Key words: hedge funds; predictive regressions; stationarity

Are hedge fund returns predictable?

While earlier empirical research found that stock, bond and hedge fund returns can be predicted with conventional financial and economic variables, recent econometric studies have shown that predictive regressions are spurious when the forecasting instrument is a non-stationary variable. After examining the predictability of hedge fund index returns with stationary forecasting variables, our findings suggest that the forecasting variables discovered in previous studies are statistically insignificant at predicting hedge fund index returns.

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THE ABILITY TO FORECAST FINANCIAL MARKET RETURNS can be economically significant in the areas of tactical asset allocation and other forms of active asset management. Predicting stock and bond returns has become the holy grail of funds management and legions of researchers have allocated tremendous resources towards this effort. Two decades ago, empirical researchers such as Keim and Stambaugh (1986), Campbell (1987) and Fama and French (1989) discovered that economy-wide variables (such as the US Treasury-bill rate, term spread, term structure of interest rates, default spread and dividend yield) exhibit predictive power in explaining the variability of equity and bond market returns. Subsequent studies by Kandel and Stambaugh (1996), Campbell and Viceira (2002), and Fleming, Kirby and Ostdiek (2001) have found that shifts in asset allocation from these predictive variables are economically significant even when the forecasting variable exhibits low forecasting power or R^2.

The empirical evidence that stock and bond returns can be predicted has led other researchers to examine whether these same forecasting variables can be employed to forecast hedge fund returns. Seminal hedge fund studies by Fung and Hsieh (2004) and Agarwal and Naik (2004) have shown that a large proportion of the variation of hedge fund returns can be explained by market-related factors, however, these replication models cannot be employed to forecast hedge fund returns. The emergence of hedge fund forecasting models by Amenc, El Bied and Martellini (2003) and Hamza, Kooli and Roberge (2006) has revealed that hedge fund returns can be predicted with economy-wide variables including the equity returns, VIX volatility index, oil prices, changes in market volume and US Treasury bill rates.

The empirical studies mentioned thus far support the view that these forecasting variables capture time-varying risk premiums in the market. However, is this evidence as statistically convincing as it appears to be? If stock, bond and hedge fund returns are truly predictable, why haven't these forecasting models been applied out-of-sample to achieve abnormal profits for active fund managers in the global funds management industry?

Spurious regressions

A new body of research has emerged that criticises the econometric techniques employed in predictive models in finance. Ferson, Sarkissian and Simin (2003) have highlighted the econometric problem of the persistence and non-stationarity of ordinary least squares (OLS) regressors and have cast doubt on the evidence of predictability. When an OLS regression of returns is estimated on the lag of a predictive variable that is persistent (i.e. non-stationary), it results in a non-standard distribution that causes an over-rejection of the null hypothesis. As a consequence, the predictive variable seems to exhibit predictability when, in fact, the entire exercise is a spurious regression. The studies by Lanne (2002), Torous, Valkanov and Yan (2004), Goyal and Welch (2007), Boudoukh, Richardson and Whitelaw (2009), and Ang and Bekaert (2007) have confirmed this weakness in previous empirical finance studies. These findings suggest that many of the models that employ non-stationary forecasting variables to predict stock, bond and hedge fund returns may be erroneous.

Stationary versus non-stationary data

To highlight this problem, it is important to understand the difference between stationary and non-stationary time series data. Stationary time series data exhibit a constant mean and variance; these data series do not change through time and are referred to as time-invariant. This means that a probability distribution for the data is the same regardless of the point in time at which the data are sampled. As a consequence, the estimated coefficients from an OLS regression will tend to exhibit stable parameters and reliable statistical inference from their standard errors.

In contrast, non-stationary data exhibit a mean and variance that is dependent on the time period from which the data are sampled. As a result, the estimated coefficients from an OLS regression are spurious. Many economic statistics are non-stationary in nature as they tend to grow steadily over time. Examples of non-stationary data include gross domestic product, the consumer price index and hourly wages over time. Hypothesis tests known as unit root tests have been developed to test the stationarity of time series data. Some of these include the Dickey and Fuller (1979) DF test and the augmented Dickey-Fuller (ADF) test, which can control for autocorrelation in the error terms of the hypothesis test.

To solve this data problem, it is possible to convert non-stationary times series data into stationary data by estimating the first difference, i.e. $x_t - x_{t-1}$ or by calculating arithmetic or log returns from the data. The difference between stationary and non-stationary data can be easily demonstrated by using the oil spot market as an example. Figure 1 illustrates oil spot prices that are non-stationary in nature as the estimated mean and variance will be dependent upon the time period you sample from. We calculate the ADF hypothesis test based on the null hypothesis of non-stationarity and we report a test statistic of 1.268 that is greater than the ADF critical value of -3.470. Thus we cannot reject the null hypothesis of non-stationarity. Figure 2 illustrates the same data as Figure 1 but the oil spot prices are converted to log or continuous compounded returns. The ADF test statistic for the time series data in Figure 2 is -13.712, which is below the critical value of -3.470 that signifies we can reject the null hypothesis of non-stationarity and report that oil returns are indeed stationary. This simple transformation of the data alleviates the problem of non-stationarity and allows the researcher to genuinely examine whether financial and economic data can truly forecast hedge fund returns. In light of this, we can reassess the stationary nature of forecasting variables that have been reported to predict hedge fund returns.

FIGURE 1: **West Texas Intermediate oil prices – non-stationary time series**
ADF test statistic 1.268, critical value = -3.470, p-value 0.998

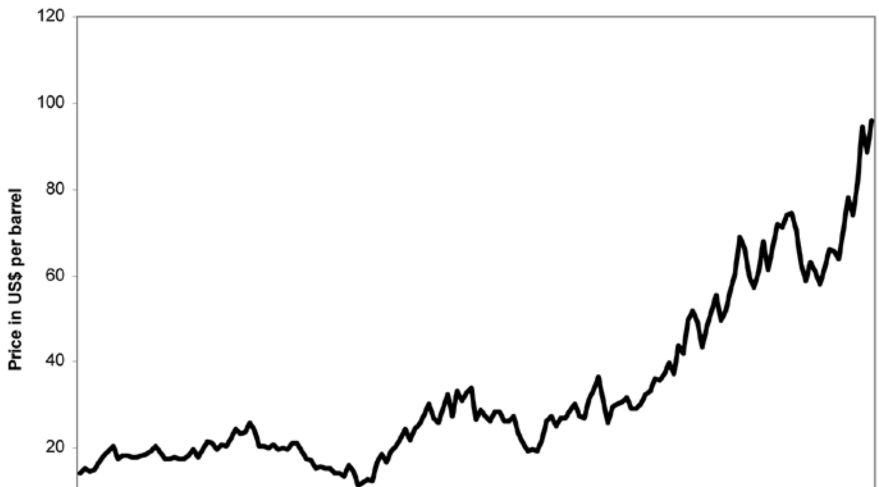

FIGURE 2: **West Texas Intermediate oil price continuous returns – stationary series**
ADF test statistic -13.712, critical value -3.470, p-value 0.000

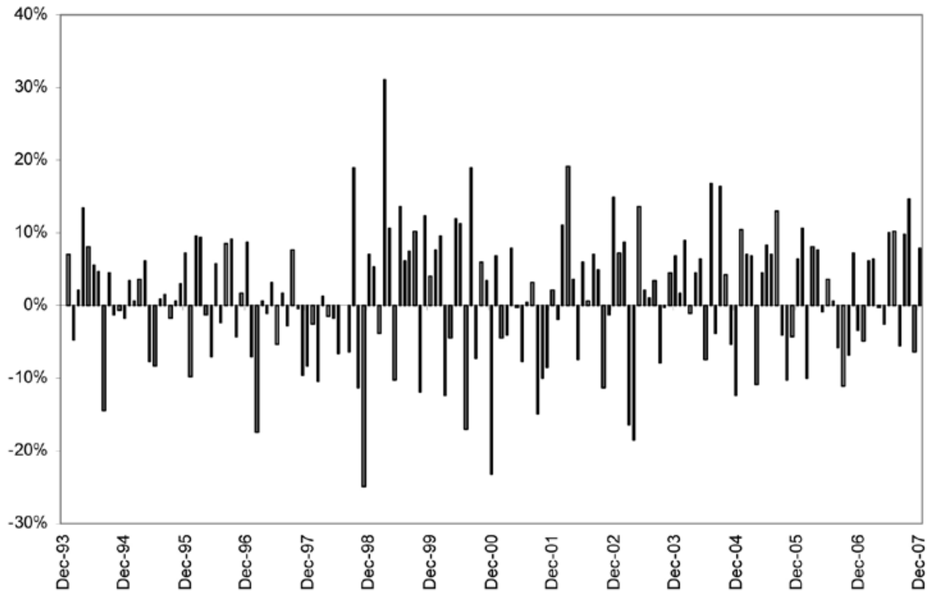

TABLE 1: **Summary statistics of various forecasting variables**

	Oil Price	Oil Return	T-Bill Yield	ΔT-Bill	ΔVIX	ΔVol.	S&P500 Return	MSCI Return
Panel A: Descriptive Statistics								
Mean	32.753	0.011	0.040	0.0001	0.085	0.025	0.008	0.006
Std. Dev.	18.893	0.088	0.016	0.002	3.568	0.145	0.040	0.042
Skewness	1.231	-0.159	-0.707	-1.097	0.514	0.009	-0.758	-0.724
Kurtosis	3.448	3.395	2.082	5.459	11.145	2.544	4.250	3.991
Median	26.305	0.017	0.047	0.0001	0.035	0.017	0.013	0.009
Max.	94.530	0.311	0.064	0.005	16.980	0.347	0.093	0.098
Min.	11.260	-0.249	0.009	-0.008	-17.840	-0.376	-0.156	-0.154
J-Bera Stat.	43.817	1.801	19.886	22.696	471.787	1.451	27.172	21.541
J-B p-value	0.001**	0.406	0.003*	0.000**	0.000**	0.484	0.001**	0.002**
Panel B: Autocorrelation (First Moment)								
AC1	0.986**	-0.065	0.992**	0.435**	-0.115	-0.487	-0.002	0.074
AC2	0.974**	-0.157	0.979*	0.320**	-0.144	-0.029	-0.040	-0.053
AC3	0.967**	0.109	0.960	0.339**	-0.116*	0.244	0.049	0.037
AC6	0.940**	0.148*	0.880*	0.275**	-0.077		0.082	0.087
Panel C: Autocorrelation (Second Moment)								
AC1	0.978**	0.066	0.988**	0.298**	0.262**	0.118	0.118	-0.009
AC2	0.959**	0.061	0.967**	0.088**	-0.007**	-0.002	0.228**	0.196*
AC3	0.950**	-0.022	0.940	0.180**	-0.002**	-0.035	0.138	-0.051
AC6	0.902**	0.113*	0.824**	0.107**	0.039		0.144	0.068
Panel D: Stationarity Test								
ADF Statistic	1.268	-13.712**	-2.006	-3.642**	-14.417**	-15.830**	-12.848**	-12.189**

This table presents the summary statistics of the forecasting variables employed in this study for the January 1994 to December 2007 period. Panel A presents the descriptive statistics and Jarque-Bera test. Panel B reports the autocorrelation of returns from one to six months. Panel C provides the autocorrelation of squared returns from one to six months. Panel D presents the augmented Dickey-Fuller test statistic based on the null hypothesis of non-stationarity. * and ** denote statistical significance at the 5% and 1% levels, respectively.

TABLE 2: **Summary statistics of hedge fund index returns**

	Convertible Arbitrage	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Incme Arbitrage
Panel A: Descriptive Statistics					
Mean	0.0038	0.0047	0.0047	0.0061	0.0018
Std. Dev.	0.0131	0.0459	0.0079	0.0163	0.0107
Skewness	-1.4360	-1.2466	0.1571	-3.7032	-3.0918
Kurtosis	6.6365	10.1041	3.5665	30.5896	19.9818
Median	0.0061	0.0122	0.0043	0.0083	0.0038
Max.	0.0306	0.1489	0.0279	0.0337	0.0168
Min.	-0.0520	-0.2674	-0.0159	-0.1301	-0.0756
J-Bera Stat.	150.3103	396.7829	2.9376	5712.2881	2286.3410
J-B p-value	0.0010**	0.0010**	0.1733	0.0010**	0.0010**
Panel B: Autocorrelation (First Moment)					
AC1	0.5254**	0.2881**	0.2496**	0.3021**	0.3761**
AC2	0.3085**	0.0241	0.1051	0.1116	0.0301
AC3	0.0966	0.0137	0.0375	0.0164	-0.0012
AC6	-0.0040	-0.1135	-0.0249	-0.0412	-0.0621
Panel C: Autocorrelation (Second Moment)					
AC1	0.3903**	0.0728	0.1569*	0.0421	0.3005**
AC2	0.3003**	-0.0114	0.2757**	-0.0201	0.0583
AC3	-0.0291	0.1128	0.0129	0.0185	0.0225
AC6	-0.0381	-0.0069	0.2207**	0.0007	0.0025
Panel D: Stationarity Test					
ADF Statistic	-6.944**	-9.761**	-9.604**	-9.503**	-8.635**

This table presents the summary statistics of the hedge fund index returns employed in this study. The summary statistics are for the period January 1994 to December 2007. Panel A presents the descriptive statistics of the hedge fund indices. Panel B reports the autocorrelation of returns from one to six months. Panel C presents the autocorrelation of squared returns from one to six months. Panel D reports the augmented Dickey-Fuller test statistic based on the null hypothesis of non-stationarity. * and ** denote statistical significance at the 5% and 1% levels, respectively.

Data and methodology

This study examines the validity of the forecasting variables discovered in Amenc et al. (2003) by re-estimating their models with predictive variables that are stationary. By utilising forecasting variables that are stationary, we can reassess the genuine power of these variables to forecast hedge fund returns. We employ the same forecasting variables and hedge fund index returns as in Amenc et al. (2003), however, we extend the 1994–2000 analysis by estimating the models out-of-sample from 2001 to 2007. The forecasting variables include oil spot prices, the US three-month Treasury bill yield, the change in the VIX Volatility index, the change in the NYSE market volume, S&P 500 returns and the MSCI World Equity Index excluding US returns. Tables 1 and 2 summarise the descriptive statistics of the forecasting variables and the hedge fund index returns, respectively.

A closer inspection of Panel D in Table 1 reveals the ADF tests of stationarity. Panel D reports that all time series data are stationary with the exception of oil spot prices and US Treasury Bill yields that were discovered as significant forecasting variables in previous hedge fund studies. In this analysis, we rectify this non-stationarity problem by transforming the data into spot oil returns and the change in the T-bill yield. The ADF tests in Panel D of Table 1 show that spot oil returns and the change in the T-bill yield are indeed stationary variables that can be readily employed in a predictive regression.

This study employs the predictive multi-factor models as in Amenc et al. (2003), however, we augment them to ensure that all forecasting variables are stationary. The augmented models employed in this study are mathematically expressed as:

$$R_{\text{Convertible},t} = \alpha + R_{\text{Convertible},t\text{-}1} + MA(\text{S\&P } 500_{t\text{-}1}) + Oil\ Return_{t\text{-}1} + \Delta\, T\text{-}bill_{t\text{-}1} + \varepsilon_t \quad (1)$$

$$R_{\text{Emerging},t} = \alpha + R_{\text{Emerging},t\text{-}1} + Oil\ Return_{t\text{-}1} + MA(\text{MSCI}_{t\text{-}1}) + \varepsilon_t \quad (2)$$

$$R_{\text{Equity Market Neutral},t} = \alpha + MA(\text{S\&P } 500_{t-1}) + Oil\ Return_{t-1} + \Delta T\text{-}bill_{t-1} + \varepsilon_t \quad (3)$$

$$R_{\text{Event Driven},t} = \alpha + R_{\text{Event Driven},t-1} + Oil\ Return_{t-1} + \varepsilon_t \quad (4)$$

$$R_{\text{Fixed Income Arbitrage},t} = \alpha + MA(\text{S\&P } 500_{t-1}) + Oil\ Return_{t-1} + \Delta VIX_{t-1} + Vol_{t-1} + \varepsilon_t \quad (5)$$

$$R_{\text{Global Macro},t} = \alpha + R_{\text{Global Macro},t-1} + MA(\text{S\&P } 500_{t-1}) + Oil\ Return_{t-1} + Vol_{t-1} + \varepsilon_t \quad (6)$$

where: $R_{i,t}$ represents the return on a hedge fund style at time t; $MA(\text{S\&P } 500_{t-1})$ is the historical three-month moving average of the return on the S&P 500; $Oil\ Return_{t-1}$ is the previous month oil price return; $\Delta T\text{-}bill_{t-1}$ is the change in the three-month treasury bill rate at time t-1; $MA(\text{MSCI}_{t-1})$ is the historical three-month moving average of the return on the Morgan Stanley Composite World Equity Index ex US; ΔVIX_{t-1} is the change in the intramonth average of the VIX volatility index; Vol_{t-1} is the dollar value of shares traded on the New York Stock Exchange; and ε_t is the error term.

TABLE 3: OLS predictive regressions with stationary forecasting variables

Regression Variable	Convertible Arbitrage	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro
Panel A: 1994–2000						
α	0.0010 (0.0018)	0.0007 (0.0061)	0.0053** (0.0013)	0.0037 (0.0022)	-0.0009 (0.0019)	0.0042 (0.0059)
$R_{i,t-1}$	0.5241** (0.1282)	0.2983* (0.0926)		0.3331* (0.0532)		-0.0106 (0.1218)
MA(S&P)	0.1303* (0.0639)		0.0347 (0.0344)		0.2323** (0.0787)	0.3728 (0.3031)
Oil returns	0.0078 (0.0135)	0.0362 (0.0598)	0.0086 (0.0116)	-0.0016 (0.0137)	-0.0047 (0.0119)	-0.0082 (0.0439)
Δ T-bill	-1.1228 (1.0692)		-1.3073 (0.4960)			
Δ VIX					-0.0012 (0.0007)	
Δ Volume					-0.0044 (0.0066)	-0.0434 (0.0270)
MA(MSCI)		-0.0240 (0.2632)				
Adj R^2	0.3886	0.0548	0.0322	0.0886	0.2424	0.0013
Panel B: 2001–2007						
α	0.0019 (0.0012)	0.0087* (0.0026)	0.0040** (0.0007)	0.0057** (0.0018)	0.0025 (0.0009)	0.0085** (0.0015)
$R_{i,t-1}$	0.3892** (0.1065)	0.2031 (0.1182)		0.2340 (0.1315)		0.0591 (0.1001)
MA(S&P)	-0.0264 (0.0422)		-0.0104 (0.0245)		0.0307 (0.0570)	0.0325 (0.0413)
Oil returns	-0.0114 (0.0143)	-0.0391 (0.0286)	0.0032 (0.0077)	-0.0235 (0.0125)	-0.0053 (0.0109)	-0.0136 (0.0156)
Δ T-bill	-0.7717 (0.4631)		-0.2859 (0.2475)			
Δ VIX					0.0000 (0.0002)	
Δ Volume					0.0061 (0.0067)	-0.0053 (0.0083)
MA(MSCI)		-0.0173 (0.0820)				
Adj R^2	0.1648	0.0131	0.0000	0.0471	0.0000	0.0000

This table presents the ordinary least squares (OLS) predictive regressions results of Thomson/Tremont hedge fund indices. The regression coefficients are estimated with Newey-West (1987) corrected standard errors for heteroscedasticity and autocorrelation. These regression estimates employ stationary forecasting variables only. The time period is from January 1994 to December 2007. The table reports the regression coefficients and the standard errors are displayed in the parentheses. * and ** denote statistical significance at the 5% and 1% levels, respectively.

To address the problem of heteroscedasticity and autocorrelation, Amenc et al. (2003) employ the Generalized Least Squares (GLS) estimation method. Fox (1997) informs us that GLS is an inappropriate estimation method (in the presence of auto-correlated errors) when the dependent variable appears as a lagged effect on the right-hand side of a model. This raises two issues. First, the statistically significant autocorrelation of returns (for one month) of hedge fund index returns in Panel B of Table 2 clearly provides us with the knowledge that the residuals in these regressions will exhibit autocorrelation. Second, equations 1 to 6 show us that this GLS problem exists here, as the dependent variable is indeed a lagged variable on the right-hand side of these models. To address the weakness of GLS and the problems of heteroscedasticity and autocorrelation, this study employs an ordinary least squares (OLS) regression with Newey and West (1987) corrected standard errors.

Empirical results

Table 3 presents the regression estimates for the 1994–2000 period and the out-of-sample results from 2001 to 2007. The first observation from Table 3 is that the size of the S&P 500 factor loading declines in the out-of-sample period and becomes statistically insignificant. Second, spot oil returns are statistically insignificant in both in-sample and out-of-sample test periods. This finding differs from previous studies that employed the non-stationary oil *prices* as the forecasting variable. It is clear that stationary oil *returns* cannot forecast hedge fund index returns, and non-stationary oil *prices* provide erroneous results when used as a forecasting variable. The third observation from Table 3 is the statistical insignificance of the *change* in T-bill yields (which is stationary) in both sample periods. Once again, previous studies show that non-stationary T-bill yields provide statistically significant results as a forecasting variable of hedge fund index returns when, in fact, they do not. Again, the results in this study differ from the findings in previous studies because we are employing changes in T-bill yields, which are a stationary variable.

Table 3 also reveals that changes in the VIX, market volume and the moving average of the global equity returns are all statistically insignificant in both sample periods. These findings are new as previous studies have concluded that these variables can also forecast hedge fund index returns. The differences in these findings can be explained by the fact that the OLS method employed in this study provides robust estimates in comparison to the weaknesses in the GLS method employed in previous studies. Table 3 reports that the single variable that seems

The lesson from this study is that forecasting models in traditional and alternative asset classes must be carefully developed in order to ensure their methodological validity.

to predict hedge fund index returns is the lagged dependent variable. One must treat this finding with caution as studies by Asness, Krail and Liew (2001) and Getmansky, Lo and Makarov (2004) inform us that many hedge fund returns exhibit significant autocorrelation, which can be explained by stale pricing, illiquidity and non-synchronous effects. Second, from a practical point of view, the publication of the monthly rates of return from hedge fund index providers generally occurs in the last seven to 14 days of the following month, which tends to be too late for this information to be exploited by an investor.

Finally, we can observe in Table 3 that the forecasting power or adjusted R^2 for all regressions declined from the 1994–2000 to 2001–2007 period, which demonstrates that these forecasting models have performed poorly out-of-sample. Overall, we can conclude that these stationary forecasting variables have not withstood the test of time as variables that can predict hedge fund index returns.

Concluding comments

The major shortcomings of previous hedge fund forecasting studies were their use of non-stationary forecasting variables in a GLS framework. This study employed forecasting variables that were stationary in a more robust OLS framework. We found that these stationary forecasting variables were indeed insignificant in both sample periods. Overall, this study provides no evidence to suggest that external forecasting variables can predict hedge fund index returns.

Recent studies have shown that stock and bond returns are not as predictable as originally thought. This study provides new evidence to suggest that hedge fund index returns are also difficult to forecast. This finding provides a warning to active asset allocators who attempt to opportunistically shift their investments in and out of asset classes and markets based on predictions of future price movements. The lesson from this study is that forecasting models in traditional and alternative asset classes must be carefully developed in order to ensure their methodological validity.

Note

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1

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