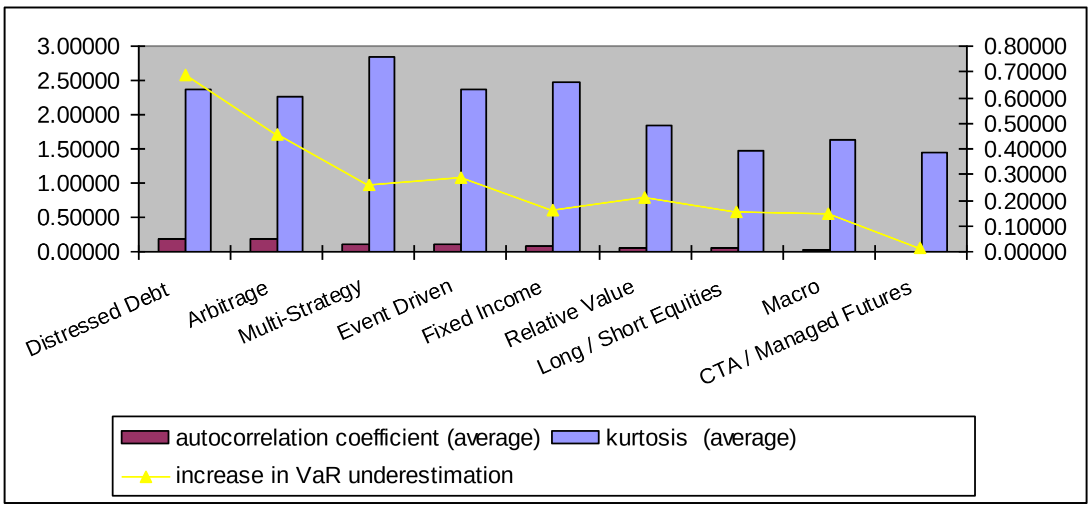


Figure 1 and 2 show that, for a given confidence level, as the autocorrelation coefficient decreases, the VaR underestimation is decreasing as well. This substantiates the intuition that traditional risk measures are underestimating the true risk to a higher extent for a less liquid strategy. The Distressed Debt strategy displays the biggest difference between estimated risk statistic computed on smoothed and unsmoothed series and the CTA/Managed Futures strategy has the lowest difference.

Table 6. Increase in VaR underestimation for two confidence levels

Investment style	Autocorrelation coefficient (average)	Kurtosis (average)	VaR underestimation 95% (average)	VaR underestimation 99% (average)	Increase in VaR underestimation
Distressed Debt	0.19422	2.36433	0.81360	1.50457	0.69096
Arbitrage	0.18999	2.27582	0.71043	1.16615	0.45572
Multi-Strategy	0.11406	2.84355	0.57557	0.83270	0.25713
Event Driven	0.10097	2.37364	0.55559	0.84130	0.28570
Fixed Income	0.06789	2.47304	0.23030	0.39026	0.15996
Relative Value	0.05277	1.83273	0.36371	0.57084	0.20713
Long / Short Equities	0.04181	1.47040	0.26920	0.42526	0.15606
Macro	0.03837	1.63757	0.17170	0.31651	0.14481
CTA / Managed Futures	0.01311	1.46006	0.13708	0.15351	0.01643
Total Average	0.06606	1.82966	0.34265	0.53713	0.19448

Figure 3. Autocorrelation, increase in VaR underestimation and kurtosis



Furthermore, Table 6 and Figure 3 illustrate that by increasing the confidence level, the difference in the VaR underestimation also increases. This marginal increase in VaR underestimation varies according to the strategy and there is obvious relation with the level of autocorrelation. The higher the autocorrelation, the higher the difference is in VaR underestimation between two confidence levels. This could be explained by higher kurtosis for higher autocorrelation coefficients.

Then, for each particular strategy, the VaR underestimation for every hedge fund within this strategy is regressed on the autocorrelation coefficient of the original series. The relationship autocorrelation-VaR underestimation shows how risk underestimation of the hedge fund returns could be worked out directly from the autocorrelation coefficient.

Table 7. Regression of VaR underestimation on autocorrelation coefficient at 95% confidence level

Investment Style	*Y* VaR underestimation 95% (average)	*b1* estimated intercept	*b2* estimated coefficient	*X* autocorrelation coefficient (average)	*b1* P-value	*b2* P-value
Distressed Debt	0.813600	-0.046440	4.428260	0.194220	0.000000	0.771380
Arbitrage	0.710430	0.030060	3.580810	0.189990	0.000000	0.704370
Multi-Strategy	0.575570	-0.027060	5.283330	0.114060	0.000000	0.789320
Event Driven	0.555590	-0.030640	5.805850	0.100970	0.000000	0.793520
Fixed Income	0.230300	0.113560	1.719690	0.067890	0.000000	0.000470
Relative Value	0.363710	0.013780	6.631750	0.052770	0.000000	0.826960
Long / Short Equities	0.269200	0.029080	5.742450	0.041810	0.000000	0.049120
Macro	0.171700	-0.042060	5.571500	0.038370	0.000000	0.189910
CTA / Managed Futures	0.137080	0.058820	5.968150	0.013110	0.000000	0.024380

Table 8. Regression of VaR underestimation on autocorrelation coefficient at 99% confidence level

Investment Style	*Y* VaR underestimation 99% (average)	*b1* estimated intercept	*b2* estimated coefficient	*X* autocorrelation coefficient (average)	*b1* P-value	*b2* P-value
Distressed Debt	1.504570	-0.172770	8.636400	0.194220	0.000000	0.549910
Arbitrage	1.166150	-0.067270	6.491530	0.189990	0.000000	0.710810
Multi-Strategy	0.832700	-0.015600	7.437230	0.114060	0.000000	0.913120
Event Driven	0.841300	-0.051560	8.842550	0.100970	0.000000	0.756250
Fixed Income	0.390260	0.194550	2.882980	0.067890	0.000000	0.000100
Relative Value	0.570840	0.002410	10.772680	0.052770	0.000000	0.981600
Long / Short Equities	0.425260	0.051610	8.935880	0.041810	0.000000	0.027910
Macro	0.316510	-0.079220	10.314220	0.038370	0.000000	0.198040
CTA / Managed Futures	0.153510	0.055180	7.498470	0.013110	0.000000	0.053290

As presented above, for different strategies there are different coefficients by which autocorrelation should be multiplied and intercept added in order to compute VaR underestimation. At a confidence level of 95%, the VaR underestimation could be computed by multiplying the autocorrelation coefficient by factor between 1.7 and 6.63 depending on the strategy, while at a confidence level of 99%, by factor between 2.88 and 10.77.

4.2. Investment Geography and Autocorrelation

Next, it was examined whether investment geography has any effect on autocorrelation. The domicile of the market, where the fund is investing is taken as a proxy for the liquidity of the asset. One may expect that investing in particular continent or market, for example North America, implies investing in liquid assets with low autocorrelation coefficient. Hence, hedge funds are classified by two criteria: continent domicile (as narrower classification) and the level of development of the market (as a broader classification).

The hedge funds are classified to different investment continent domiciles: Asia, Australia, Africa and Middle East, Europe, Latin America, North America and Global market as a separate category. Since the database contains no indication where Emerging markets could be classified, they are considered as Global investments. The following results were obtained analyzing the data according to the criteria shown in the table below:

Table 9. Continent and autocorrelation coefficient

Continent	Coefficients	Standard Error	t Stat	P-value
Intercept (North America)	0.08403	0.00472	17.79254	0.00000
Latin America	0.00090	0.01669	0.05380	0.95710
Asia	-0.00738	0.00915	-0.80643	0.42004
Europe	-0.01520	0.00924	-1.64378	0.10030
Middle East & Africa	-0.01521	0.04887	-0.31125	0.75563
Australia / New Zealand	-0.02904	0.02477	-1.17203	0.24125
Global	-0.04036	0.00657	-6.14536	0.00000

The results illustrate that average coefficients are not statistically different among continents where hedge funds are investing. There is only some statistically significant difference between North America and Global investments. Opposite of one's expectation, North America has higher autocorrelation coefficient compared to Global markets, in which category the emerging markets are included. This means that continent domicile is not a good proxy for asset liquidity.

In addition, similar to previous research, the paper examines whether the development of the market has any effect on autocorrelation. This time, the hedge funds are classified to 3 (three) different categories, depending on the level of development of the financial market in the country where it is invested: emerging markets, developed markets and global market as mix of both groups of markets. Arbitrarily, Eastern Europe, Argentina, Asia ex Japan, Asia Pacific, Brazil, Greater China, India, Latin America, and Africa are considered as emerging markets, then Australia, Japan, North America, USA, Taiwan and Korea are considered as developed markets, while Global investments and Asia with Japan are considered as global markets. Analysing the data in view of the aforesaid criterion, the following results were attained:

Table 10. Level of market development and autocorrelation coefficient

Level of market development	Coefficients	Standard Error	t Stat	P-value
Intercept (global market)	0.03284	0.00362	9.07045	0.00000
Developed markets	0.02873	0.00473	6.07031	0.00000
Emerging Markets	-0.02258	0.00773	-2.92027	0.00352

The above figures illustrate that there is statistically significant difference in average autocorrelation coefficients among 3 (three) levels of development of the financial markets. However, as in the previous case, geographical domicile as a proxy for the development of the market and its liquidity, affects the autocorrelation contrary to one's expectations. Assets in developed markets have higher autocorrelation coefficients (0.06157=0.03284+0.02873) compared to emerging markets (0.01026=0.03284-0.02258). Investing in developed markets does not imply investing in liquid instruments by default, since in the developed markets there are segments of the market, for instance, new market instruments, which are illiquid.

4.3. Fund / Asset Size and Autocorrelation

Furthermore, it is observed whether fund size and asset size have influence on the autocorrelation coefficient. One may expect that smaller funds which do not have opportunity to operate on the economy of scale with lower profit margin, will invest in less liquid assets with higher autocorrelation and higher profit. Therefore, it would be expected that as hedge fund size and assets size increase, autocorrelation should decrease and oppositely.

Hedge funds are grouped in seven groups according to the level of fund size and in other seven groups according to the level of asset size, keeping in mind that groups should have approximately the same number of observations. Under this criterion, the following figures have been obtained:

Table 11. Fund size (in millions of US$) and autocorrelation

Fund size	Coefficients	Standard Error	t Stat	P-value
Intercept (<10)	0.04039	0.00635	6.36227	0.00000
10-25	0.01243	0.00958	1.29711	0.19467
25-50	0.01884	0.00966	1.95022	0.05122
50-100	0.02742	0.01006	2.72484	0.00646
100-200	0.05161	0.00995	5.18745	0.00000
200-500	0.04855	0.01002	4.84429	0.00000
500-10,000	0.03531	0.00981	3.60010	0.00032

Figure 4. Fund size (in millions of US$) and autocorrelation

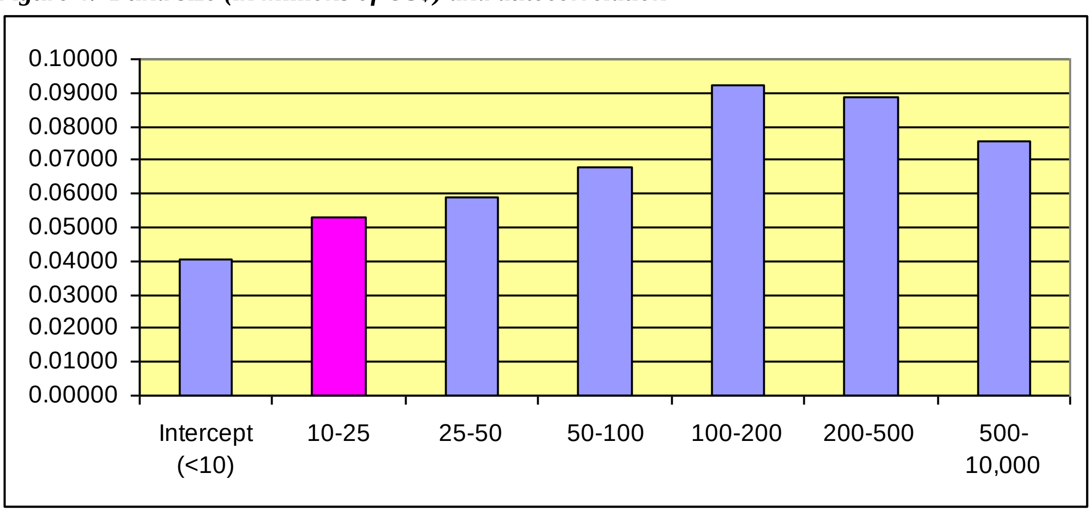
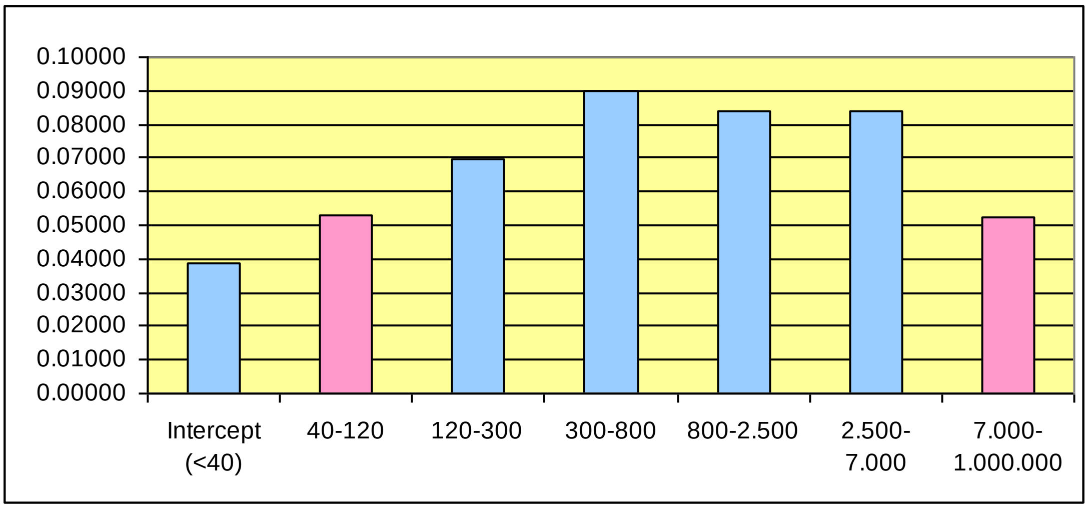


Table 12. Asset size (in millions of US$) and autocorrelation

Asset size	Coefficients	Standard Error	t Stat	P-value
Intercept (<40)	0.03840	0.00756	5.07997	0.00000
40-120	0.01440	0.01074	1.34141	0.17986
120-300	0.03137	0.01064	2.94924	0.00320
300-800	0.05153	0.01040	4.95526	0.00000
800-2.500	0.04560	0.01070	4.26168	0.00002
2.500-7.000	0.04531	0.01136	3.98719	0.00007
7.000-1.000.000	0.01387	0.00967	1.43466	0.15146

Figure 5. Asset size (in millions of US$) and autocorrelation



The data demonstrates that the relationship between size and autocorrelation is not linear and proportional as one might have expected. Autocorrelation coefficient increases with the size of the fund up to the category of funds with 200 millions US$, after which it decreases for the funds with higher size level. Average autocorrelation coefficient differs with high statistical significance among various level of fund size. Only the category of funds with 25 millions US$ are not significantly different from the category of funds with less than 10 millions US$.

Results for the fund size effect and asset size are similar, where 800 millions US$ are breakeven fund category. The autocorrelation coefficient increases with the size of the fund up to the category of funds with 800 millions US$, after which it decreases for the funds with higher level of size. It should be noted that autocorrelation coefficients for the category of funds with 120 millions US$ and over 1.000.000 millions US$ have lower statistical significance.

4.4. Cash-Flows Dynamics, Remuneration Policy and Autocorrelation

This section examines whether the hedge fund features regarding the cash-flow dynamics and remuneration policy have any relationship with autocorrelation.

Firstly, the following relationships were examined: autocorrelation coefficient - redemption frequency, autocorrelation coefficient - notification frequency and autocorrelation coefficient - subscription frequency. The data used from the hedge fund database displayed a very diverse frequency period. Therefore, for the purpose of this project, the classification was simplified and all frequencies were classified to only 3 (three) different categories. The benchmark period according to which the periods were classified was 1 month, which corresponds to the monthly reporting of hedge funds. The hedge fund frequency periods were classified to: below 1 month, 1 month and above 1 month. Upon analyzing the data, according to all criteria, the outcome was the following:

Table 13. Redemption frequency and autocorrelation coefficient

Redemption frequency effect	Coefficients	Standard Error	t Stat	P-value
Intercept (below 1 month)	0.02965	0.00783	3.78519	0.00016
1 month	0.04026	0.00840	4.79318	0.00000
above 1 month	0.10558	0.01858	5.68352	0.00000

Table 14. Notification frequency and autocorrelation coefficient

Notification frequency	Coefficients	Standard Error	t Stat	P-value
Intercept (below 1 month)	0.03633	0.00516	7.03904	0.00000
1 month	0.03146	0.00686	4.58641	0.00000
above 1 month	0.05568	0.00712	7.81502	0.00000

Table 15. Subscription frequency and autocorrelation coefficient

Subscription frequency	Coefficients	Standard Error	t Stat	P-value
Intercept (below 1 month)	0.02855	0.00749	3.81394	0.00014
1 month	0.04457	0.00811	5.49456	0.00000
above 1 month	0.03577	0.01291	2.77168	0.00560

The analysis illustrates that the average autocorrelation coefficient is increasing with the increase in the level of the redemption frequency, notification frequency and subscription frequency. Also, the obtained significant t-statistics and low P-values prove that mean coefficients are statistically different among three level of the frequency - period. This result may uphold the expectation that funds with longer period of redemption, subscription and notification have more freedom to mark-to-model the assets in wider ranges.

In addition, the relationship between the autocorrelation coefficient and lock-up period was examined. The data was divided in two categories: hedge funds with lock-up period and without lock-up period.

Table 16. Lock-up period and autocorrelation coefficient

Lock-up period	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept (lock up)	0.08140	0.00582	13.99177	0.00000
no lock-up	-0.01915	0.00664	-2.88129	0.00398

As outlined, funds with lock-up periods showed higher autocorrelation coefficients than the funds with no lock-up period. Again the result may verify the expectation that funds with lock-up periods have more freedom to mark-to-model the assets in wider ranges.

Next, the assumption that there might be some relation between performance and management fees and autocorrelation was tested. For instance, it was analysed whether managers with lower fees are motivated to invest in illiquid funds in order to compensate for their lost profit or opposite, whether managers with high fees attempt to smooth the data to a higher extent, in order to justify their high fees and make their fund less risky. Therefore, it was examined whether autocorrelation coefficients are significantly different for different level of management and performance fees.

The management fees range from minimum 0% to maximum 25%, where I have classified the funds in 3 bands: fees less then 1%, more then 1%, and less then 1.5 % and more then 1.5%. The performance fees range form minimum 0% to 50%, and funds have been classified in the following 3 bands: with 0% performance fees, with less than 20% and funds with more then 20%. According to these criteria, the results are as follows:

Table 17. Management fees and autocorrelation coefficient

Management fees	Coefficients	Standard Error	t Stat	P-value
Intercept (<=1%)	0.07568	0.00489	15.48163	0.00000
1%-1.5%	-0.01162	0.00672	-1.72920	0.08385
>1.5%	-0.01711	0.00694	-2.46384	0.01379

Table 18. Performance fees and autocorrelation coefficient

Performance fees	Coefficients	Standard Error	t Stat	P-value
Intercept (<=20%)	0.06643	0.00290	22.89411	0.00000
no fees	-0.00088	0.01472	-0.05969	0.95241
>20%	-0.00706	0.01298	-0.54438	0.58621

Significant t-statistics and low P-values for the management fees verify that mean autocorrelation coefficients are statistically different among three levels of management fees. Contrary, insignificant t-statistics and high P-values for performance fees confirm that average autocorrelation coefficients are equal among the three levels of performance fees. The analysis demonstrates that the mean autocorrelation coefficient is decreasing with the increase in the level of management fees, but it is invariant to the performance fees.

In addition, the influence of other factors on autocorrelation, such as high watermark, hurdle rate, effect of exchanges (listed fund, non-listed fund), leverage (leveraged fund, non-leveraged fund) and penalty (no penalty, with penalty) were examined as well. For example, one may expect that high watermark and high hurdle rate might motivate the manager to smooth the data to a greater extent. Furthermore, it might be that if the fund is listed on exchange, the manager will have less opportunity for smoothing. Also, one can presume that leverage of the fund is connected with autocorrelation, or that the penalty provisions for withdrawing the investment before the deadline may influence autocorrelation.

Table 19. Hurdle rate and autocorrelation coefficient

Hurdle Rate	Coefficients	Standard Error	t Stat	P-value
Intercept (with hurdle rate)	0.06151	0.00776	7.92240	0.00000
no hurdle rate	0.00503	0.00832	0.60434	0.54565

Table 20. High watermark and autocorrelation coefficient

High Watermark	Coefficients	Standard Error	t Stat	P-value
Intercept (use high watermark)	0.05264	0.01231	4.27480	0.00002
no high watermark	0.01362	0.01264	1.07747	0.28134

Table 21. Exchange listings and autocorrelation coefficient

Exchange	Coefficients	Standard Error	t Stat	P-value
Intercept (listed on exchange)	0.06358	0.00572	11.12344	0.00000
not listed on exchange	0.00327	0.00654	0.50001	0.61710

Table 22. Leverage and autocorrelation coefficient

Leverage	Coefficients	Standard Error	t Stat	P-value
Intercept (leveraged)	0.06737	0.00427	15.79340	0.00000
non-leveraged	-0.00214	0.00562	-0.38072	0.70343

Table 23. Penalty and autocorrelation coefficient

Penalty provision	Coefficients	Standard Error	t Stat	P-value
Intercept (with penalty provision)	0.06606	0.00574	11.51347	0.00000
no penalty provision	0.00099	0.00658	0.14987	0.88087

However, as the table below illustrates, low t-statistics and high P-values for these factors, reveal that they are statistically insignificant in explaining any difference in autocorrelation across classified data.

As shown by the above results, an average autocorrelation coefficient depends on the magnitude of the subscription frequency, notification frequency, redemption frequency, and on the length of the lock-up period and management fees. Conversely, the average autocorrelation coefficient does not differ among different levels of hurdle rate, high watermark, leverage of the fund, level of performance fees and whether the fund is listed on the exchange or not.

5. Conclusions

This paper tested the presence of autocorrelation in the hedge fund returns, it presented, in addition, a quantified relationship between VaR underestimation and the autocorrelation coefficient and examined whether there is relationship between autocorrelation and some hedge fund attributes.

It was confirmed that VaR underestimation increases with the increase of the autocorrelation coefficient for the given confidence level or VaR underestimation increases with the increase of the confidence level for a given autocorrelation coefficient. Furthermore, it was found that the difference between VaR underestimation at two confidence levels increases with the increase of the autocorrelation.

Next, it was demonstrated that autocorrelation is related to the hedge fund strategy, where the Distressed Debt strategy has the biggest autocorrelation and CTA/Managed Futures strategy, the lowest. Also, in the structure of estimated autocorrelation coefficients, Distressed Debt strategy showed the biggest proportion of positive and lowest proportion of negative and zero coefficients out of all its estimated coefficients.

Then, it was identified that the continent domicile of the investment does not have significant influence on autocorrelation, while development of the market has. Contrary to what one may expect, emerging markets have lower autocorrelation than developed markets, so probably it may not be generalized that investing in developed markets implies investing in liquid assets, since even in developed markets there are illiquid segments of the market.

Furthermore, autocorrelation increases with the size of the fund up to some level and then starts to decrease. Similar finding was revealed for the assets under management. This finding juxtaposes one’s expectation that autocorrelation has a proportional relationship with the fund and asset size.

Next, it could be concluded that autocorrelation is closely connected with cash-flow dynamics, since tests for the influence of several indicators which could be regarded as the proxy for hedge fund cash-flows, showed significant results. Redemption, notification, and subscription frequency and lock-up period have significant influence on autocorrelation. With the increase in the time distance (decrease of the frequency), autocorrelation increases as well.

Also, it was shown that management fees, which could be regarded as one aspect of remuneration policy, have inverse relationship with autocorrelation, while performance fees have no significant relationship at all with autocorrelation. It might be that mangers with high management fees have less incentive to invest in illiquid assets, or a lower motive to smooth performance.

Also, results demonstrated that other factors like high watermark, hurdle rate, leverage, and listing on the exchange and penalty provisions have an insignificant link with autocorrelation.

This study was focused only on the first-order autocorrelation, but it could be expanded to take in consideration the higher order of autocorrelation. Also, the examination of the relationship between autocorrelation and hedge fund attributes could be further extended to examine which of the factors have a stronger impact: strategy, size, cash management policy or remuneration policy?

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Appendix

Definition of Hedge Fund Strategies

Arbitrage	A strategy which produces a risk-free profit
Convertible arbitrage	A strategy of arbitraging the mispricing between convertible bonds and their underlying equity
Distressed debt	A strategy of trading the securities of the companies in reorganization or bankruptcy, with different level of seniority
Event driven	A strategy that seeks to benefit from impending, predictable or possible future events
Fixed income	A strategy of exploiting mispricing in the global market for interest rate securities and their derivatives
Long/short equity	A strategy where the portfolio has both long and short positions
Macro funds	A strategy where funds that take macro views (on interest rates, currencies etc) and position their investments accordingly
Multi-strategy	A strategy that is a combination of a number of investment strategies
Relative value	A strategy of exploiting the mispricing of one asset against another to generate a low risk profit