

Performance Evaluation and Conditioning Information: The Case of Hedge Funds

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Abstract

In this paper we investigate whether there are any significant differences in the ability of constant and time-varying expected return asset pricing models to detect superior performance in hedge funds. Our results strongly suggest that the static models traditionally employed to measure and evaluate hedge fund performance are misspecified. Allowing for conditioning information to predict changes in the risk and performance measures of hedge funds increases the statistical significance of the performance evaluation. In addition, incorrectly assuming constant expected returns appears to lead to underestimation of the abnormal performance of hedge funds.

Investment performance evaluation evolves around the construction of passive replicas or benchmarks. The latter can either be based on a fund's bottom line risk-return profile, i.e. the moments of a fund's return distribution, or on a fund's exposure to the relevant return generating factors. The Sharpe ratio and Jensen's alpha are the simplest and best-known examples of both these approaches. Over the past three decennia, Jensen's original one-factor model has undergone many extensions. Most of these are aimed at more fully capturing the return generating process. Another type of extension, which has attracted quite a lot of attention recently, is to drop the assumption of a constant expected return and evaluate investment performance in a conditional framework.¹ The conclusion that emerges from these studies is that inferences on the performance and the persistence of an actively managed portfolio may be significantly altered when one allows for conditional, instead of unconditional, moments. A change in the risk profile of a portfolio over the evaluation period can have a dramatic impact on the measured abnormal performance. This is in line with a point made earlier by Chan (1988), who argued that the benefits of contrarian strategies, as reported in De Bondt and Thaler (1985) for example, may largely be the result of a misspecification of the model used to measure normal returns. When the risk of the winner and loser portfolios is allowed to be time-dependent, most of the cumulative abnormal return of the contrarian strategy seems to disappear.

The issue of time-varying expected returns is especially acute when evaluating portfolios with strongly fluctuating risk exposures, such as the portfolios held by CTAs and hedge funds for example. Due to their private nature, hedge funds have little restrictions on borrowing, short-selling, the use of derivatives, etc. than more

regulated vehicles such as mutual funds. This allows for investment strategies that are typically highly opportunistic in nature. Most hedge fund managers have substantial experience in the global capital markets, either as an investment manager, investment analyst or as a proprietary trader, which is often presented to investors as a virtual guarantee for superior performance. To verify the above claim, several authors have studied hedge fund performance using multi-factor asset pricing models.² Doing so, it is typically assumed that the risk exposures as well as the expected abnormal performance of hedge funds remain constant over time. However, with hedge fund strategies being highly opportunistic, opportunities coming and going and many hedge funds reacting to this by rotating between a number of significantly different strategies, this appears a highly unrealistic assumption.

In this paper we investigate whether there are any significant differences in the ability of constant and time-varying expected return asset pricing models to detect superior performance in hedge fund returns.³ We take into account the fact that hedge fund managers trade on public information and follow dynamic trading strategies by allowing the measures of risk and abnormal performance to vary with a set of predetermined, publicly available information. Our results make it clear that allowing for conditioning information to predict changes in the risk and performance measures of hedge funds increases the statistical significance of the performance evaluation. In addition, incorrectly assuming constant expected returns appears to lead to underestimation of the abnormal performance of hedge funds: Across the various models considered, the conditional measures of abnormal performance exceed the static measures by an average return of 0.84%. The number of funds that exhibit superior skills increase by 10.4% when one allows for a conditional estimation of the models.

The paper is organized as follows. Section I introduces the methodology. In section II we present the data sets used. In section III we test the ability of conditional asset pricing models to measure hedge fund performance and discuss the evaluation results. Section IV concludes the paper.

I. Methodology

Starting with Jensen (1968), the traditional approach to portfolio performance evaluation is to regress the portfolio return in excess of the return on the one-month Treasury bill p_t onto a set of K return-generating factors f_t , implicitly assuming that the regression parameters are constant.

$$p_t = \alpha + \beta f_t + \varepsilon_t \quad (1)$$

The performance of the portfolio is then evaluated by testing the statistical significance of the intercept term α in (1). The assumption of constant parameters implies that the portfolio manager's strategy does not make any use of publicly available information, which often is not a valid assumption. We can introduce time variation in the manager's risk exposures by assuming a linear relationship between β and a set of L mean zero instruments available at time $t-1$, z_{t-1} . Similarly, we can assume a linear relationship between α and z_{t-1} .⁴ α and β then become equal to

$$(\alpha_t | z_{t-1}) = \alpha_0 + \alpha_1 z_{t-1} \quad (2)$$

$$(\beta_t|z_{t-1}) = \beta_0 + \beta_1 z_{t-1} \quad (3)$$

where $(\cdot|z_{t-1})$ denotes a parameter that is conditional upon z_{t-1} , α_0 is the average abnormal performance of the portfolio, β_0 is a K -vector of average measures of risk, α_1 and β_1 are L and LK -vectors of parameter estimates, and $z_{t-1} = Z_{t-1} - E(Z)$ is a L -vector of normalized deviations from Z_{t-1} .

Because hedge fund managers trade on public information and follow dynamic trading strategies, the managers' abnormal return and the risk of the managed portfolios are allowed to be time-dependent in equations (2) and (3). They change as new information arrives to the market. $\alpha_1 z_{t-1}$ captures the time variation in the measure of abnormal performance and measures the departure from the mean level of abnormal performance α_0 . Similarly $\beta_1 z_{t-1}$ captures the time variation in the measures of risk and measures the departure from the mean level of risk β_0 . When no information is conveyed to the market the conditional measures reduce to the static α and β in (1).

Replacing α and β in (1) by $(\alpha_t|z_{t-1})$ and $(\beta_t|z_{t-1})$ in (2) and (3) yields the conditional model of performance evaluation first proposed by Ferson and Warther (1996) and Ferson and Schadt (1996)

$$p_t = \alpha_0 + \alpha_1 z_{t-1} + \beta_0 f_t + \beta_1 f_t z_{t-1} + \varepsilon_t \quad (4)$$

where α_0 is the conditional counterpart of the Jensen (1968) measure of abnormal performance. Equation (4) is a regression of the portfolio excess return onto a constant, L lagged instruments, the excess return on K factor mimicking portfolios, and the product of the excess return on the factor mimicking portfolios with the lagged information variables. The conditional model (4) adds a L -vector z_{t-1} and a LK -vector $f_t z_{t-1}$ to the regression traditionally used to measure performance. These regressors pick up the variations through time in the performance and risk measures that are related to changing economic conditions.

Because the omission of some information variables from the actual information set used by hedge fund managers could result in heteroscedasticity in the regression errors, the standard errors in (4) are corrected for possible heteroscedasticity (see Ferson and Schadt (1996)). Note also that the static model (1) is nested in the conditional model (4). In particular, the conditional model can be assessed against the static model by testing the restrictions $\alpha_1 = 0$, $\beta_1 = 0$, and $\alpha_1 = \beta_1 = 0$ in (4).

We examine three different specifications of the conditional factor model. The first specification assumes that the world market portfolio captures all the time-series variation in hedge fund returns. The second specification also recognizes the role of size and book-to-market value as pervasive sources of risk. In the third model, the market portfolio and five macroeconomic variables are assumed to explain the relationship between conditional risk and conditional expected returns. The data used to estimate these models as well as the hedge fund data are discussed in the next section.

II. The Data

A. *Hedge Funds*

The data used in this study were obtained from the Zurich Capital Markets (previously MAR/Hedge) database.⁵ Per April 2000, the database contained monthly (net of fee) return data on 1476 hedge funds and funds of funds. In this study, however, we concentrate on the 77 funds for which at least ten years of consecutive monthly return data is available, from May 1990 until April 2000. This includes the period 1997-1998, which, with crises in Asia and Russia and the subsequent collapse of LTCM, was an especially difficult time for hedge funds. Obviously, concentrating on survivors only will introduce survivorship bias. Given the limited data set available, however, there is no easy way to correct this.⁶

Hedge fund investment strategies tend to be quite different from the strategies followed by traditional money managers, making extensive use of derivatives and leverage. In principle every fund follows its own proprietary strategy, which makes hedge funds a very heterogeneous group. There are, however, a number of ‘ideal types’ to be distinguished. Zurich Capital Markets uses the following main- and subcategories:

Global: International - Funds that concentrate on economic change around the world and pick stocks in favoured markets. Make less use of derivatives than macro funds (see below).

Global: Emerging - Funds that focus on emerging markets. Because in many emerging markets short selling is not permitted and without the presence of futures markets, these funds tend to be long only.

Global: Established - Funds that look for opportunities in established markets.

Global: Macro - These funds tend to go wherever there is a perceived profit opportunity and make extensive use of leverage and derivatives. These are the funds that are responsible for most media attention.

Event Driven: Distressed Securities - Funds that trade the securities of companies in reorganization and/or bankruptcy, ranging from senior secured debt to common stock.

Event Driven: Risk Arbitrage - Funds that trade the securities of companies involved in a merger or acquisition, typically buying the stocks of the company being acquired while shorting the stocks of its acquirer.

Market Neutral: Long/Short Equity - This category makes up the majority of hedge funds. Exposure to market risk is reduced by simultaneously entering into long as well as short positions.

Market Neutral: Convertible Arbitrage - Funds that buy undervalued convertible securities, while hedging all intrinsic risks.

Market Neutral: Stock Arbitrage - Funds that simultaneously take long and short positions of the same size within the same market, i.e. portfolios are designed to have zero market risk.

Market Neutral: Fixed Income Arbitrage - Funds that exploit pricing anomalies in the global fixed income (derivatives) market.

Fund of Funds: Diversified - Funds that invest in a variety of hedge funds.

Fund of Funds: Niche - Funds that only invest in a specific type of hedge funds.

A further classification of the 77 hedge funds and fund of funds that we will use in this study can be found in table I. Throughout we use the return on 1-month US Treasury bills to measure excess returns.

<< Insert Table I >>

B. Benchmark Portfolios

The set of risk factors used to estimate performance follows directly from Solnik (1974), Fama and French (1993), and Ferson and Harvey (1993). These factors are (1) the market factor, (2) two fundamental factors (size and book-to-market value of equities) and (3) five macroeconomic factors (a measure of exchange rate risk, the term structure of interest rates, a proxy for the international risk of default on short maturity securities, inflation risk, and industrial production). To accommodate the fact that many of the hedge funds in our database operate internationally, the market and macroeconomic factors considered are measured internationally as well. Details relating to the construction of the market, fundamental, and macroeconomic variables are reported in panel A of table II.

<< Insert Table II >>

To construct portfolios that mimic the realization of the fundamental and macroeconomic factors, we use the methodology proposed by Fama and French (1993) and Chan, Karceski, and Lakonishok (1998). We collect the returns in excess of the one-month US T-bill rate on the components of the Russell 3000 index that have data available for size and book-to-market value over the period April 1990 –

April 1999 and that have been trading continuously over the period April 1985 – April 2000. This restricts the sample size to 675 companies.

For the fundamental factors, starting from April 1990, we sort the stocks into five portfolios according to the firm's attribute (portfolio 1 has the highest, say, market capitalization; portfolio 5, the lowest). The return on the factor-mimicking portfolio over the next 12 months is then measured as the difference in the average returns on the portfolios with the highest and lowest attributes. Subsequently, the procedure is rolled forward using the next April's attributes and the next 12 months of returns.

For the macroeconomic factors, the procedure differs slightly. We first consider a 5-year period (say, May 1985 – April 1990), over which we regress the stock excess returns on the relevant factor's unexpected component⁷ and on the excess return on the world equity index. The relevant attribute on which to sort the stocks into portfolios is then the stock loading on the macroeconomic factor. As previously, the difference in the average return on the highest-ranked and the lowest-ranked portfolio represents the return on the factor-mimicking portfolio in each of the subsequent 12 months. The procedure is then rolled forward to the next 5-year period (say, May 1986 – April 1991) and the stocks are once again sorted into five portfolios according to their sensitivities to the macroeconomic factor that is being mimicked.

The above procedure produces 120 estimates of the excess return on the factor mimicking portfolios. Summary statistics of the factor risk premia are presented in panel B of table II. The annualized market risk premium equals 8.10%. The prices of risk associated with size and book-to-market value are important in economic terms

too. The small size portfolio outperforms the large size portfolio by an average annualized return of 11.22%, while the value portfolio beats the growth portfolio by an average return on 5.59%. The prices of risk associated with the macroeconomic factors, however, are less important in economic terms and less volatile than the market or the size portfolios.

Panel C in table II reports the correlation matrix in the excess returns on the factor mimicking portfolios. With the noticeable exception of size and book-to-market, the correlations between the factor mimicking portfolios are small, suggesting that multicollinearity should not be a problem.

C. The Set of Global Instruments

The set of instruments that we use follows from Ferson and Harvey (1993) and Harvey (1995). These include the first lag in the return and the dividend yield on the world equity portfolio, a lagged measure of the term structure of interest rates, and the lag in a proxy for the global risk of default on money market instruments. Two further points are worth mentioning. First, the instruments have a mean of zero (see Ferson and Schadt (1996) or Christopherson, Ferson, and Glassman, (1998)). Second, the information variables are true predictors in the sense that they are constructed only with information that is already available at the time portfolio performance is evaluated.

III. Empirical Results

A. Statistical Significance of Conditioning Information

Valid conclusions regarding the ability of the conditional models to measure performance can only be drawn within a well-specified model. To ensure that this condition is met, model (4) is estimated and the following three hypotheses are tested. First, we test whether the measures of performance are time-varying by looking at the significance of α_1 in (4). Second, the ability of the conditioning variables to predict changes in the measures of risk is investigated. Finally, the joint significance of α_1 and β_1 in (4) is examined. These tests are heteroscedasticity-consistent and are χ^2 distributed with L , LK , and $L(K+1)$ degrees of freedom respectively.

<< Insert Table III >>

Table III panel A reports the percentage of funds for which the hypothesis of no marginal explanatory power of the conditioning variables is rejected. The information variables are jointly significant at the 5% level. The hypothesis of a constant measure of abnormal performance ($\alpha_1 = 0$) is rejected for approximately 50% of the hedge funds. The measures of risk also appear to be time-varying, the evidence being stronger for the conditional six-factor models and weaker for the conditional market model. When the significance of α_1 and β_1 is tested jointly, the evidence overwhelmingly suggests that both the measure of abnormal performance and the measures of risk are time dependent. The evidence is particularly strong for the conditional six-factor model where the hypothesis of a constant α and β in equation (1) is rejected for all 77 funds. This strongly suggests that the static models

traditionally employed to measure performance are misspecified. In other words, these models may fail to accurately establish whether a hedge fund outperformed its benchmark on a risk-adjusted basis.

Table III panel A reveals that the information variables are jointly significant. However, panel A does not tell us which information variables have forecasting power over the measure of abnormal performance and the measures of risk. This information is reported in panels B and C of table III. For example, when the conditional market model is used to measure normal returns, the return on the market portfolio predicts the abnormal performance of 32.47% of the hedge funds (at 5%). Taking the results in panels B and C together, it appears that the term structure of interest rates has the lowest forecasting ability (term spread predicts the measures of abnormal performance and risk for approximately 15% of the funds only). Default spread has the most forecasting power over the measures of abnormal performance. Dividend yield helps predict most of the variations in the measures of risk.

Fama and French (1989), Chen (1991), and Estrella and Hardouvelis (1991) show that the information variables predict equity returns because of their ability to proxy for changes in the business cycle. More specifically, an above average market return, an above average dividend yield, an above average default spread, and a below average term structure of interest rates announce poor economic prospects in the future and therefore higher returns required by investors. Since the information variables predict the business cycle, the signs of α_1 in equation (4) can tell us whether funds exhibit better performance in up or in down markets.

<< Insert Table IV >>

The results in table IV only consider the parameters that significantly differ from zero at 5% in panel B of table III. The table presents, for those significant α_1 , the average coefficient on the lagged information variables and the proportion of funds that have positive (negative) α_1 coefficients. Panel A, for example, indicates that, out of all the coefficients on the lagged market returns that were statistically significant at 5%,⁸ 95.95 percent are positive. The average of the coefficients on the lagged market returns that are significant at 5% is 0.0015. Because during business troughs, the market return takes on relatively high values, a positive coefficient for the lagged market return indicate that managers on average show superior performance in down markets. Similar conclusions can be drawn for dividend yield and, in most cases, for the term structure of interest rates. Abnormal performance is above average when dividend yield (term spread) takes on high (low) values; namely, during business troughs.

The conclusion that abnormal performance is counter-cyclical does not work out for default spread though. The coefficient on default spread is more often negative than positive, with average values ranging from -0.0248 to -0.0186 . It follows that a below-average default spread in periods of economic expansion indicates that the abnormal performance of hedge funds will be above-average one-period ahead. This would in turn suggest that hedge funds managers perform better in up-markets. This point notwithstanding, the general conclusion seems to be that hedge fund managers tend to show above-average performance in down markets.

B. Hedge Fund Performance Evaluation

The main conclusions so far are twofold. First, it is important to allow the measures of risk and abnormal performance to be time-dependent instead of restricting them to be constant. Second, system (4) seems correctly specified and can be used to evaluate abnormal performance.

Table V reports the percentage of hedge funds that performed better than their risk-adjusted benchmarks. The results from the conditional models are reported in panel A. For comparison, the results for the static models are summarized in panel B. Looking first at the results from the conditional models, 80.52% of the hedge funds performed better than the market as a whole on a risk adjusted basis (at 5% significance). The inference is even stronger within the context of the conditional six-factor model. The conditional three-factor model indicates that no less than 75% of the hedge funds exhibited positive abnormal performance. The conclusions therefore are overwhelmingly in favor of the hypothesis that hedge funds managers have superior skills.

<< Insert Table V >>

For comparison, we also report the measures of abnormal performance from the more standard static models. Consistent with the results reported in earlier studies, we find that most hedge funds outperformed their benchmark on a risk-adjusted basis. However the inferences from the static models are weaker. On average 10.4% more funds exhibit abnormal performance when we allow for conditioning information. The same conclusion applies when we look at the average across the 77 funds of the t – statistics

on the measure of abnormal performance. The average t – statistic ranges from 3.14 to 3.76 for the conditional models and from 2.56 to 3.13 for the static models. Allowing for conditioning information improves the statistical significance of the measures of abnormal performance.

The average adjusted R – squared increases substantially when we allow for time variation in the parameter estimates. While the adjusted goodness-of-fit statistics only range from 13.2% to 20% for the static models, the conditional models capture on average between 22.8% and 33.5% of the variation in hedge fund returns.⁹ This reinforces the view put forward earlier that conditional models provide a more accurate picture of hedge funds than static models.

In economic terms, when we allow for the measures of risk and performance to be time-dependent, the average abnormal performance across the 77 funds is also higher. On an annually compounded basis, the average conditional abnormal performance ranges from 8.43% for the conditional three-factor model to 9.74% for the conditional market model. The inferences from the static models are less strong with average abnormal performance ranging from 7.26% to 9.20%. The conditional measures of abnormal performance exceed the static measures by 0.53% for the market model, 0.82% for the six-factor model, and a striking 1.17% for the three-factor model. Graphs of the frequency distributions of the alphas obtained from the various models can be found in figure 1-3. Altogether, the evidence in table V suggests that on a risk-adjusted basis the performance of hedge funds is better than indicated by static models.

<< Insert Figures 1-3 >>

The results presented thus far are aggregated across the 77 hedge funds analyzed in this study. Table VI looks at the relative performance of the different categories of funds mentioned in the data section. On average, the Event Driven, Global Macro and Global Established funds performed better than the others, with average conditional abnormal performance exceeding 10%. With an average conditional abnormal performance of only 5%, the one Global Emerging Markets fund in our dataset performed the worst. This is not too surprising though, as over the period studied emerging markets funds have had to deal with several major crises. It is interesting to note that the performance of funds of funds is substantially worse than that of non-fund of funds. This strongly suggests that the average fund of funds manager is unable to add enough value to make up for the fees that he charges (typically 1.5% management fee plus 10% incentive fee), which makes funds of funds quite an expensive way to manage one's hedge fund investments. Similar inferences, although less strong, are obtained from the static models on the right-hand-side of table VI.

<< Insert Table VI >>

IV. Concluding Remarks

This paper investigates the abnormal performance of hedge funds from the perspective of both unconditional and conditional asset pricing models. The two main conclusions are as follows. First, static models are misspecified in the sense that instruments available at time $t-1$ help predict the variation in the measures of risk and abnormal performance. Second, allowing for conditioning information increases the measured abnormal performance, both in statistical and economic terms. Across the various models considered, the conditional measures of abnormal performance exceed the static measures by an average return of 0.84%. The number of funds that exhibit superior skills increase by 10.4% when one allows for a conditional estimation of the models.

A final note concerns the fact that although the traditional multi-factor model is a popular tool for performance evaluation amongst practitioners as well as academics, there are indications that the model might not be appropriate for hedge fund performance evaluation. The low determination coefficients make it clear that, even with time-varying parameters, the model has difficulty capturing the complex and highly opportunistic nature of hedge fund strategies. In addition, recent research has made it clear that hedge fund returns are typically far from normally distributed, part of which might be due to non-linear exposures to the relevant return generating factors resulting from the use of options and dynamic trading strategies. Clearly, these issues deserve further study.

References

Agarwal, Vikas and Narayan Naik, 2001, Characterizing systematic risk of hedge funds with buy-and-hold and option-based strategies, Working Paper London Business School.

Amin, Gaurav, and Harry Kat, 2001a, Hedge fund performance 1990-2000: Do the money machines really add value?, forthcoming *Journal of Financial and Quantitative Analysis*.

Amin, Gaurav, and Harry Kat, 2001b, Welcome to the dark side: Hedge fund attrition and survivorship bias over the period 1994-2001, Working Paper ISMA Centre, University of Reading.

Capocci, Daniel, 2001, An analysis of hedge fund performance 1984-2000, Working Paper University of Liege.

Chan, K C, 1988, On the contrarian investment strategy, *Journal of Business* 61, 147 – 164.

Chan, Louis K. C., Jason Karceski and Josef Lakonishok, 1998, The risk and return from factors, *Journal of Financial and Quantitative Analysis* 33, 159 – 188.

Chen, Nai-fu, 1991, Financial investment opportunities and the macroeconomy, *Journal of Finance* 46, 529 – 554.

Chen, Zhiwu and Peter Knez, 1996, Portfolio performance measurement: Theory and applications, *Review of Financial Studies* 9, 507 – 551.

Christopherson, Jon A., Wayne E. Ferson, and Debra Glassman, 1998, Conditioning manager alphas on economic information: Another look at the persistence of performance, *Review of Financial Studies* 11, 111 – 142.

Darst, Elizabeth, 2000, Performance evaluation for alternative investments: The effect of firm characteristics and fund style on the performance of hedge funds, Working Paper Harvard University.

De Bondt, Werner F. M. and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793 – 805.

Edwards, Franklin R. and Mustafa O. Caglayan, 2001, Hedge fund performance and manager skill, *Journal of Futures Markets* 21, 1003 – 1028.

Eckbo, B. Espen, and David C. Smith, 1998, The conditional performance of insider trades, *Journal of Finance* 53, 467 – 498.

Estrella, Arturo and Gikas A. Hardouvelis, 1991, The term structure as a predictor of real economic activity, *Journal of Finance* 46, 555 – 576.

- Fama, Eugene F. and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23 – 49.
- Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3 – 56.
- Ferson, Wayne E. and Campbell R. Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, 527 – 566.
- Ferson, Wayne E. and Rudi Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425 – 461.
- Ferson Wayne E. and Vincent Warther, 1996, Evaluating fund performance in a dynamic market, *Financial Analysts Journal* November-December, 20 – 28.
- Fung, William and David Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies* 10, 275 – 302.
- Fung, William and David Hsieh, 1998, Performance attribution and style analysis: From mutual funds to hedge funds, Working Paper Fuqua School of Business.
- Fung, William and David Hsieh, 2001, The risk in hedge fund strategies: Theory and evidence from trend followers, *Review of Financial Studies* 14, 313 – 341.
- Harvey Campbell R., 1989, Time varying conditional covariances in tests of asset pricing models, *Journal of Financial Economics* 24, 289 – 317.
- Harvey Campbell R., 1995, Predictable risk and returns in emerging markets, *Review of Financial Studies* 8, 773 – 816.
- Jensen Michael C., 1968, The performance of mutual funds in the period 1945-1964, *Journal of Finance* 23, 389 – 416.
- Liang, Bing, 1999, On the performance of hedge funds, *Financial Analysts Journal* 55, No. 4, 72 – 85.
- Priestley, Richard, 1996, The APT, macroeconomic and financial factors and expectations generating processes *Journal of Banking and Finance*, 20, 869 – 890.
- Schneeweis, Thomas and Richard Spurgin, 1998, Multifactor analysis of hedge fund, managed futures, and mutual fund return and risk characteristics *Journal of Alternative Investments*, 1, 1 – 24.
- Schneeweis, Thomas and Richard Spurgin, 1999, Quantitative analysis of hedge fund and managed futures return and risk characteristics, Working Paper CISDM.
- Solnik, Bruno, 1974, An equilibrium model of the international capital market, *Journal of Economic Theory* 8, 500 – 524.

Footnotes

1. See for example Chen and Knez (1996), Ferson and Schadt (1996), Christopherson, Ferson, and Glassman (1998), or Eckbo and Smith (1998).
2. See for example Fung and Hsieh (1997, 1998, 2001), Schneeweis and Spurgin (1998, 1999), Liang (1999), Darst (2000), Agarwal and Naik (2001), Capocci (2001), or Edwards and Caglayan (2001).
3. Throughout this study we assume that multivariate OLS regression is appropriate for hedge fund performance evaluation. It is important to note, however, that given the sometimes very high degree of non-normality of hedge fund returns this need not necessarily be the case.
4. The assumption of a linear relationship between the regression parameters and a set of publicly available instruments was first introduced by Harvey (1989) and has been used extensively ever since (see, for example, Ferson and Harvey (1993)).
5. This is the same dataset as used by Amin and Kat (2001a) in their study of hedge fund performance.
6. Amin and Kat (2001b) estimate that concentrating on survivors will overestimate the average hedge fund return by 1.89% per annum and the return on the average fund of funds by 0.63% per annum.
7. The unexpected components on the macroeconomic variables were generated using the Kalman filter with time-varying parameters (see Priestley (1996)). These results are available upon request.
8. A quick look at table III panel B tells us that for 32.47 percent of hedge funds, the coefficient is significant at 5%.

9. Although low compared to what is usually found for mutual funds, determination coefficients like this are typical for individual hedge funds. See for example Fung and Hsieh (1997) or Agarwal and Naik (2001).

Table I
Hedge funds: Classification

This table classifies the 77 hedge funds in our data set into 4 different categories.

| Category | Number of Funds | | |
|----------------|-----------------|----------|--------------|
| | Total | US-based | Non US-based |
| Market neutral | 11 | 11 | 0 |
| Global | 28 | 16 | 12 |
| Event driven | 15 | 11 | 4 |
| Funds of funds | 23 | 11 | 12 |

Table II
Excess Returns on the Factor Mimicking Portfolios

Panel A: Definition of the Risk Factors

| Risk Factor | Definition |
|-------------------------------|---|
| <i>Market Factor:</i> | |
| - Market portfolio | Return on world equity index in excess of the US one-month Treasury bill |
| <i>Fundamental Factors:</i> | |
| - Size | Market value of the constituents of the Russell 3000 index |
| - Book-to-market | Book value to market value of the constituents of the Russell 3000 index |
| <i>Macroeconomic Factors:</i> | |
| - Exchange rate | Percentage change in the US dollar against major currency index |
| - Term structure | Difference in the yields on the US 10 year Treasury bond and US 3 month Treasury bill |
| - Default spread | Difference in the 3 month Euro\$ deposit rate and the yield on 3 month US Treasury bill |
| - Inflation | Percentage change in global consumer price index |
| - Industrial production | Change in the log of global industrial production |

Table II – Continued

Panel B: Summary Statistics for the Factor Risk Premia

| | Excess return | Excess return on the mimicking portfolio associated with | | | | | | |
|------------------------|--------------------------|--|---------------------|-------------------------|---------------------|---------------------|---------------------------|----------------------------|
| | on market portfolio (RM) | Size (MV) | Book-to-market (BM) | Exchange rate risk (FX) | Term structure (TS) | Default spread (DS) | Unexpected inflation (UI) | Industrial production (IP) |
| Mean | 0.0065 | -0.0099 | 0.0045 | -0.0031 | 0.0003 | 0.0004 | 0.0020 | -0.0023 |
| Annualized Mean Return | 8.10% | -11.22% | 5.59% | -3.70% | 0.36% | 0.51% | 2.42% | -2.74% |
| Standard Deviation | 0.0415 | 0.0379 | 0.0241 | 0.0239 | 0.0229 | 0.0207 | 0.0204 | 0.0222 |
| Minimum | -0.1445 | -0.1453 | -0.0683 | -0.0874 | -0.0395 | -0.0872 | -0.0433 | -0.0800 |
| Maximum | 0.1111 | 0.0786 | 0.0787 | 0.0578 | 0.0775 | 0.0629 | 0.0877 | 0.0629 |

Panel C: Correlation in the Factor Risk Premia

| | RM | MV | BM | FX | TS | DS | UI | IP |
|----|-------|-------|-------|-------|-------|------|------|----|
| RM | 1 | | | | | | | |
| MV | 0.05 | 1 | | | | | | |
| BM | -0.24 | -0.57 | 1 | | | | | |
| FX | -0.24 | 0.07 | -0.05 | 1 | | | | |
| TS | 0.05 | -0.50 | 0.31 | -0.19 | 1 | | | |
| DS | -0.11 | -0.37 | 0.22 | -0.21 | 0.21 | 1 | | |
| UI | 0.15 | -0.35 | 0.34 | -0.21 | 0.40 | 0.03 | 1 | |
| IP | -0.24 | 0.04 | 0.25 | -0.01 | -0.08 | 0.26 | 0.04 | 1 |

Table III
Statistical Significance of Conditioning Information

Panel A reports the percentage of funds that reject at 5% the hypotheses that $\alpha_1 = 0$, $\beta_1 = 0$, and $\alpha_1 = \beta_1 = 0$ in the regression

$$p_t = \alpha_0 + \alpha_1 z_{t-1} + \beta_0 f_t + \beta_1 f_t z_{t-1} + \varepsilon_t.$$

p_t is the return on the hedge fund in excess of the one-month US Treasury bill, f_t is a K -vector of factors, z_{t-1} is a vector of mean zero pre-determined instruments available at time $t-1$, α_0 , α_1 , β_0 , and β_1 are estimated parameters. The standard errors are corrected for possible heteroscedasticity. Panel B (Panel C) reports the percentage of funds that reject at 5% the hypothesis that the lagged information variable has no forecasting power over the measure of abnormal performance (risk). Three conditional models are estimated: the market model, the Fama and French three-factor model, and a six-factor model that considers the market factor and five macroeconomic variables. The data are end-of-month and the model is estimated over the period May 1990 – April 2000.

| | Conditional Market Model | Conditional Three- Factor Model | Conditional Six- Factor Model |
|--|-----------------------------|------------------------------------|----------------------------------|
| Panel A: Test of Constant Measures of Abnormal Performance and Risk | | | |
| - $\alpha_1 = 0$ | 49.35% | 55.84% | 49.35% |
| - $\beta_1 = 0$ | 61.04% | 89.61% | 98.70% |
| - $\alpha_1 = \beta_1 = 0$ | 85.71% | 98.70% | 100% |
| Panel B: Prediction of Abnormal Performance One-Period Ahead | | | |
| - Return on market portfolio | 32.47% | 28.57% | 35.06% |
| - Dividend yield | 23.38% | 29.87% | 24.68% |
| - Term structure | 10.39% | 11.69% | 14.29% |
| - Default spread | 24.68% | 38.96% | 18.18% |
| Panel C: Prediction of Risk One-Period Ahead | | | |
| - Return on market portfolio | 3.90% | 22.51% | 18.40% |
| - Dividend yield | 45.45% | 31.60% | 24.03% |
| - Term structure | 23.38% | 12.99% | 13.64% |
| - Default spread | 36.36% | 22.51% | 19.48% |

Table IV
Abnormal Performance and the Business Cycle

Average α_1 is the average coefficient on the lagged information variables, $p(\alpha_1 > 0)$ is the percentage of funds that have positive α_1 coefficients, $p(\alpha_1 < 0)$ is the percentage of funds that have negative α_1 coefficients. Only the parameters that are significantly different from zero at 5% in panel B of table III are considered.

| | Average α_1 | $p(\alpha_1 > 0)$ | $p(\alpha_1 < 0)$ |
|--|--------------------|-------------------|-------------------|
| Panel A: Conditional Market Model | | | |
| - Return on market portfolio | 0.00150 | 95.95% | 4.05% |
| - Dividend yield | 0.02084 | 88.76% | 11.24% |
| - Term structure | -0.00087 | 24.76% | 75.24% |
| - Default spread | -0.01862 | 52.31% | 47.69% |
| Panel B: Conditional Three-Factor Model | | | |
| - Return on market portfolio | 0.00114 | 95.45% | 4.55% |
| - Dividend yield | 0.02368 | 91.30% | 8.70% |
| - Term structure | -0.00101 | 22.22% | 77.78% |
| - Default spread | -0.02012 | 36.67% | 63.33% |
| Panel C: Conditional Six-Factor Model | | | |
| - Return on market portfolio | 0.00127 | 96.30% | 3.70% |
| - Dividend yield | 0.02694 | 94.74% | 5.26% |
| - Term structure | 0.00214 | 54.55% | 45.45% |
| - Default spread | -0.02478 | 28.57% | 71.43% |

Table V
Conditional and Unconditional Abnormal Performance

Panel A reports p , the percentage of funds that reject at 5% the hypothesis that $\alpha_0 = 0$ in the conditional model

$$p_t = \alpha_0 + \alpha_1 z_{t-1} + \beta_0 f_t + \beta_1 f_t z_{t-1} + \varepsilon_t.$$

Panel B reports the percentage of funds that reject the hypothesis that $\alpha = 0$ in the unconditional model

$$p_t = \alpha + \beta f_t + \varepsilon_t.$$

p_t is the return on the hedge fund in excess of the one-month US Treasury bill, f_t is a K -vector of factors, z_{t-1} is a vector of mean zero pre-determined instruments available at time $t-1$, α_0 , α_1 , β_0 , and β_1 are estimated parameters. The standard errors are corrected for possible heteroscedasticity. Average t -ratio is the average of the t -ratios associated with the hypothesis that $\alpha_0 = 0$ in panel A and $\alpha = 0$ in panel B. Average \bar{R}^2 is the average adjusted R -squared of the regression. $\bar{\alpha}$ is the annually compounded average measure of abnormal performance. It is estimated as $\left[1 + \left(\sum_{i=1}^{77} \alpha_{0,i} / 77\right)\right]^{12} - 1$ in panel A and $\left[1 + \left(\sum_{i=1}^{77} \alpha_i / 77\right)\right]^{12} - 1$ in panel B. Three models are estimated: the market model, the Fama and French three-factor model, and a six-factor model that considers the market factor and five macroeconomic variables. The data are end-of-month and the model is estimated over the period May 1990 – April 2000.

| | p | Average t -ratio | Average \bar{R}^2 | $\bar{\alpha}$ |
|------------------------------------|--------|--------------------|---------------------|----------------|
| Panel A: Conditional Models | | | | |
| - Market model | 80.52% | 3.55 | 0.228 | 0.0974 |
| - Three-factor model | 75.32% | 3.14 | 0.335 | 0.0843 |
| - Six-factor model | 83.12% | 3.76 | 0.324 | 0.0942 |
| Panel B: Static Models | | | | |
| - Market model | 74.03% | 3.13 | 0.132 | 0.0920 |
| - Three-factor model | 62.34% | 2.56 | 0.200 | 0.0726 |
| - Six-factor model | 71.43% | 3.03 | 0.188 | 0.0859 |

Table VI
Average Abnormal Performance of Hedge Funds: Results by Sub-Category

The table reports the average measure of abnormal performance per category of funds. The abnormal returns are compounded annually. The number of hedge funds considered by category is reported in parenthesis.

| | Conditional Models | | | Unconditional Models | | |
|---------------------------|--------------------|--------------------|------------------|----------------------|--------------------|------------------|
| | Market Model | Three-Factor Model | Six-Factor Model | Market Model | Three-Factor Model | Six-Factor Model |
| Funds of Funds (23) | 0.0615 | 0.0542 | 0.0653 | 0.0605 | 0.0492 | 0.0610 |
| Event Driven (15) | 0.1148 | 0.0911 | 0.1085 | 0.1074 | 0.0805 | 0.1025 |
| Global: Macro (5) | 0.1377 | 0.1829 | 0.1452 | 0.1299 | 0.1316 | 0.1259 |
| Global: Emerging (1) | 0.0549 | 0.0372 | 0.0894 | 0.0366 | 0.0209 | 0.0337 |
| Global: Established (17) | 0.1398 | 0.1116 | 0.1241 | 0.1289 | 0.0950 | 0.1123 |
| Global: International (5) | 0.0762 | 0.0503 | 0.0710 | 0.0721 | 0.0436 | 0.0621 |
| Market Neutral (11) | 0.0810 | 0.0744 | 0.0789 | 0.0795 | 0.0690 | 0.0741 |

Figure 1: Frequency distribution for the alphas: Result from the market model

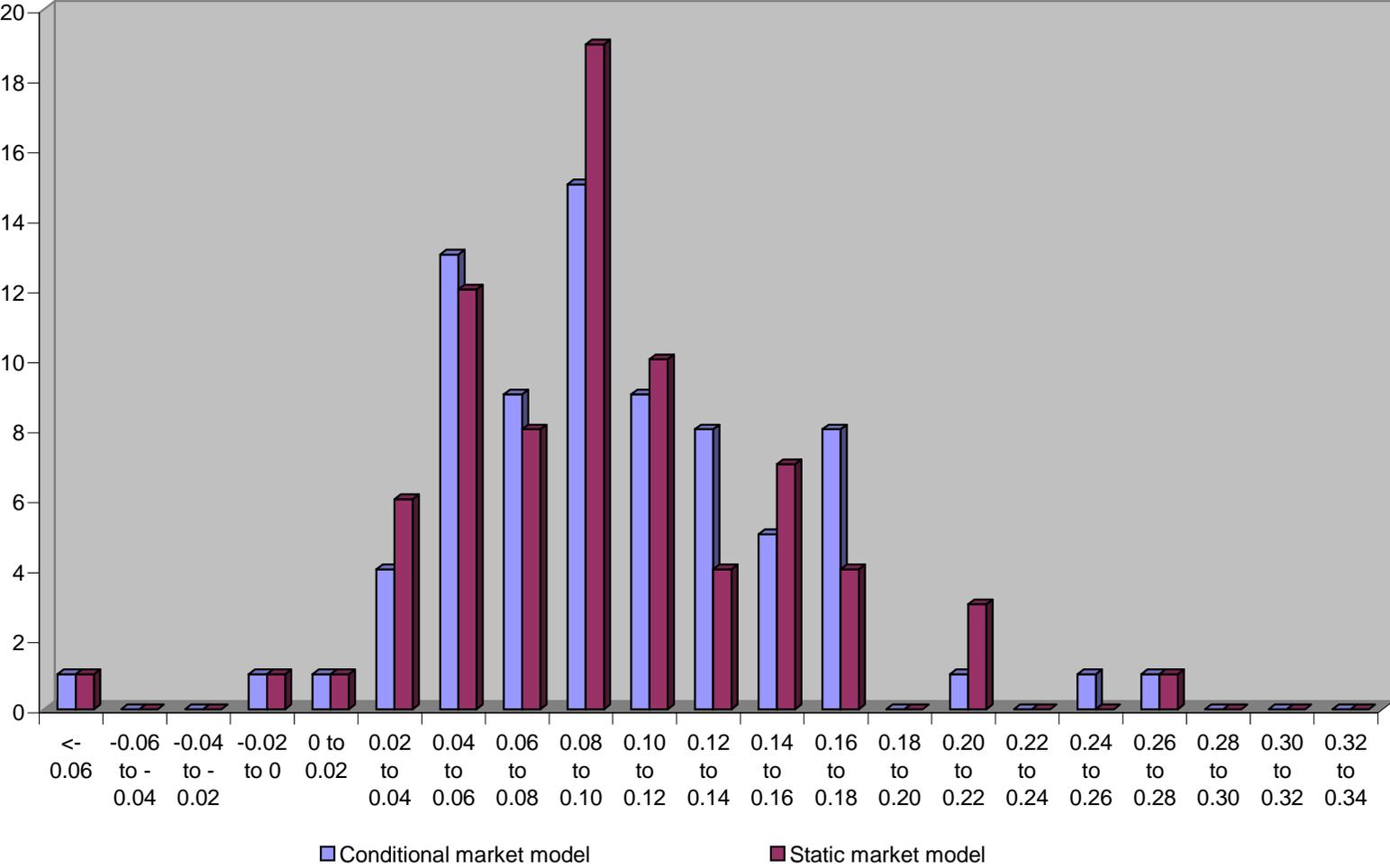


Figure 2: Frequency distribution for the alphas: Result from the three-factor model

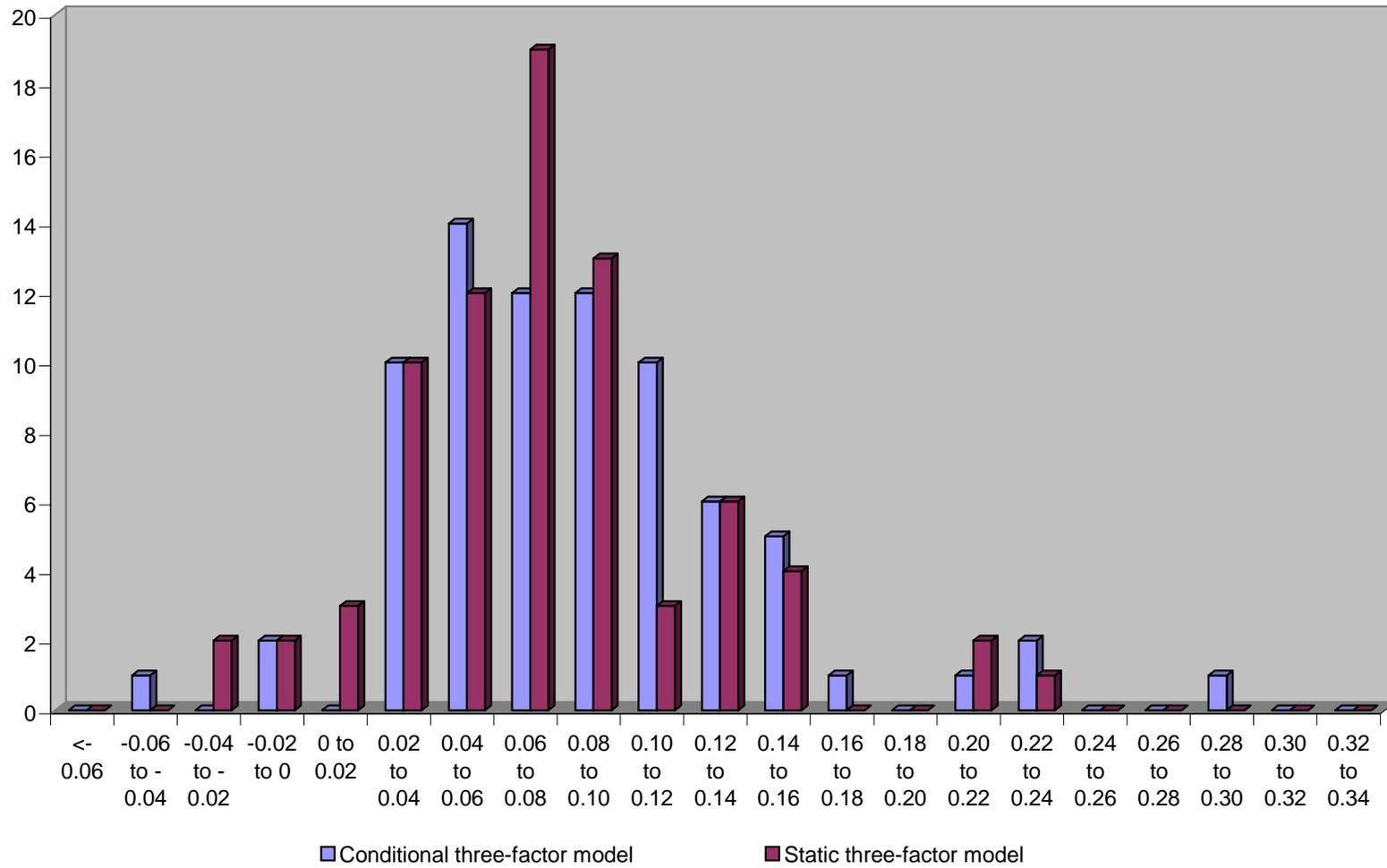


Figure 3: Frequency distribution for the alphas: Result from the six-factor model

