Original Article

The persistence of hedge fund strategies in different economic periods: A support vector machine approach

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ABSTRACT This article researches two issues that are related to the hedge fund industry. The first is the statistical methodology used in the evaluation and prediction of hedge fund performance. As the returns of hedge funds are non-normal (suffer from fat tails), ordinary least squares (OLS) and other commonly used statistical methods may not reflect optimal results. Hence, this article introduces the use of support vector machines (SVM) to test and hence predict the performance of hedge fund strategies within different economic periods. The article also compares the SVM results with feedforward neural networks (NN) and OLS. The second issue is to investigate the ability of a specific hedge fund strategy to always outperform the average market during different economic periods. The results show that SVM has outperformed the NN analysis in its prediction accuracy. Moreover, those preliminary results show that the importance of hedge fund strategies varies (non-persistent) during different economic periods in affecting the monthly returns. However, the emerging markets trading strategy shows more persistence than other hedge fund strategies.

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INTRODUCTION

The hedge fund industry is usually put on the spot by the media for their reputation in outperforming the market. Although each hedge fund has established its own niche by adopting its own trading model or strategy, it can be grouped based on its strategy. A large number of strategies are available for hedge funds to adopt. (Examples of strategies include: common equity long, equity long/short, equity market neutral, ETFs indexes, fixed income, distressed securities and emerging markets).

This article presents two main contributions that are important to our understanding of the hedge fund industry. The first contribution is to evaluate the current statistical methods used to evaluate the performance of hedge funds. As the returns of hedge funds are non-normal and suffer from fat tails, common statistical analysis such as ordinary least squares (OLS) will not work. Hence, the contribution answers the research question: can we use a better statistical methodology than OLS or NN? As a result, the article adds to the previous literature by introducing the SVM approach to the finance area in order to overcome the problems encountered with commonly used statistical methods. The article compares the performance of SVM, NN and OLS. The previous finance literature is very familiar with the OLS and NN but not with the SVM. The results presented in this article show that the SVM has better predictability accuracy than both the OLS and NN.

The second contribution is to use the SVM to relate the hedge fund industry performance (that is, monthly returns) to the different strategies adopted in different economic factors. Hence, the research question would be: is there any hedge fund strategy that can always

outperform the rest of the market? The results show that there is no specific hedge fund strategy that is consistently outperforming the market in ALL economic periods. However, the emerging markets strategy shows more persistence than other strategies.

The article is organized as follows: the following section introduces a review of previous literature and compares between a commonly used statistical method NN and the SVM. The next two sections discuss in detail the data and methodology used. The results are reported in the subsequent section followed by the limitations section. And finally, the last Section concludes the article.

LITERATURE REVIEW

Hedge fund performance has been investigated by several studies in the past few years, especially after the proliferation through media outlets about the outstanding returns and risks that they undertake. However, when comparing studies that investigate the hedge fund performance to other investment tools such as mutual funds, we can conclude that much fewer studies are carried out.¹ One of the reasons for such lower number of studies about the hedge fund industry, as pointed out in Capocci and Hubner,¹ is that the hedge fund industry is self-reporting, which makes it hard for researchers to get reliable data. Previous literature has also pointed out the weaknesses of using the available data. Limitations of data are discussed in a later section.

This article adds to the literature by investigating the performance of hedge funds. Specifically, this article investigates the introduction of support vector machines (SVM) to the finance area and the investigation of hedge

fund performance during different economic time periods.

The introduction of a new methodology to the hedge fund performance research is motivated by pervious literature that documented the non-normality of returns to such an investment vehicle. As the data are non-normal, the evaluation of the hedge fund performance can be biased. For example, a statistical analysis such as OLS regression assumes normality. If used, the reported evaluation of hedge fund performance could be distorted. Another example, using the traditional Sharpe ratio (which assumes normality) to evaluate the hedge fund performance may lead to inaccurate findings. Gregoriou,² for instance, compared the Sharpe and modified Sharpe ratios in ranking nine hedge funds. The results show that the modified Sharpe ratio was more accurate than the Sharpe ratio. Gregoriou² proposed a modified value-at-risk (VaR) and modified Sharpe ratio to solve the problem of non-normal returns within alternative investments. However, Eling and Schuhmacher³ show that ranking based on Sharpe ratio is very similar to other performance measures for hedge funds.

Literature that points out the non-normality in hedge fund performance is numerous, such as Eling⁴ who compares between hedge fund returns and traditional investments, and showed that hedge fund returns show significant autocorrelation and fat tails. Kat and Miffre⁵ used the non-normality risks as a source of hedge fund returns to evaluate the hedge fund performance. They found that non-normality risks with tactical asset allocation contribute at least 23 per cent of the abnormal hedge fund performance. This non-normality is not specific to a region or a period; it has also been documented that Asia-Pacific hedge fund

returns suffer from fat tails.⁶ The reason for non-normality of hedge fund performance can be due to their excessive volatility compared to mutual funds and market indices.⁷

The second motivation of this article is to use SVM to evaluate the persistence of hedge fund returns. Previous literature showed that the hedge fund performance is persistent in some cases only. Hence, more research is assumed to be needed to shed light on more cases of persistence. We add to the literature by investigating the role of different strategies in the persistence of hedge fund performance in different economic periods. The sample period is between December 1999 and December 2005. This period is divided into three parts, pre-recession, during-recession and post-recession.

The sensitivity of performance persistence is examined by Agarwal and Naik.⁸ In their study, they find that the highest performance persistence occurs in a quarterly horizon (compared to annual and semi-annual), suggesting short-term performance persistence. Moreover, Agarwal and Naik⁹ show that performance persistence is more pronounced to losing funds, as losers continue to lose as opposed to outperformers who continue to win.

Harri and Brorsen's¹⁰ study confirms that some styles are more persistent than others. They show that performance of hedge funds that adopt the market neutral and two fund-of-fund styles in addition to the styles: event-driven, global and macro global are more persistent than other hedge funds. In addition, Capocci¹¹ proves the persistence of hedge fund returns in some cases only, which coincides with the above-mentioned literature.

The use of different statistical approaches has been documented in previous literature. Malik and Nasereddin¹² forecast output using oil prices

using different statistical methods. In this case, they compare between simple random walk, auto regressive (4), linear with lagged oil and GDP, conventional artificial neural network (ANN) with GDP and oil, cascaded ANN with GDP and cascaded ANN with GDP and oil. The results from their study show that the cascaded ANN has the lowest mean absolute error and the lowest mean error.

SVM has been documented, as well as NN. Li *et al*¹³ conducted a research study in the US stock market. They compared the ANN approach to the SVM approach. The study found that when forecasting volatility, the GARCH-based SVM outperformed the GARCH-based ANN; however, when forecasting volatility trend, the GARCH-based ANN outperformed the GARCH-based SVM.

Similarities between NN and SVM

Both NN and SVM are tools used for classification and prediction.¹⁴ When used for prediction, NN/SVM are provided with historical data (or example data of which the relationship between the inputs and outputs are known) to learn the relationship between the input and output data. Similar to regression, sample data are used to create the SVM/NN model and then the model is used to predict outputs for a specific set of inputs. The main difference with regression is that with both NN and SVM, the relationship between the input variables and the output variables is not explained (black box model). In other words, NN and SVM will not explain how each input variable will affect the output variable, whereas in regression, by looking at the regression formula, the effect of each input variable can be explained (white box model). But

experimentally, both NN and SVM outperform nonlinear regression in terms of prediction accuracy.

NN has been successfully used in many areas including finance and economics.^{15–17} There are few papers in the finance area that explore the use of SVM in finance.¹⁸ The reason is that interest in SVM as a prediction and classification tool is relatively new. When compared, SVM has outperformed NN in many areas, thus showing promise as the prominent classification and prediction tool.

Differences

In terms of structure, NN and SVM are similar; what is different is how they train. In NN (see Figure 1), training is carried out by finding the best set of weights that minimize the error in the training data. There are two main problems with the basic NN:

1. There are many local optimums, and thus NN are known to getting stuck with local optimum solutions (versus global optimum solutions).
2. There is no procedure to pick the optimum number of hidden nodes. It is usually a trial and error type approach that can be time consuming.

Unlike NN, SVM does not have the problem with local optimal because of the way training is carried out. In SVM, the nonlinear solution space (inputs–output relationships) is transformed into a higher space using a kernel function to a quadratic function that only has a single optimum. There are several kernel functions that can be used including Linear, Polynomial, Radial Basis Function (RBF) and

Where: X is the input to the NN/SVM
 Y is the output of the NN/SVM
 P is the Processing unit (Also known as Neuron)
 w is the calculated weight during the training process of NN/SVM
 u is the weighted sum of all of the inputs
 $A(u)$ is the activation function
Bias is 1 or -1

Figure 1: Basic structure of NN and SVM.

Sigmoid (S-shaped). There is no way in advance to know which function will perform the best, and thus some experimentation is needed for each data set to find the best kernel function.

Data

Returns of individual hedge funds were collected from the Center for International Securities and Derivatives Markets (CISDM) for the period March 2000 –December 2005. The

ends of quarter-monthly returns for hedge funds were used to find the important hedge fund strategies.

The data acquired from CISDM contained many missing values for independent variables within the data points. For example, for the January of 2005 data there was no information about the type of stock for 574 data points (is it common stock or preferred stock and so on) There were two ways to deal with this issue. The first was to use the median value for that

independent variable. The second was to eliminate the data points that had missing data about the independent variables. As many of our independent variables were of the binary nature (for example, common stock had two values: one if it is a common stock, and zero if it was not), we decided to eliminate data points that had missing information about independent variables.

The collected variables are:

- (Dependent variable) Monthly returns for individual hedge funds.
- (Independent variables) Strategies/styles of hedge funds: equity long only, equity long/short, equity market neutral, event-driven multi-strategy, fixed income, fixed income – Mortgage Backed Security (MBS), fixed income arbitrage, global macro, market timing, merger arbitrage, multi strategy, option arbitrage, other relative value, distressed securities, capital structure arbitrage, convertible arbitrage, relative value multi strategy, sector focus, short bias, offshore and emerging markets.
- (Independent variables) Methodology of hedge funds: bottom up, top down, fundamental, technical, systematic, discretionary, relative value, directional and other.
- (Independent variables) Instruments used: common stock, preferred stock, corporate investment grade bonds, government bonds, convertible bonds, options, futures forward contracts, swaps, credit default swaps, rights warrants, mutual funds, ETFs indexes, Asset Backed Security (ABS) MBS, Collateralized Debt Obligation (CDO), trade claims and bank debt.
- (Control variables): minimum investment, redemption notice period, management fees, incentive fees, assets under management and redemption frequency.

METHODOLOGY

Type of NN used

There are many types of NN used for prediction. The most popular is feedforward NN.¹⁹ Hornik *et al*²⁰ showed that a feedforward NN with a single hidden layer can approximate any continuous function. For this reason, a feedforward NN with a single hidden layer was used in our analysis.

Type of SVMs used

A standard SVM was used. For our data set, we looked at four different kernel functions (Linear, Polynomial, RBF and Sigmoid). An SVM with an RBF kernel function performed the best in terms of minimizing the Mean Square Error (MSE).

CROSS-VALIDATION

As in this article we are not mainly interested in the interpolating capabilities of our models (model fit) but are more interested in the extrapolating capabilities of our models (forecasting capability), cross-validation was used. As illustrated in Table 1, the data set was divided into five categories (A, B, C, D and E). The first four data sets (A, B, C and D) were used to build the models (Regression, NN and SVM). The prediction capability of each model was then tested using the last data set (E). In other words, after building the models with the first four data sets (A, B, C and D), we used those independent variables in the last data set (E) to calculate the predicted value of the dependent variable (Return). Then we compared the predicted value with the actual value, thus allowing us to calculate the mean square error and adjusted R^2 . The process was then repeated four times, each time using different data sets for

Table 1: An illustration of the cross validation

<i>Model</i>	<i>Data sets used to build the models (Sample)</i>	<i>Data set used to validate the model (Out-of-sample)</i>
1	ABCD	E
2	BCDE	A
3	ACDE	B
4	ABDE	C
5	ABCE	D

building the models and a different data set to validate the model (as per Table 1). The mean squared error and the adjusted R^2 were then aggregated for each model (MSEs and adjusted R^2 were averaged) in order to get the values reported in Tables 2 and 3.

EMPIRICAL RESULTS

Table 2 presents a comparison between the SVM R -squared and NN R -squared.²¹ The same variables were used in both techniques. The predictability of the two models based on the R -squared is discussed in this section. Overall, the results show that the SVM consistently outperformed the NN in all of the months that were studied. In some instances, such as in September 2000, the SVM R -squared was 27 per cent, whereas the NN R -squared was 0 per cent. A majority of the results showed a big difference between the SVM R -squared and the NN R -squared. In only a few instances the difference was small and only one showed the lowest difference of 1 per cent, which was in June 2001. The R -squared range is from 1 per cent to 27 per cent for the SVM and 0 per cent to 16 per cent for the NN.

The number of points analyzed ranged from 429 data points in March 2000 to 1189 in

October 2005. The number of unused data points was high in the early years (2000–2003), whereas the number of unused data points was much smaller in later years. These data points were not used because they were missing values for some of the independent variables.

The NN performed poorly in most of the months, especially between March 2000 and September 2001. In all of those reported months, the R -squared was 0 per cent. This period spans the pre-recession and during recession periods. The best-reported r -squared was 16 per cent in December 2001. The SVM performance was not affected by the time periods, although the single digit R -squared incidents were more pronounced in the early years rather than in 2005.

Table 3 presents a comparison between the SVM MSE and NN MSE. In all the reported cases, SVM MSE was smaller than the NN MSE except for one case (February 2005). This confirms the same results discussed in Table 1 about the outperformance of the SVM over the NN.

Tables 4, 5 and 6 present the results of the SVM. In these tables, the independent variables are ranked based on their importance as a determinant of the dependent variable (returns). The reported variables are the most significant top ten variables in terms of contribution to the

Table 2: A comparison between SVM R -squared and NN R -squared

<i>Month</i>	<i>Year</i>	<i>N</i>	<i>SVM</i> <i>R-squared (%)</i>		<i>NN</i> <i>R-squared(%)</i>
3	2000	429	9	>	0
6	2000	448	3	>	0
9	2000	476	27	>	0
12	2000	500	6	>	0
3	2001	535	11	>	0
6	2001	553	1	>	0
9	2001	569	21	>	0
12	2001	601	20	>	16
3	2002	646	20	>	1
6	2002	677	16	>	1
9	2002	723	14	>	10
12	2002	755	9	>	5
3	2003	806	10	>	0
6	2003	830	8	>	0
9	2003	871	13	>	8
12	2003	904	16	>	12
3	2004	957	7	>	0
6	2004	1003	18	>	2
9	2004	1046	22	>	11
12	2004	1091	12	>	5
1	2005	1123	19	>	8
2	2005	1127	15	>	0
3	2005	1137	6	>	1
4	2005	1132	11	>	2
5	2005	1150	17	>	4
6	2005	1158	13	>	5
7	2005	1172	15	>	3
8	2005	1163	14	>	4
9	2005	1177	22	>	14
10	2005	1189	26	>	0
11	2005	1175	24	>	8
12	2005	1168	20	>	11

Table 3: A comparison between SVM MSE and NN MSE

<i>Month</i>	<i>Year</i>	<i>N</i>	<i>SVM MSE</i>		<i>NN MSE</i>
3	2000	429	0.008784	<	0.0107844
6	2000	448	0.004264	<	0.0044646
9	2000	476	0.000979	<	0.0035529
12	2000	500	0.002751	<	0.0030044
3	2001	535	0.001929	<	0.0023513
6	2001	553	0.003042	<	0.003221
9	2001	569	0.002718	<	0.0034557
12	2001	601	0.001166	<	0.0014231
3	2002	646	0.000988	<	0.0012205
6	2002	677	0.001948	<	0.0023083
9	2002	723	0.001992	<	0.0020738
12	2002	755	0.001217	<	0.001276
3	2003	806	0.000773	<	0.0008697
6	2003	830	0.001222	<	0.0013555
9	2003	871	0.000956	<	0.0010116
12	2003	904	0.000786	<	0.0008184
3	2004	957	0.000896	<	0.0010326
6	2004	1003	0.000506	<	0.0006029
9	2004	1046	0.000767	<	0.0008774
12	2004	1091	0.000884	<	0.0009571
1	2005	1123	0.000677	<	0.000766
2	2005	1127	0.068810	>	0.0007767
3	2005	1137	0.001035	<	0.0010919
4	2005	1132	0.001041	<	0.0011495
5	2005	1150	0.000967	<	0.0011147
6	2005	1158	0.000556	<	0.0006065
7	2005	1172	0.001046	<	0.0011917
8	2005	1163	0.000710	<	0.0007925
9	2005	1177	0.001208	<	0.001335
10	2005	1189	0.000671	<	0.001124
11	2005	1175	0.000525	<	0.0006294
12	2005	1168	0.000788	<	0.0008732

prediction capability of the model. The variables include both the strategies, which this article is interested in, as well as the control variables. The difference between those tables is the difference in the economic time period analyzed.

Table 4 shows the important variables for the pre-recession period. The period covered in this table is between March and December 2000. The results do not show persistence in the strategy/style adopted by hedge funds. However, sector focus and offshore strategies were important variables for 3 months (June, September and December 2000). Sector focus was the most important in one of those months (June 2000), whereas offshore was the most important independent variable in December 2000. In addition, the emerging markets strategy/style was important in two of the four months analyzed (June and September 2000) and was the most important in September 2000. Moreover, the rights warrants strategy/style was one of the most important strategies in 2 months (September and December).

It is also noted that although the emerging markets style was not one of the top most

important variables in December 2000, global macro was. Other styles/strategies such as fundamental, technical, corporate bonds were non-persistent strategies in the determination of hedge fund returns.

Table 5 shows the important variables during recession. In this case, the emerging markets strategy/style is persistent in determining the returns. In such, it was ranked the most important variable in all four months (March, June, September and December of 2001). This remarkable strategy persistence during the recession period suggests that persistence occurs in only a few times. This shows that if hedge funds managers were able to invest in the emerging markets (that is, time the market with this specific strategy), they would have affected the returns. Other strategies did not show such persistence. However, during the recession period some of the strategies that were not presented in the pre-recession were among the most important variables such as short bias, government bonds, and event-driven multi-strategy. These results are consistent with the common trading strategies during a recession.

Table 4: Important variables that affect the returns of hedge funds for the pre-recession period

<i>March 2000</i>	<i>June 2000</i>	<i>September 2000</i>	<i>December 2000</i>
Weekly	Sector	Emerging markets	Offshore
Bottom up	Corporate bonds	Active	Monthly
Top down	Active	Futures forward cont	Rdmpt notice period
Fundamental	Quarterly	Corporate bonds	Incentive fee ANN
Relative value	Emerging markets	Options	Rights warrants
Swaps	Offshore	Equity long/short	Options
Technical	Futures forward cont	Quarterly	Sector
Discretionary	Monthly	Rights warrants	Global macro
ABS MBS	Options	Offshore	Quarterly
Preferred stock	Bottom up	Sector	Corporate bonds

Table 5: Important variables that affect the returns of hedge funds during the recession period

<i>March 2001</i>	<i>June 2001</i>	<i>September 2001</i>	<i>December 2001</i>
Emerging markets	Emerging markets	Emerging markets	Emerging markets
Sector	Rights warrants	Monthly	Bottom up
Equity long/short	Options	Futures forward cont	Preferred stock
Monthly	Offshore	Equity long/short	Government bonds
Active	Merger arbitrage	Short bias	Relative value
Rdmpt notice period	Active	Sector	Fundamental
Offshore	Common stock	Corporate bonds	ABS MBS
Convertible arbitrage	Monthly	Options	Top down
Global macro	Quarterly	Event-driven multi strategy	Trade claims
Quarterly	Event-driven multi strategy	Offshore	ETFs indexes

For example, because of the falling share prices, short-bias funds normally outperform long-bias funds. Moreover, as government bonds are among the safest securities, they are in demand during recession periods. And finally being picky in timing, the market is consistent with the event-driven multi-strategy.

Table 6 presents the independent variables ranked based on their importance as a determinant of the dependent variable (returns). The period covered is the post-recession time, which is from March 2002 to December 2005. In this period, as a robustness check, in addition to the quarterly end-of-month analysis, we conducted the analysis for all of the months in 2005. The results confirm the non-persistence of strategies as important determinants to hedge fund returns.

LIMITATIONS OF DATA

The data collected for the hedge fund industry are self-reported based on the regular

information (usually monthly) that is released to existing and potential investors. Jones²² reported in an article published by *The Financial Times* that about 20 per cent of hedge funds misrepresent the reporting data about the fund or its performance to its investors during the due diligence process.

There are two additional reported data biases documented by previous literature:

The first bias is the survivorship bias. This bias occurs because of the exclusion of failed or defunct hedge funds from the database. This may cause the performance of hedge funds to suffer from an upward bias. There are two commonly used definitions of this bias: One is the difference in hedge fund performance between surviving and dissolved (or defunct) funds.^{1,7} And the second definition is the difference in hedge fund performance between living and all funds.^{1,23}

The survivorship bias is more likely to be a problem in data collected before 1994.²⁴ Although our sample spans from 1999, there

Table 6: Important variables that affect the returns of hedge funds for the post-recession period

<i>March 2002</i>	<i>June 2002</i>	<i>September 2002</i>	<i>December 2002</i>	<i>March 2003</i>
Emerging markets	Emerging markets	Emerging markets	Corporate bonds	Fundamental
Short bias	Bottom up	Options	Options	Bottom up
Equity long/short	Rights warrants	Monthly	Offshore	Top down
Sector	Fundamental	Equity long/short	Equity long/short	Convertible bonds
Futures forward cont	Systematic	Futures forward cont	Futures forward cont	ETFs indexes
Active	Active	Rights warrants	Common stock	Preferred stock
Offshore	Technical	Quarterly	Monthly	Relative value
Options	Corporate bonds	Offshore	Active	Systematic
Corporate bonds	Swaps	Corporate bonds	Rights warrants	Technical
Bottom up	Discretionary	Active	Quarterly	Mutual funds
<i>June 2003</i>	<i>September 2003</i>	<i>December 2003</i>	<i>March 2004</i>	<i>June 2004</i>
Bottom up	Emerging markets	Monthly	Options	Min investment
Fundamental	Equity long only	Quarterly	Emerging markets	Rdmpt notice period
Technical	Global macro	Emerging markets	Equity long/short	Mgmt fee ANN
ETFs indexes	Offshore	Bottom up	Rights warrants	Incentive fee ANN
Swaps	Quarterly	Top down	Bottom up	Corporate bonds
Government bonds	Monthly	Fundamental	Min investment	Preferred stock
Top down	Active	Technical	Offshore	Rights warrants
Preferred stock	Options	Convertible bonds	Quarterly	Convertible bonds
Discretionary	Annually	ETFs indexes	Common stock	Common stock
Convertible bonds	Distressed securities	Swaps	Active	Offshore
<i>September 2004</i>	<i>December 2004</i>	<i>January 2005</i>	<i>February 2005</i>	<i>March 2005</i>
Emerging markets	Corporate bonds	Fundamental	Offshore	Fundamental
Equity long/short	Rights warrants	Bottom up	Futures forward cont	Bottom up
Options	Options	Top down	Equity long/short	Preferred stock
Sector	Monthly	ETFs indexes	Emerging markets	Top down
Futures forward cont	Equity long/short	Rdmpt notice period	Fundamental	Swaps
Offshore	Emerging markets	Discretionary	Corporate bonds	Relative value
Quarterly	Sector	Systematic	Bottom up	ETFs indexes
Corporate bonds	Futures forward cont	Preferred stock	Options	Government bonds
Active	Quarterly	Futures forward cont	Rights warrants	Convertible bonds
Rights warrants	Offshore	Government bonds	Common stock	Directional

Table 6 *Continued*

<i>April 2005</i>	<i>May 2005</i>	<i>June 2005</i>	<i>July 2005</i>	<i>August 2005</i>
Equity long/short	Options	Equity long/short	Bottom up	Equity long/short
Active	Futures forward cont	Active	Options	Options
Options	Equity long/short	Futures forward cont	Corporate bonds	Quarterly
Corporate bonds	Bottom up	Corporate bonds	Equity long/short	Offshore
Futures forward cont	Offshore	Quarterly	Fundamental	Corporate bonds
Offshore	Fundamental	Sector	Preferred stock	Fundamental
Quarterly	Rights warrants	Options	Swaps	ETFs indexes
Monthly	Corporate bonds	Monthly	ETFs indexes	Monthly
Sector	ETFs indexes	Offshore	Active	Common stock
Rights warrants	Top down	Rights warrants	Monthly	Futures forward cont
<i>September 2005</i>	<i>October 2005</i>	<i>November 2005</i>	<i>December 2005</i>	
Bottom up	Options	Emerging markets	Futures forward cont	
Fundamental	Futures forward cont	Corporate bonds	Options	
ETFs indexes	Offshore	Futures forward cont	Rights warrants	
Bank dept	Corporate bonds	Options	Fundamental	
Futures forward cont	Rights warrants	Fundamental	Bottom up	
Trade claims	Equity long/short	Rdmpt notice period	Monthly	
Options	Common stock	Common stock	Offshore	
Rights warrants	Fundamental	Rights warrants	Equity long/short	
Emerging markets	Bottom up	Bottom up	Emerging markets	
Top down	Quarterly	Equity long/short	Quarterly	

could be a possibility that the collected data may still suffer from this bias because of the self-reporting issue.

The second bias is the backfill bias. This bias occurs because the data are backfilled with performance data after new hedge funds are added to the database.^{1,25} In addition, this may cause the performance to be upwardly biased.

CONCLUSIONS

The hedge fund industry performance is of interest to many academic and professional

studies because of the publicity about huge returns or steep losses. This article investigates the persistence of some strategies as determinant to hedge fund returns during different economic time periods using the SVM approach (and in comparison to other commonly used statistical methods such as NN and OLS). The economic period investigated is between 2000 and 2005. This article divides this period into three sub-periods: pre-recession, during recession and post-recession. The results show that, first, the SVM has better prediction accuracy than NN and OLS because of its flexibility in data fit. And

second, the results show that hedge fund strategies are not persistent in the determination of returns. However, the emerging markets strategy/style during the recession was persistent to hedge fund returns. Other strategies were consistent to be non-persistent.

The implications of these results are beneficial to both academics and professionals. First, it confirms the previous literature that the OLS has a very poor accuracy in predicting the performance if the data are non-normal with fat tails. However, this article highlights that NN can be outperformed by the SVM, which provides a better prediction accuracy. Second, timing the market is still an important strategy. Therefore, consistently investing in a fixed strategy will not consistently outperform the market. However, the emerging market strategy has more persistence than other strategies adopted by hedge funds, especially during down time.

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