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Hedge Fund Performance with the Treynor-Black Model

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Honors Thesis

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Abstract

This paper seeks to analyze the information ratio differences between long/short hedge funds over the past two decades using the Treynor-Black model. The Treynor-Black model is a method to derive an optimal portfolio allocation across safe and risky assets, based off of expected alphas of active investments and the unsystematic volatility that can be attributed to each given security. We first developed and implemented a model to forecast information ratios on a database of long/short hedge funds. With the predicted information ratios, we calculated out-of-sample allocation weights from a Treynor-Black active portfolio model. These weights were then tested in a long/short format against a Naive model that invests equally in all hedge funds. By subtracting the Naive weights from the Treynor-Black weight recommendations, we were able to test the efficacy of the Treynor-Black model under performance-neutral circumstances.

We found that the Treynor-Black model outperforms in a market that is trending upwards, such as 2017. In a market with a correction, as seen in December 2018, the Treynor-Black model performs in-line with the Naive, generating minimum excess return but taking on no additional risk. Following a market correction into another upwards market (seen in 2019), the Treynor-Black model is not nearly as effective. Due to the importance of the previous year's information ratio, the recommended allocations expected a continuation of market risk and overcorrected. We conclude that information ratio predictions combined with the Treynor-Black model can help generate alpha in a bull market, while taking on average downside risk in a turbulent market, instead of undue downside exposure as seen in some funds.

Dedication

I would like to extend my sincerest thanks to my advisor, Dr. Jon Fulkerson, for his guidance and insight throughout this extensive project. He has taught me not only the process of research, but how to think and logically consider an issue from all sides. I would also like to thank Dr. Nancy Haskell, who first sparked my interest in research. Her encouragement and advice on my final Econometrics research paper motivated my efforts on this thesis. Thank you – I have learned so much from you both.

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Introduction

Hedge fund assets comprise trillions worldwide and they are a longstanding and important part of the finance world. They serve as investment vehicles for institutional and accredited investors, using a variety of generally high risk-high reward strategies through different asset classes and investments. Hedge funds can invest using options, derivatives, short-selling, and more, or can choose to do just long/short equity investing. With so many options, and so many hedge funds, asset managers around the world face the simple question: which fund should manage their capital?

In this paper, we seek to provide clarity on a corner of the market, studying long/short hedge funds over the past two decades through the lens of information ratios and the Treynor-Black model. Long/short funds are structured identical to other hedge funds but are mandated to invest only long or short as their investment strategy. This means that they are restricted to two methods of generating gains: buy and hold equity or sell it short. Many hedge funds employ unconventional strategies through derivatives that may not yield themselves well to an analysis of their respective information advantages, and therefore they will be excluded from our research.

Long-short hedge funds choose investments by their risk-reward ratios. Essentially, they look at their expected return from a particular investment and compare it to the risk they would be taking on by investing in, or shorting, the stock. Both parts of this analysis are key – a fund can generate strong returns by taking on a disproportionate amount of risk, but exposes itself to potentially losing everything, and a fund can have low return with very low risk, providing a secure place to allocate capital but losing potential gains. In finance, this principle has led to the rise of a number of different methods meant to quantify the relationship between risk and reward.

One such measure, known as the information ratio or appraisal ratio, quantifies excess portfolio returns beyond a benchmark, alongside the consistency of those returns. A high information ratio indicates strong risk-adjusted returns, and a low information ratio means that the return may not be able to justify the risk. The information ratio is a common performance measure, and can be used to understand the skill of a hedge fund manager in security selection. As it is a measure of skill and performance, understanding the information ratio and applying it to a selection of hedge funds could result in an improved allocation capital for investors. Information ratios, considering their relationship to performance, could potentially be used to forecast hedge fund returns and more.

In this paper, we look to answer four key questions. First, can information ratios actually be used to forecast hedge fund returns? Second, in an out-of-sample test, are those predicted returns accurate? Third, is it possible to use predicted information ratios through the Treynor-Black model to create a fund-of-funds investment portfolio? And fourth, does the Treynor-Black model allocation improve selection of an investment portfolio when compared to a naïve equal-weight model?

To answer these questions, this paper will follow four steps, each of which builds on the last. First, we will develop a model to forecast information ratios, delving into what the ratio represents and what factors drive it. Second, we will implement the forecasting model on a set of long/short hedge funds and predict forward information ratios. Third, we will use our predicted information ratios to implement the Treynor-Black active portfolio model and generate recommended hedge fund weights. Fourth, we will test the Treynor-Black portfolio versus a naïve, equal weight portfolio. This will be through a simulated long-Treynor-Black and short-naïve model, conducted out-of-sample over three years. Lastly, we will discuss the implications of our results, and interesting things to note.

Literature Review

Prior Hedge Fund Literature

Since the 1990s, the hedge fund industry has grown in importance as an investment vehicle for pension funds, accredited investors, and other institutions. However, standard estimates of the hedge fund industry belie its true importance and performance. In 2016, where estimated worldwide hedge funds assets under management ranged from $2.3-3.7 trillion, true underlying assets were estimated and found to be above $5 trillion (Barth, Joenvaara, Kauppila, and Wermers, 2021), and their importance to financial markets is understated by standard estimates. Barth et al. then went on to describe that public-reporting funds have significantly lower returns than funds that do not report, which is likely due to an alpha differential rather than systematic risk exposure. In our research, this indicates that the likely broader performance of hedge funds will be understated as we rely on a public, self-reporting database.

Adding to the discussion on performance, Fung and Hsieh (2021) analyzed style classifications and found that funds' performance 'decays' over time, with "less than 20% of long/short equity hedge funds delivering significant, persistent, stable positive non-factor related returns." There was no fund size effect in the data, but they did find that long/short hedge funds generally have factor-independent returns in contrast to classic long-only or long-biased hedge funds. In this paper, we will be analyzing long/short funds, and this research establishes two questions to consider. First, does performance (in terms of information ratios) persist? And second, are long/short funds generally factor-independent, or do they have systematic exposure?

Baquero, ter Horst, and Verbeek (2005) analyzed hedge fund sampling issues, drawing some key conclusions on performance, persistence, and survival. The assumption behind the relationship between performance, persistence, and survival is simply this: investors take past performance as an indicator of future performance. However, sustained outperformance is rare and difficult to maintain, and the opposite side of the coin - sustained underperformance - leads to funds being dissolved and assets returned to investors. Therefore, there are some major risks raised with hedge fund data. A high attrition rate, where funds with poor performance are dissolved, leads to some sampling bias. Self-selection contributes to the same, where funds refuse to report to public databases depending on their performance in the given time period. Correspondingly, funds with good performance are both more likely to report and continue to exist, which potentially skews public database information on hedge fund performance.

Though Baquero, ter Horst, and Verbeek (2005) discuss fund performance and risks for US-based funds from 1994 to 2000, the broader implications of their research must be considered. They found performance persistence to exist on a quarterly level more so than an annual level, with annual level persistence not being statistically significant. Strong hedge fund manager performance therefore is an indicator of future performance on a shorter-term basis. With this research in mind, we opted for a model that incorporates a year's forecast but analyzes performance on a monthly level.

Measuring Hedge Fund Performance with the Information Ratio

A common measure of hedge fund manager performance is known as the Information Ratio, summarized by Sharpe as a more general form of the Sharpe Ratio. The ratio was widely used when Thomas Goodwin summarized its calculation and implications in "The Information Ratio" (1998) and is still relevant today. As a calculation, the Information Ratio is simply the average excess return of the portfolio versus a relevant benchmark, divided by the volatility of the excess return. As such, it's a standard representation of reward to risk, and is an excellent way to understand the return a hedge fund manager can generate, along with the risk taken on for that return. High performance with higher volatility can indicate a poor manager, but the same return with low volatility is a potential hallmark of skill.

First, you define excess return as the return of the portfolio:

$$ER_t = R_{Pt} - R_{Bt}$$

Then, you calculate the Information Ratio with the variance of returns:

$$IR = \frac{ER}{\hat{\sigma}_{ER}^2}$$

This information ratio, originally known as the appraisal ratio, is derived from Fischer Black and Jack Treynor's seminal paper, "How to Use Security Analysis to Improve Portfolio Selection" (1973) wherein they lay out a model for portfolio allocation. The Treynor-Black model relies on treating funds as a three-part portfolio. First, there are riskless assets - today, generalized to be US Treasury Bills. Second, there is a highly diversified portfolio, which captures market exposure with minimal specific risk to the underlying equities. Third, there is the true active portfolio, comprised of both security specific risk and market risk.

Though the Treynor-Black model focuses on specific weight calculations between risky and risk-free assets, they also explain an appraisal ratio-weighted calculation for the internal active portfolio. That calculation for an optimal fund-weighting is used extensively as the basis of this thesis. Each investment in the Treynor-Black model is to be weighted according to its expected return (alpha) and its risk exposure. Risk exposure here is security specific; even with diversification, it is impossible to rid a portfolio of market-wide risks, though it can be minimized through the risky asset vs. risk-free asset weightings. Black and Treynor additionally lay out an additional clarification on their ideal active portfolio. As security mispricing on the average would mean half are above their true value, and half below, the ideal portfolio would have equal long/short weight. As later discussed, we use this assumption to test a long/short portfolio and measure if Treynor-Black allocation can help generate excess returns in a fund of funds allocation.

Data Overview

Key Factors

The data used for this project was collected from a number of different sources, including both quantitative fund metrics and return history, along with specific hedge fund characteristics.

Performance Data To estimate hedge fund 'performance,' we relied on annual and monthly returns in percentage points, as reported by Morningstar's Global Hedge Fund Database (2021). Morningstar's data was organized as panel data, with multiple funds over an extended period of time. Post-2000, the data was well-populated with a variety of funds and strategies reported every year. Each of the hedge funds in the data persists until it stops reporting or no longer exists, and no funds persist for the entirety of the data period. Though believed to be accurate, this data is self-reported and is therefore potentially exposed to survivorship or performance bias, where funds that did well or perhaps had some sort of advantage over the market are more likely to exist in the data for an extended period of time. Funds with poorer performance may choose to stop reporting to the database or may simply stop existing. Funds that value privacy for the sake of performance, generally with higher returns, may choose not to make their returns available to such a database, which could result in the hedge fund return universe from Morningstar deviating significantly from the true return scope and scale of hedge funds. Additional information that was not available from the Morningstar database was respective capital gains taxes on hedge funds – funds with short-term investments and more turnover would be subject to higher one-year tax rates, when compared to long-term capital gains taxes for investments held for an extended period of time.

Fund Metrics Fund metrics, also sourced from the same Morningstar hedge fund database, are any pieces of information specific to the funds within the performance sample that could add additional clarity or restrictions to my analysis. The primary data we relied on here was fund size, fee structure, domicile, currency denomination, and strategy (long/short). Using the reported fund data, we converted non-numerical values into a useable format for our regressions, and also created modified variables for regression specifications.

Benchmark Performance Another piece of data essential for this project is the market return per month for the time period analyzed, obtained from Yahoo Finance (2021). The market return, in this case the S&P 500, will function as the benchmark for hedge funds. This is the most representative index available for US-based long/short hedge funds. There was also general Factor benchmark performance used to calculate the fund information ratios, sourced from Kenneth French's Data Library (2020).

Risk Premia and Risk-Free Rates The last piece of data needed is the associated equity risk premiums per month for each investment historically, along with the US risk-free rate for the same time period. This data was obtained from Aswath Damodaran (2021), an NYU professor who calculates standardized metrics every month. The market ascribes a certain necessary return for stocks in excess of the risk-free rate, and this particular risk-reward ratio will help contrast and benchmark hedge fund risk allocation versus the risk allocation of the benchmark, the S&P 500.

Data Cleaning Process

Before analyzing the data, we cleaned the data so that it accurately represented and sampled our target set hedge funds. In this step, we also dealt with potential outliers and modified the data to minimize bias.

First, from the total hedge fund database, we restricted the funds to be used by category. For the purposes of the long/short comparison that we will be building, and because conventional long/short portfolios work better with benchmark comparisons than alternative hedge fund strategies, we ended with seven classifications of long/short funds, by region, size, or by market.

Then, we restricted potential fund outliers. Based on monthly performance, we eliminated data points where monthly return for a particular fund exceeded 100%. Although such return is possible, it is rare and liable to skew the data. There were only 7 observations in the entire data set where return exceeded 100%.

After eliminating outliers, we removed funds with insufficient data for analysis. Funds that did not have yearly returns available were dropped, as well as funds that did not have complete monthly returns. This is simply a method to make sure the data has no major gaps that would make forecasting inaccurate.

Finally, to minimize reporting and survivorship bias, we dropped the first and last reporting years for funds. In self-reporting databases, hedge funds are potentially more likely to begin reporting in months/years where they have generated abnormally high returns. Similarly, funds with abnormally low returns are liable to stop reporting or go out of business, so the last reporting year would also be inaccurate for our model.

Table 1, below, indicates the number of observations remaining per hedge fund strategy after the data restrictions imposed above.

Table 1: Hedge Fund Categories

Hedge Fund Category	Observations
Asia/Pacific Long/Short Equity	3,264
China Long/Short Equity	26,004
Emerging Markets Long/Short Equity	8,628
Europe Long/Short Equity	10,404
Global Long/Short Equity	10,452
U.S. Long/Short Equity	23,088
U.S. Small Cap Long/Short Equity	7,428

Generating Variables

With cleaned and organized hedge fund data, the next step was to generate any variables potentially useful for regression models, testing, or just for understanding the data itself.

Using *monthlynetassets*, a month-by-month measure of underlying assets at hedge funds, we conducted a yearly average to come up with an annual average asset value per fund that reported, defined as *averageassets*. To minimize the lookahead bias likely from a straight average, we also used *monthlynetassets* and trimmed the data to get an end-of-year asset value simply called *assets*. We opted to use December values, filling in with November and October values where missing so that our data from this metric would best represent the fourth-quarter hedge fund asset value. For both *averageassets* and *assets*, we added natural log versions that may be useful in regression specification. We then generated a *firmassets* variable that would account for firm-size, as funds under a single firm may follow a fundamentally similar strategy or be comparatively smaller than other hedge funds. Using *monthlynetassets*, we then created *assetproportion*, a variable that measured the proportion of firm assets that the fund consisted of, and the natural log of the *firmassets*.

We also created three variables to specifically address the managers of the hedge funds at hand. Considering that we will be using the information ratio in this project, which is also known as a measure of security selection and allocation skill, these metrics are key. Morningstar reported both the average manager tenure by fund, and the longest manager tenure by fund. Both of these could independently measure the experience of managers, so we created *avgmanagertenure* and *longestmanagertenure*, but an understanding of the two yielded some new information. In cases where the average manager tenure is lower than the longest manager tenure, the fund has been subject to a change in management. With this principle, we created *managerturnoverbinary*, where manager turnover can be accounted for.

Then, using Morningstar data, we created a number of fund fee-structure metrics. *Feesbool* was true if management charged above the standard hedge fund rate (2% management, 20% performance), as a measure of management's opinion on the worth of their fund. *Feesrange* functioned similarly but accounted for deviations both upwards and downwards in fund fees. If a fund charged above 2.25% management or below 1.75% management, the variable would return True. The same applies on performance fees above 22.5% and below 17.5%. Another variable, *feesaltstruc*, aggregated and accounted for other fund incentive and operation metrics that were difficult to isolate alone. A firm with high watermarks, clawbacks, or a deferred load emphasis would be marked by the binary variable, and if this sort of emphasis has any impact on the information ratio, the variable would account for it.

For further analysis, we isolated positive and negative returns from our dataset. By fund and year, we created *posreturns* and *negreturns*, which contained the return of the fund on an annual basis if the return was positive or negative, respectively. If not, the variable would simply be zero. This isolation of upward and downward allows us to understand the importance of upwards and downwards shifts in the information ratio. For example – does high outperformance (positive returns) indicate a continuing trend, or will it be significant with a negative coefficient when we conduct our regression? It could also be that only one of the two is significant in predicting information ratios, meaning that moves in one direction matter a lot more as a trend for the future. Creating these new variables helps us better understand this relationship.

Final Data Summary Statistics

Below are data summaries for the variables described in the previous section.

Table 2: Yearly Returns, by year

Year	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
2001	876	12.53	20.57	-9.71	40.41
2002	960	1.87	19.89	-21.42	26.27
2003	1,176	38.36	28.91	6.72	74.41
2004	1,428	17.81	15.79	3.29	34.68
2005	1,788	14.69	15.67	-2.72	35.89
2006	2,124	22.64	22.12	5.24	45.37
2007	2,580	24.51	31.29	-3.73	63.32
2008	2,928	-26.96	24.51	-58.63	-0.03
2009	3,360	46.31	43.17	10.39	89.835
2010	3,960	15.08	18.08	-0.945	32.51
2011	4,740	-6.26	12.53	-21.98	6.49
2012	5,964	12.27	15.18	-1.36	27.69
2013	7,188	21.22	17.55	2.16	43.24
2014	7,644	13.79	23.11	-8.31	50.08
2015	8,484	11.47	26.72	-15.69	45.22
2016	9,396	-3.36	19.78	-25.01	17.07
2017	9,768	21.46	20.27	1.61	43.41
2018	8,592	-12.46	17.45	-31.58	7.30
2019	6,312	17.90	18.30	0.09	40.93
Total	**89,268**	**10.53**	**26.53**	**-18.51**	**39.54**

Table 3: Monthly Returns, by year

Year	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
2001	876	1.02	5.82	-5.2	7.6
2002	960	0.14	5.21	-5.545	5.69
2003	1,176	2.66	4.14	-1.53	7.82
2004	1,428	1.38	3.79	-2.58	6.09
2005	1,788	1.16	4.04	-3.44	5.68
2006	2,124	1.68	4.10	-2.73	6.40
2007	2,580	1.73	4.48	-3.03	6.81
2008	2,928	-2.74	8.36	-12.54	5.39
2009	3,360	3.15	7.01	-3.57	11.06
2010	3,960	1.23	5.52	-4.885	7.43
2011	4,740	-0.46	5.59	-6.75	4.96
2012	5,964	1.01	4.75	-4.01	5.83
2013	7,188	1.63	4.60	-3.18	6.65
2014	7,644	1.03	4.75	-3.87	6.34
2015	8,484	0.98	7.70	-7.09	10.49
2016	9,396	-0.25	5.98	-5.53	5.20
2017	9,768	1.60	4.05	-2.21	5.68
2018	8,592	-1.12	5.24	-7.33	4.46
2019	6,312	1.43	5.47	-4.00	7.06
Total	**89,268**	**0.76**	**5.66**	**-4.98**	**6.47**

Table 4: Monthly Net Assets, by year*

Year	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
2001	583	74.5	86.3	5.24	203
2002	691	93.2	122	6.60	220
2003	816	112	140	6.00	305
2004	981	145	194	8.57	424
2005	1,129	174	229	7.70	488
2006	1,341	219	306	10.50	622
2007	1,534	408	1440	12.50	686
2008	1,887	287	866	10.00	519
2009	1,990	172	484	6.73	348
2010	2,368	129	242	8.0	340
2011	2,390	134	260	6.26	361
2012	2,383	154	295	5.69	441
2013	2,474	168	316	7.43	446
2014	2,604	178	334	9.20	428
2015	2,626	183	339	6.500	485
2016	2,128	190	353	4.75	600
2017	1,987	196	462	2.00	480
2018	2,167	215	619	1.08	496
2019	1,955	260	864	1.77	519
Total	**34,034**	**190**	**537**	**5.76**	**444**

**This is reported in millions for Mean, Standard Deviation, 10th Percentile, and 90th Percentile*

Table 5: Variable Summary Statistics

Summary Statistics	Observations	Mean	Standard Deviation	10^{th} Percentile	90^{th} Percentile
longestmanager tenure	77,664	15.44	6.30	8.50	24.25
avgmanager tenure	77,664	14.79	5.74	8.50	23.42
mgmtfee	84,408	1.48	0.42	1.00	2.00
maxmgmtfee	21,948	1.40	0.54	1.00	2.00
performancefee	79,176	18.98	3.68	15.0	20.00
average_assets	89,268	192**	54.3**	134**	260**
ln_avgassets	89,268	19.03	0.26	18.71	19.38
assets	8,451	194**	540**	6.03**	451**
ln_assets	8,449	17.76	1.79	15.61	19.94
ln_avgtenure	77,664	2.59	0.58	2.14	3.15
ln_longesttenure	77,664	2.62	0.60	2.14	3.19
feesbool	89,268	0.69	0.46	0.00	1.00
feesrange	89,268	0.64	0.48	0.00	1.00
feesaltstruc	89,268	0.72	0.45	0.00	1.00
firmassets	89,268	72.4**	344**	0.00	151**
ln_firmassets	34,062	17.73	1.79	15.56	19.91
assetproportion	34,021	1.00	0.00	1.00	1.00
posreturns	7,439	15.38	21.19	0.00	39.54
negreturns	7,439	-4.85	10.30	-18.51	0.00

***The marked values are reported in millions*

Regression Models and Empirical Analysis

With cleaned data and variables generated, we can begin the analysis necessary to answer the core questions of this research paper.

1. Build a model to forecast information ratios,
2. Implement the forecasting model and predict information ratios,
3. Use the Treynor-Black active portfolio model to generate recommended weights, and,
4. Test the Treynor-Black active portfolio against a naïve model in a long/short analysis.

After completing these steps, we will summarize our results and compare between the different time periods tested.

Building an Information Ratio Forecasting Model

To forecast a hedge fund's information ratio, there are a few steps to follow. First, we will identify return benchmarks (regional market indices that act as the 'universe' for the hedge funds). Second, using those benchmarks in a factor model, we will compute the beta, or sensitivity, of hedge fund returns to the benchmark using a regression. Third, using beta and regression residuals, we will calculate the information ratio. Fourth, we will discuss the calculated information ratios and potential drivers for our forecasting model.

Identifying Benchmarks

We will be using a set of three factors for each category of fund. Funds are generally separated by their region, though there is a set of emerging markets funds and U.S. smallcap funds. Our method for selecting was regional, and all fund categories were also measured against the international benchmark. The data had significant variability in domicile for the hedge funds. However, Morningstar reported fund-specific strategies shown in the category section of the table below. With this in mind, we selected factor benchmarks carefully based on geography and primary target investment universe. For example, China Long/Short Equity is best described by the China benchmark. However, China, as a part of the Asia/Pacific, may also be driven in part by that benchmark. The specific factor benchmarks used are summarized in the chart below.

Table 6: Hedge Fund Factor Overview

Hedge Fund Category	Factor 1 Benchmark	Factor 2 Benchmark	Factor 3 Benchmark
Asia/Pacific Long/Short Equity	Asia/Pacific ex Japan	Japan	International
China Long/Short Equity	China	Asia/Pacific ex Japan	International
Emerging Markets Long/Short Equity	Emerging Markets	International	-
Europe Long/Short Equity	Europe	International	-
Global Long/Short Equity	International	U.S.	Developed ex-US
U.S. Long/Short Equity	U.S.	North America	International
U.S. Small Cap Long/Short Equity	U.S.	North America	International

Creating a Factor Model

After we identified the regional benchmarks, we ran a regression on each fund-year to analyze the coefficients and residuals so that we could calculate information ratios for each fund.

$$MonthlyRet = \beta_0 + \beta_1 * Factor1 + \beta_2 * Factor2 + \beta_3 * Factor3$$

Below, in Tables 7-9, the results of the above regression are reported. 2018, with a December market correction, had significantly lower returns than other years, with losses particularly concentrated in China.

Table 7: Hedge Fund Factor Summary, 2017

Hedge Fund Category	Average Yearly Alpha	Factor 1 Beta	Factor 2 Beta	Factor 3 Beta
Asia/Pacific Long/Short Equity	25.58	-0.10	-0.01	0.05
China Long/Short Equity	24.05	0.12	0.31	-0.54
Emerging Markets Long/Short Equity	25.00	-0.06	0.11	0.00
Europe Long/Short Equity	15.41	0.00	-0.08	0.00
Global Long/Short Equity	21.65	1.81	-1.07	-0.82
U.S. Long/Short Equity	18.30	-1.36	1.52	-0.20
U.S. Small Cap Long/Short Equity	14.35	-5.15	5.96	-0.71

Table 8: Hedge Fund Factor Summary, 2018

Hedge Fund Category	Average Yearly Alpha	Factor 1 Beta	Factor 2 Beta	Factor 3 Beta
Asia/Pacific Long/Short Equity	-13.79	0.30	-0.13	0.70
China Long/Short Equity	-23.44	0.17	0.42	2.70
Emerging Markets Long/Short Equity	-12.85	0.15	2.35	0.00
Europe Long/Short Equity	-1.35	0.51	0.08	0.00
Global Long/Short Equity	-7.63	8.19	-4.68	-2.94
U.S. Long/Short Equity	-5.22	-3.34	2.01	1.58
U.S. Small Cap Long/Short Equity	-4.52	-0.33	-1.20	1.86

Table 9: Hedge Fund Factor Summary, 2019

Hedge Fund Category	Average Yearly Alpha	Factor 1 Beta	Factor 2 Beta	Factor 3 Beta
Asia/Pacific Long/Short Equity	9.42	0.04	0.04	-0.22
China Long/Short Equity	27.35	0.10	0.09	-0.48
Emerging Markets Long/Short Equity	15.77	0.44	-0.45	0.00
Europe Long/Short Equity	9.48	0.57	-0.74	0.00
Global Long/Short Equity	12.54	6.26	-3.67	-2.64
U.S. Long/Short Equity	20.51	12.56	-15.41	3.22
U.S. Small Cap Long/Short Equity	15.83	13.01	-15.52	2.73

Calculating the Information Ratio

With the above regression equation, we calculated the information ratio by dividing the beta constant by the variance of the residuals. Tables 10-12 summarize the calculated information ratios by year, and the R^2 values by year and by category. Our regression for calculating information ratios had an R^2 value on average of 24% and ranged from 0% to 91%. It appears that the coefficient of determination for this regression varied heavily by fund but was on average towards the lower end of the spectrum.

Table 10: Information Ratios, by year

Year	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
2001	876	0.24	1.21	-0.11	0.32
2002	960	0.06	0.48	-0.19	0.32
2003	1,176	0.48	0.61	0.12	1.05
2004	1,428	0.34	0.40	0.03	0.79
2005	1,788	0.31	1.30	-0.03	0.40
2006	2,124	0.36	0.45	0.05	0.81
2007	2,580	0.25	0.38	-0.01	0.56
2008	2,928	-0.08	0.11	-0.21	0.01
2009	3,360	0.27	0.30	0.05	0.61
2010	3,960	0.13	0.32	-0.05	0.40
2011	4,740	0.00	0.22	-0.16	0.11
2012	5,964	0.16	0.25	0.00	0.41
2013	7,188	0.27	0.35	0.02	0.64
2014	7,644	0.21	0.43	-0.08	0.58
2015	8,484	0.08	0.29	-0.11	0.30
2016	9,396	-0.01	0.20	-0.17	0.20
2017	9,768	0.54	2.47	0.02	1.08
2018	8,592	-0.13	3.64	-0.63	0.11
2019	6,312	0.34	2.85	-0.01	0.45
Total	**89,268**	**0.18**	**1.64**	**-0.16**	**0.50**

Table 11: Information Ratio R^2, by year

Year	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
2001	876	0.24	0.14	0.06	0.38
2002	960	0.20	0.13	0.06	0.42
2003	1,176	0.20	0.15	0.03	0.40
2004	1,428	0.31	0.17	0.08	0.56
2005	1,788	0.26	0.16	0.07	0.45
2006	2,124	0.37	0.19	0.13	0.67
2007	2,580	0.17	0.14	0.03	0.35
2008	2,928	0.26	0.17	0.06	0.51
2009	3,360	0.28	0.17	0.05	0.52
2010	3,960	0.27	0.20	0.03	0.53
2011	4,740	0.18	0.15	0.02	0.39
2012	5,964	0.19	0.16	0.02	0.42
2013	7,188	0.23	0.16	0.04	0.43
2014	7,644	0.26	0.22	0.03	0.59
2015	8,484	0.24	0.18	0.06	0.52
2016	9,396	0.23	0.14	0.05	0.41
2017	9,768	0.22	0.15	0.05	0.44
2018	8,592	0.26	0.15	0.07	0.46
2019	6,312	0.33	0.18	0.11	0.59
Total	**89,268**	**0.24**	**0.17**	**0.05**	**0.49**

Table 12: Information Ratio R^2, by Category

Category	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
Asia/Pacific Long/Short Equity	3,264	0.26	0.17	0.07	0.49
China Long/Short Equity	26,004	0.23	0.15	0.06	0.43
Emerging Markets Long/Short Equity	8,628	0.20	0.17	0.02	0.45
Europe Long/Short Equity	10,404	0.16	0.15	0.01	0.36
Global Long/Short Equity	10,452	0.28	0.19	0.07	0.55
U.S. Long/Short Equity	23,088	0.29	0.18	0.06	0.55
U.S. Small Cap Long/Short Equity	7,428	0.28	0.18	0.07	0.52
Total	**89,268**	**0.24**	**0.17**	**0.05**	**0.49**

We noted an interesting and steady higher information ratio early in the sample, from 2003 to 2007, which ended with the financial crisis. The R^2 values over the same time period were correspondingly higher, and neither of these metrics have wholly recovered since the financial crisis. Looking at R^2 by category, it is generally higher for global and U.S. long/short funds. Even small-cap focused hedge funds in the U.S. generated an on-average information ratio well above their peers from different locales. Europe was an outlier in the data set, having an economically lower average information ratio.

From the information ratios, it appears that some funds take on more systematic risks than others. This risk could be because of their trading/investing strategies, with hedge funds choosing to take on risk in a non-standard long/short manner. Another potential issue is misclassification by Morningstar for hedge funds, which would mean the misclassified fund's information ratio is unlikely to be accurately calculated. The benchmark choices for this analysis were made carefully, but funds that invest in globally in reality, but only a specific geography by their category, may also have differing information ratios from what we calculated above.

Discussing a Potential Information Ratio Forecasting Model

To build an information ratio forecasting model, we decided to use some time-variate drivers and year fixed effects. Due to the difficulty in obtaining absolute, complete data, we were unable to include more granular fund information. The sample information ratio regression included the following variables: *infratio*, *ln_assets*, *assetproportion*, *posreturns*, and *negreturns*. With these, we could isolate three key drivers of the next year's information ratio.

First, the last year's information ratio (*infratio*) is a potential driver of next year's information ratio. A hedge fund manager does not lose their skill in security selection overnight, and strong investing choices made in a single year can benefit the hedge fund for years to come. Conversely, poor selections in a single year can handicap performance for years to come. Both of these situations depend on the information ratio, or skill, of the previous year.

Second, the underlying assets of a fund (*ln_assets, assetproportion*) can lead to a large differential between returns, depending on their capital controls. Outflows can decimate funds if they occur at the wrong time, and large inflows following a strong year can force managers to allocated capital to less-certain ventures. These dynamics characterize a strong relationship between assets and returns.

Third, the hedge fund returns from the previous year, divided by up and down moves into *posreturns* and *negreturns*, respectively, are also a key driver of performance. As mentioned with assets, strong performance can drive inflows that drive down performance in later periods. Certain funds may have differing relationships between performance in one year and the next and isolating the impact of upwards and downwards moves can help us identify which trend has a greater impact on the information ratio of the next year. Lastly, we included year fixed effects so that we could isolate the impact of the year to hedge fund returns.

Implementing the Forecasting Model and Predicting Information Ratios

Now that we have our calculated information ratios historically and have discussed potential drivers of an information ratio regression, the next step is to test them. In order to do this, we will first run regressions from 2001 to 2017, 2018, and 2019. Then, we will conduct and out-of-sample prediction test, using the same three years for comparison: 2017, 2018, and 2019. Our regression specifications did not change with the years, besides the addition of the binary year effect variables. The formulas below summarize the regression outputs, and the three tables following show the statistical significance of various coefficients.

Standard Information Ratio Regression Equation:

$$infratio_{t+1} = \beta_0 + \beta_1 * infratio_t + \beta_2 * ln\_assets_t + \beta_3 * assetproportion_t + \beta_4 * posreturns_t + \beta_5 * negreturns_t + \beta_6 * yr01 + \beta_7 * yr02 + \cdots + \beta_{final} * yr **_{final}$$

2017 Information Ratio Regression:

$$infratio_{2017} = -116{,}737 - 0.09 * infratio_{2016} - 0.01 * ln\_assets_{2016} + 116{,}737.6 * assetproportion_{2016} + 0 * posreturns_{2016} + 0 * negreturns_{2016} - 0.51 * yr01 - 0.15 * yr02 - 0.17 * yr03 - 0.06 * yr04 - 0.18 * yr05 - 0.24 * yr06 - 0.60 * yr07 - 0.30 * yr08 - 0.40 * yr09 - 0.55 * yr10 - 0.39 * yr11 - 0.20 * yr12 - 0.15 * yr13 - 0.49 * yr14 - 0.47 * yr15$$

2018 Information Ratio Regression:

$$infratio_{2018} = -111{,}941 - 0.13 * infratio_{2017} - 0.02 * ln\_assets_{2017} + 111{,}941.6 * assetproportion_{2017} + 0 * posreturns_{2017} + 0 * negreturns_{2017} + 0.11 * yr01 + 0.47 * yr02 + 0.46 * yr03 + 0.58 * yr04 + 0.47 * yr05 + 0.40 * yr06 + 0.03 * yr07 + 0.32 * yr08 + 0.23 * yr09 + 0.07 * yr10 + 0.23 * yr11 + 0.43 * yr12 + 0.50 * yr13 + 0.15 * yr14 + 0.16 * yr15 + 0.62 * yr16$$

2019 Information Ratio Regression:

$$infratio_{2019} = 169{,}143.5 - 0.13 * infratio_{2018} - 0.03 * ln\_assets_{2018} - 169{,}143 * assetproportion_{2018} + 0 * posreturns_{2018} + 0 * negreturns_{2018} - 0.24 * yr01 + 0.13 * yr02 + 0.10 * yr03 + 0.22 * yr04 + 0.12 * yr05 + 0.05 * yr06 - 0.31 * yr07 - 0.01 * yr08 - 0.12 * yr09 - 0.27 * yr10 - 0.10 * yr11 + 0.09 * yr12 + 0.15 * yr13 - 0.19 * yr14 - 0.18 * yr15 + 0.28 * yr16 - 0.33 * yr17$$

The above regression equations were constructed from Tables 13, 14, and 15, which summarize on the following pages the coefficients for each variable and their respective significance level. P>|t| values that are below 0.05 are significant at the 95% level.

Table 13: Information Ratio Panel Regression, 2017

Variable	Coefficient	P>|t|
infratio	-0.09	0.00
ln_assets	-0.01	0.46
assetproportion	116,737.6	0.86
posreturns	0.00	0.56
negreturns	0.00	0.96
yr01	-0.51	0.00
yr02	-0.15	0.07
yr03	-0.17	0.03
yr04	-0.06	0.41
yr05	-0.18	0.01
yr06	-0.24	0.00
yr07	-0.60	0.00
yr08	-0.30	0.00
yr09	-0.40	0.00
yr10	-0.55	0.00
yr11	-0.39	0.00
yr12	-0.20	0.00
yr13	-0.15	0.01
yr14	-0.49	0.00
yr15	-0.47	0.00
_cons	-116,737	0.86

Table 14: Information Ratio Panel Regression, 2018

Variable	Coefficient	P>|t|
infratio	-0.13	0.00
ln_assets	-0.02	0.11
assetproportion	111,941.6	0.86
posreturns	0.00	0.77
negreturns	0.00	0.94
yr01	0.11	0.20
yr02	0.47	0.00
yr03	0.46	0.00
yr04	0.58	0.00
yr05	0.47	0.00
yr06	0.40	0.00
yr07	0.03	0.56
yr08	0.32	0.00
yr09	0.23	0.00
yr10	0.07	0.18
yr11	0.23	0.00
yr12	0.43	0.00
yr13	0.50	0.00
yr14	0.15	0.00
yr15	0.16	0.00
yr16	0.62	0.00
_cons	-111,941	0.86

Table 15: Information Ratio Panel Regression, 2019

Variable	Coefficient	P>|t|
infratio	-0.13	0.00
ln_assets	-0.03	0.04
assetproportion	-169,143	0.79
posreturns	0.00	0.85
negreturns	0.00	0.57
yr01	-0.24	0.01
yr02	0.13	0.13
yr03	0.10	0.21
yr04	0.22	0.00
yr05	0.12	0.09
yr06	0.05	0.46
yr07	-0.31	0.00
yr08	-0.01	0.93
yr09	-0.12	0.08
yr10	-0.27	0.00
yr11	-0.10	0.07
yr12	0.09	0.14
yr13	0.15	0.01
yr14	-0.19	0.00
yr15	-0.18	0.00
yr16	0.28	0.00
yr17	-0.33	0.00
_cons	169,143.5	0.79

Studying the results from Tables 13-15, we found an interesting year effect. Looking at the year fixed effects (*yr***), and studying the significance, the 2017 regression has most year effects as significant besides 2002 and 2004. Uniquely, the year effects are negative, and 2018 brings about a complete turn in fixed effects. The coefficients for 2008 are wholly positive and significant except for 2001, 2007, and 2010. Comparing the coefficients – on these same years, particularly the turbulent 2001 and 2007, the coefficient contracted as well. 2019 had a similar flip, with a mix of coefficient signs and significance, though these signs and coefficients were definitely less consistent than the previous two predictions. This shift is expected, with the late-2018 correction resulting in a changing market, as discussed later in the paper.

With the above regression models, we arrived at the following predicted information ratio results by year.

Table 16: Information Ratio Summary Statistics, by year

Year	Observations	Mean	Standard Deviation	10th Percentile	90th Percentile
2017	170	0.56	0.03	0.53	0.60
2018	168	-0.12	0.12	-0.25	-0.01
2019	156	0.31	0.08	0.23	0.41

The above predicted information ratio results have some unique variability. The mean of the predicted information ratio for 2017 is higher than the other two years, and 2018 had a negative information ratio forecast across the board. 2017 was a stable year in the post-financial crisis bull market, and thus this upwards trend likely pushed up information ratios estimates. 2018 market performance suffered from a correction in December that eliminated the gains from the year, and 2019 led the recovery from that correction to new highs. The accuracy of these returns, in terms of the second research question, is still uncertain. From a comparison to historical values, we noted that the regression model appeared to move extreme values closer to the mean across all three years. The variability seen in the actual fund information ratios is not present in the predicted information ratios, which was expected as extreme values are difficult to predict. As a note on the data – observations here declined significantly as the regression model dropped funds that lacked complete data on an asset basis, which was difficult to obtain. Still, our sample size, above 150 for all three years, is strong.

Using the Treynor-Black Model

With predicted information ratios, we will shift to generating the weights recommended by the Treynor-Black model. The active investment portion of the Treynor-Black model is calculated as follows, using predicted fund information ratios:

$$w_{i,t+1} = \frac{(\widehat{IR}_{i,t+1})}{\sum_{i=1}^{n\_t} \widehat{IR}_{t+1}}$$

$\widehat{IR} = predicted\ information\ ratio$

$w_i = recommended\ weight\ for\ fund\ i$

The above calculation depends on an initial selection of a number of funds to invest in. The sum will be taken for the top information-ratio-ranked funds of the investable universe. Although an investor could invest across the entire universe of funds instead of picking the top *x* number of funds, it is simply not economical to diversify to such a degree. We ranked funds by their highest predicted information ratio, and incremented our fund selection by units of five, ranging from five funds up to 25 funds. The weighting system described above would theoretically place a larger weight of the portfolio into hedge fund managers with high potential for success, as indicated by the information ratio.

Testing the Treynor-Black Model vs. a Naïve Model

Given that we now have calculated forward information ratios, we can switch to the discussed Treynor-Black active weight model and generate a potential hedge fund investment portfolio. The performance of this portfolio based on the model weights versus naïve weights will indicate whether there is any return potentially available from the information ratio prediction and subsequent weighting system.

For the construction of our long/short hedge fund trading portfolio, we used the Treynor-Black Model active weights as our long investment. The naïve model was created as an equal weight portfolio, with its formula below. Out of the same investments picked by a predicted information ratio ranking, the naïve model simply assigned each an equal percentage depending on the target number of holdings. Effectively speaking, the naïve model is simply where an investor puts in an equal amount of capital into each holding. The naïve model here is the short of the portfolio.

$$w_{i,t+1} = \frac{1}{n_t}$$

$n_t = number\ of\ chosen\ investable\ funds$

$w_i = recommended\ weight\ for\ fund\ i, constant\ for\ all\ funds$

With long Treynor-Black and short Naïve sets of weights, we then took the net weight against each other as the target long/short weight. If the weighting between funds does not matter, the portfolio would return effectively nothing out of sample, because we are long and short in equal value. If the weighting does have an impact, the return will be different from zero – a higher return would indicate that the long leg (Treynor-Black) is generating excess return, and a negative return would indicate that the short leg (Naïve) is generating more return, and that the Treynor-Black model is not adding value.

The out-of-sample test was conducted on 2017, 2018, and 2019, with example funds with holdings at 5, 10, 15, 20, and 25. Each of these was tested under two common portfolio management strategies: Buy and Hold, and Rebalance. As both of these strategies are tested, it's important to note that both begin with the same defined weight from the Treynor-Black Model weights minus the Naïve Model weights. For the Buy and Hold strategy, weights were set at the beginning of the investment period and left untouched for a year. Funds with outperformance would therefore represent a higher proportion of the ending portfolio value, and funds that underperformed would grow smaller. However, this strategy is more exposed to a change in fortunes – a high performing fund taking losses would have greater weight in the middle of the period in this strategy, and so losses to the investment portfolio would be greater. The second strategy we tested was a Rebalance strategy, where the portfolio manager would return to the defined net weights at the end of every month. This would represent taking profits and buying more of your losers, and due to its strict adherence to the information ratio net weights, would best represent the efficacy of the Treynor-Black model as an allocation method. The rebalance strategy would be tied better to our net weights, with less exposure to the market.

For each of the strategies and time-periods below, there is some brief discussion of trends, and there is a broader discussion at the end to compare the different models and their returns. Observations for all tests are at 12, because these tests were conducted on an annual basis. Each month represents one observation in the data.

Buy and Hold, 2017

Table 17: Buy and Hold Portfolio Correlations, 2017

Portfolio Correlations	**Market Return**	**5-Fund Portfolio**	**10-Fund Portfolio**	**15-Fund Portfolio**	**20-Fund Portfolio**	**25-Fund Portfolio**
Market Return	1.00					
5-Fund Portfolio	0.19	1.00				
10-Fund Portfolio	-0.02	0.15	1.00			
15-Fund Portfolio	-0.29	-0.19	0.83	1.00		
20-Fund Portfolio	-0.20	-0.11	0.92	0.92	1.00	
25-Fund Portfolio	-0.20	-0.20	0.89	0.90	0.97	1.00

Table 18: Buy and Hold T-Test Results, 2017

T-Test Results	**Observations**	**Mean***	**T-Value**
5-Fund Portfolio	12	0.00	0.21
10-Fund Portfolio	12	0.04	5.60
15-Fund Portfolio	12	0.03	3.04
20-Fund Portfolio	12	0.03	2.96
25-Fund Portfolio	12	0.02	2.81

*reported in percentage points

Table 19: Buy and Hold Statistical T-Test Results, 2017

Statistical T-Test Results	H_a: mean < 0 Prob(T<t)	H_a: mean != 0 Prob(T<t)	H_a: mean > 0 Prob(T<t)
5-Fund Portfolio	0.58	0.84	0.42
10-Fund Portfolio	0.99	0.02	0.00
15-Fund Portfolio	0.99	0.01	0.01
20-Fund Portfolio	0.99	0.01	0.01
25-Fund Portfolio	0.99	0.02	0.01

The 5-fund portfolio was correlated with the market, but adding more funds changed it to an inverse relationship with the market. The 10-fund portfolio, which is the closest to market-neutral per the correlation table, also had the highest mean monthly return. The mean return across the board appears to be economically insignificant, but statistically, all portfolios with greater than 5 holdings are significant at the 5% level. Therefore, for Funds>5, mean return is statistically expected to be different from zero, and with greater significance, mean return is expected to be larger than zero.

Rebalance, 2017

Table 20: Rebalance Portfolio Correlations, 2017

Portfolio Correlations	Market Return	5-Fund Portfolio	10-Fund Portfolio	15-Fund Portfolio	20-Fund Portfolio	25-Fund Portfolio
Market Return	1.00					
5-Fund Portfolio	0.20	1.00				
10-Fund Portfolio	0.03	0.22	1.00			
15-Fund Portfolio	-0.29	-0.08	0.79	1.00		
20-Fund Portfolio	-0.20	-0.02	0.92	0.91	1.00	
25-Fund Portfolio	0.20	-0.10	0.88	0.90	0.97	1.00

Table 21: Rebalance T-Test Results, 2017

T-Test Results	Observations	Mean	T-Value
5-Fund Portfolio	12	0.00	0.12
10-Fund Portfolio	12	0.04	5.52
15-Fund Portfolio	12	0.03	2.91
20-Fund Portfolio	12	0.03	2.67
25-Fund Portfolio	12	0.02	2.56

*reported in percentage points

Table 22: Rebalance Statistical T-Test Results, 2017

Statistical T-Test Results	H_a: mean < 0 Prob(T<t)	H_a: mean != 0 Prob(T<t)	H_a: mean > 0 Prob(T<t)
5-Fund Portfolio	0.55	0.91	0.45
10-Fund Portfolio	0.99	0.00	0.00
15-Fund Portfolio	0.99	0.01	0.01
20-Fund Portfolio	0.99	0.02	0.01
25-Fund Portfolio	0.99	0.03	0.01

The rebalance portfolio for 2017 had some similar trends as seen in the buy and hold, except with two market-correlated funds. However, the 10-Fund portfolio is only market correlated by a slight margin, and is still the closest to market neutral of the portfolios. It also has the highest mean monthly return. Statistically speaking, for Funds>5, mean return is again expected to be significantly different, and greater than, zero.

2017 Portfolio Strategy Comparison

With 2017 being a standard bull-market year, the buy-and-hold strategy was likely to be more effective. It appears from the data that those top performers sustained their edge through the year and rebalancing back to the 'losing' funds detracted from potential return.

The mean monthly returns in both funds were positive, which tends to indicate that the Treynor-Black model has value to add.

Buy and Hold, 2018

Table 23: Buy and Hold Portfolio Correlations, 2018

Portfolio Correlations	Market Return	5-Fund Portfolio	10-Fund Portfolio	15-Fund Portfolio	20-Fund Portfolio	25-Fund Portfolio
Market Return	1.00					
5-Fund Portfolio	-0.91	1.00				
10-Fund Portfolio	-0.83	0.95	1.00			
15-Fund Portfolio	-0.61	0.77	0.87	1.00		
20-Fund Portfolio	-0.37	0.51	0.56	0.80	1.00	
25-Fund Portfolio	-0.26	0.28	0.33	0.66	0.90	1.00

Table 24: Buy and Hold T-Test Results, 2018

T-Test Results	Observations	Mean	T-Value
5-Fund Portfolio	12	0.28	0.50
10-Fund Portfolio	12	0.61	0.93
15-Fund Portfolio	12	0.28	0.71
20-Fund Portfolio	12	0.97	2.08
25-Fund Portfolio	12	0.46	0.77

*reported in percentage points

Table 25: Buy and Hold Statistical T-Test Results, 2018

Statistical T-Test Results	H_a: mean < 0 Prob(T<t)	H_a: mean != 0 Prob(T<t)	H_a: mean > 0 Prob(T<t)
5-Fund Portfolio	0.69	0.63	0.31
10-Fund Portfolio	0.81	0.37	0.19
15-Fund Portfolio	0.75	0.49	0.25
20-Fund Portfolio	0.97	0.06	0.03
25-Fund Portfolio	0.77	0.46	0.23

In the 2018 buy and hold model, all portfolios are inversely correlated with the market, but as the fund number rises, the correlation trends down towards zero. This indicates that the funds, as we move lower in the information ratio ranking, are taking on more market exposure, and that the positive mean monthly return in the low-fund-count portfolios was derived from an effectively short-market position. As more positions are added, logically speaking, this would reduce significant market directional exposure and tend towards neutral or slightly positive, as seen in the data. The only results that are statistically significant in this model are for the 20-fund portfolio at the 95% level, where the mean monthly return is expected to be greater than zero. The 20-fund portfolio also has the highest mean monthly return out of the set of funds above.

Rebalance, 2018

Table 26: Rebalance Portfolio Correlations, 2018

Portfolio Correlations	Market Return	5-Fund Portfolio	10-Fund Portfolio	15-Fund Portfolio	20-Fund Portfolio	25-Fund Portfolio
Market Return	1.00					
5-Fund Portfolio	-0.91	1.00				
10-Fund Portfolio	-0.84	0.93	1.00			
15-Fund Portfolio	-0.67	0.83	0.93	1.00		
20-Fund Portfolio	-0.43	0.61	0.62	0.77	1.00	
25-Fund Portfolio	-0.46	0.56	0.59	0.75	0.95	1.00

Table 27: Rebalance T-Test Results, 2018

T-Test Results	Observations	Mean	T-Value
5-Fund Portfolio	12	0.21	0.45
10-Fund Portfolio	12	0.59	0.95
15-Fund Portfolio	12	0.38	0.88
20-Fund Portfolio	12	1.22	2.32
25-Fund Portfolio	12	0.91	1.39

*reported in percentage points

Table 28: Rebalance Statistical T-Test Results, 2018

Statistical T-Test Results	H_a: mean < 0 Prob(T<t)	H_a: mean != 0 Prob(T<t)	H_a: mean > 0 Prob(T<t)
5-Fund Portfolio	0.67	0.66	0.33
10-Fund Portfolio	0.82	0.36	0.18
15-Fund Portfolio	0.80	0.40	0.20
20-Fund Portfolio	0.98	0.04	0.02
25-Fund Portfolio	0.90	0.19	0.10

In the 2018 rebalance portfolio, we see similar correlation trends as earlier, though the correlation across the board does seem to be slightly more market inverse with a rebalancing portfolio. Though the difference is too small to draw conclusions from at a lower number of funds, it appears that the 25-fund portfolio is more market inverse when rebalanced. Considering the structure of our long/short portfolio, this actually means that the lowest-ranked (by information ratio) funds in the 2018 rebalance portfolio were long the market, and the short position taken for bottom-ranked funds increased the market-inverse exposure. The T-test for this portfolio was uniformly insignificant, besides the 20-fund portfolio at the 95% level. As the T-test is comparing whether returns significantly differ from zero, it is appropriate that the 20-fund portfolio also has the highest mean monthly return.

2018 Portfolio Strategy Comparison

2018, for the first 11months, was similar to 2017 in terms of performance. However, in December 2018, there was a large market correction that decimated market index returns to end the year negative. Comparing the 25-fund portfolio market correlation, this indicates the funds that were long on the market but added last to the portfolio and shorted, suffered in weighting throughout the year with buy-and-hold. With reduced weights, they were unable to contribute alpha when the net-short-market position became useful in December. The rebalancing method, however, reallocated capital at the start of the month, and improved the market-inverse position as we saw in the correlation table.

We expected that this market move would have unique results with our regression model, and it looks like our statistical significance was adversely impacted. For the regression model, it is interesting to see how performance will be in 2019, immediately following the market correction. We expected model accuracy to decline for 2019, in both strategies.

Buy and Hold, 2019

Table 29: Buy and Hold Portfolio Correlations, 2019

Portfolio Correlations	Market Return	5-Fund Portfolio	10-Fund Portfolio	15-Fund Portfolio	20-Fund Portfolio	25-Fund Portfolio
Market Return	1.00					
5-Fund Portfolio	-0.69	1.00				
10-Fund Portfolio	-0.66	0.99	1.00			
15-Fund Portfolio	-0.75	0.99	0.99	1.00		
20-Fund Portfolio	-0.76	0.99	0.97	0.99	1.00	
25-Fund Portfolio	-0.77	0.98	0.97	0.98	1.00	1.00

Table 30: Buy and Hold T-Test Results, 2019

T-Test Results	Observations	Mean	T-Value
5-Fund Portfolio	12	-0.13	-0.36
10-Fund Portfolio	12	-0.06	-0.26
15-Fund Portfolio	12	-0.19	-0.70
20-Fund Portfolio	12	-0.12	-0.54
25-Fund Portfolio	12	-0.08	-0.43

*reported in percentage points

Table 31: Buy and Hold Statistical T-Test Results, 2019

Statistical T-Test Results	H_a: mean < 0 Prob(T<t)	H_a: mean != 0 Prob(T<t)	H_a: mean > 0 Prob(T<t)
5-Fund Portfolio	0.36	0.73	0.64
10-Fund Portfolio	0.40	0.80	0.60
15-Fund Portfolio	0.25	0.50	0.75
20-Fund Portfolio	0.30	0.60	0.70
25-Fund Portfolio	0.34	0.68	0.66

The 2019 buy-and-hold portfolio deviated significantly from the previous models. First, it actually still had a market inverse correlation, but the inter-portfolio correlation was higher by a large margin. The 5-fund portfolio had a correlation of 0.9778 with the 25-fund portfolio, indicating strongly that the top-25 information ratio-ranked funds all had similar performance during the year. This is especially shown when analyzing the lack of statistical significance. All portfolios were not statistically different from zero, and the mean monthly return actually indicated a negative average return. Economically and statistically, this negative return is effectively zero, and the similar performance of all funds over the year shown by correlation reduces the potential results we could draw from the data.

Rebalance, 2019

Table 32: Rebalance Portfolio Correlations, 2019

Portfolio Correlations	Market Return	5-Fund Portfolio	10-Fund Portfolio	15-Fund Portfolio	20-Fund Portfolio	25-Fund Portfolio
Market Return	1.00					
5-Fund Portfolio	-0.71	1.00				
10-Fund Portfolio	-0.69	1.00	1.00			
15-Fund Portfolio	-0.75	1.00	0.99	1.00		
20-Fund Portfolio	-0.76	0.99	0.99	0.99	1.00	
25-Fund Portfolio	-0.77	0.99	0.98	0.99	1.00	1.00

Table 33: Rebalance T-Test Results, 2019

T-Test Results	Observations	Mean	T-Value
5-Fund Portfolio	12	0.00	0.01
10-Fund Portfolio	12	0.02	0.08
15-Fund Portfolio	12	-0.08	-0.27
20-Fund Portfolio	12	-0.04	-0.17
25-Fund Portfolio	12	-0.02	-0.11

*reported in percentage points

Table 34: Rebalance Statistical T-Test Results, 2019

Statistical T-Test Results	H_a: mean < 0 Prob(T<t)	H_a: mean != 0 Prob(T<t)	H_a: mean > 0 Prob(T<t)
5-Fund Portfolio	0.50	0.99	0.50
10-Fund Portfolio	0.53	0.94	0.47
15-Fund Portfolio	0.40	0.79	0.60
20-Fund Portfolio	0.44	0.87	0.56
25-Fund Portfolio	0.46	0.92	0.54

The 2019 rebalance portfolio was fundamentally similar to the buy-and-hold strategy over the same period, with market-inverse correlations but strong inter-fund correlations. Again, none of the portfolio returns were statistically different from zero in either direction. The mean return for the 5- and 10-fund portfolio flipped signs, tending slightly positive.

2019 Portfolio Strategy Comparison

Comparing the two 2019 portfolios, we see similar performance and the predicted inaccuracy derived from 2018 data. The December drawdown appears to have significantly altered the Treynor-Black recommended weights on this different set of funds, as the top-performers from 2018 were likely short the market as the year ended and 2019 began. With 2019 being a strong continuation of the broad bull market, these funds were unprepared to perform, and the model was likely therefore inaccurate.

Treynor-Black Long/Short Model Results

The Treynor-Black vs. Naïve long/short strategy was tested under three major market conditions. In 2017, we tested a trending bull market after years of upwards movement. 2018 extended the same trend up until December, where there was a significant market correction leading to the market ending down for the year. 2019 acted as a return to the mean of the past few years, with the market recovering in impressive fashion from the correction and setting record highs. This unique order of events allows us to draw conclusions about our model's efficacy in differing market environments.

From the above major market periods, we see that the model is effective in upwards trending markets (2017), where the last year had strong returns. In a market drawdown (2018) during an upwards trending market, the model is still effective, but less so. Its statistical significance and magnitude of returns are greatly reduced to effectively zero. Following a market drawdown, as financial markets recover and again trend up (2019), the portfolio is ineffective. The adverse impact of the previous year's drawdown results in a position with negative return, and there is no statistical significance to speak of. In the end, however, the Treynor-Black active portfolio method weighting is an effective way to allocate capital. Although it appears to take two consecutive years to adapt to a market shift, the long/short method used in our research provides effective low return in up markets, combined with minimal downside risk as seen in 2018. Even in a market drawdown or after with a mis-specified model (2019), long/short strategy returns did not deviate significantly from zero.

The fact that fund return was so inversely correlated with the market was surprising. Given that we were testing a long/short portfolio, we thought that there would be more market exposure, or at least market neutrality with the level of diversification in the funds themselves and the fund-of-funds portfolio. As mentioned by Fung and Hsieh (2021) in the literature review, long/short funds are generally factor- and market-independent, yet this set of funds had significant market inverse correlation in generating return.

Conclusion

The Treynor-Black model over 2017, 2018, and 2019, proved to be effective in a trending-up market, safe in a volatile correction, and poor in a market recovery. These results could potentially be driven from two major factors. In generating this model, we began with forecasting information ratios on a factor basis. Then, we conducted a Treynor-Black weight model on those results. Speculating on this, our performance results in 2017 and 2018 could be drawn from either strong information ratio predictions that allowed the Treynor-Black model to outperform, or from the efficacy of the model itself in correcting for risk and maximizing return.

The trading strategy between Treynor-Black and the Naïve model has strong returns in 2017. However, this strategy is economically neutral for several reasons. First, hedge funds charge high fees that this simplified model did not account for. Second, hedge funds in the optimal portfolio (2017, rebalance) generally do not allow for rapid investment and divestment on a monthly basis. Combined with general transactional and management costs, along with taxes, the Treynor-Black and Naïve model together are not very effective. One thing to note with this long/short model is that return was reported on a monthly basis. Therefore, the return percentages in the T-Test tables above, when annualized, have low but stable return in 2017. Under specific conditions, the combined model can generate alpha for a fund-of-funds, though this paper can only speculate on this, as we have not incorporated or tested the real costs such a strategy would face.

However, the Treynor-Black model has proven to have strong returns independently, beyond the Naïve model. Therefore, based on this research, utilizing the Treynor-Black model and information ratio predictions to make fund-of-fund investment decisions will likely offer returns above an equal-allocation portfolio without significantly altering the risk of the portfolio.

From an information ratio/appraisal ratio side, this research points to the importance of the information ratio in making hedge fund investment decisions. Individuals or institutions making investing decisions, or considering a set of hedge funds, should look at the information ratio and consider its implications before allocating capital. A high information ratio may not persist, and a fund with strong performance may not continue.

Looking forward to other potential research, an analysis of this data with more complete data, on underlying assets under management or fund flows, could significantly improve regression results. The model could also be extended to the turbulent 2020 markets once sufficient fund data is reported, allowing for a test of the Treynor-Black model in a market with a more sustained downturn.

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Appendix

Appendix 1: Variable Summary

Variable Name	Variable Description
monthlynetassets	Reports assets of underlying funds on a monthly basis in USD
secid	Security ID, acts as an identifier for each hedge fund
year	Year identifier
month	Month identifier
yearlyret	Yearly return by hedge fund in percentage point form
monthlyret	Monthly return by hedge fund in percentage point form
stdev	Standard deviation of the predicted information ratios
variance	Standard deviation of information ratios, squared
average_assets	Average hedge fund net assets (yearly average of *monthlynetassets*)
ln_avgassets	Natural log of *average_assets*
assets	Hedge fund net assets in Q4 of every year (drawn from *monthlynetassets*)
ln_assets	Natural log of *assets*
avgmanagertenure	Average hedge fund manager tenure at the fund
ln_avgtenure	Natural log of *avgmanagertenure*
longestmanagertenure	Longest hedge fund manager tenure at the fund
ln_longesttenure	Natural log of *longesttenure*
mgmtfee	Hedge fund money management fees charged to investors
performancefee	Hedge fund variable (performance-based) fees charged to investors
highwatermark	A hedge fund fee restriction wherein the fund only pays the hedge fund manager if the hedge fund meets or exceeds its previous peak net asset value
clawback	Paid out money or benefits can be withdrawn by the firm from managers
deferredload	Sales commissions that are paid when investors withdraw capital from the hedge fund
feesbool	A generated binary variable that returns 1 if management fees or performance funds are below the standard 2/20 rate
feesrange	A generated binary variable that returns 1 if management fees or performance funds are outside of a 12.5% range of the standard 2/20 rate
feesaltstruc	A generated binary variable that returns 1 if any of the three atypical hedge fund fee and payment structures are present (*highwatermark, clawback, deferredload*)
posreturns	A generated variable that captures yearly hedge fund returns only if they are positive
negreturns	A generated variable that captures yearly hedge fund returns only if they are negative

Appendix 1, continued: Variable Summary

Variable Name	Variable Description
firmassets	A generated variable that represents the monthly parent firm assets (created by a sum by firm of *monthlynetassets*)
assetproportion	A generated variable that represents the proportion of parent firm assets that a hedge fund controls (created by dividing *monthlynetassets* by *firmassets*)
ln_firmassets	Natural log of *firmassets*
fundcount	A generated variable that counts the number of hedge funds in the sample that are under a single firm
*yr***	A generated binary variable that returns 1 for the year (labeled ** on the left, created for all years in sample)
infratio	A calculated variable that contains the information ratios by year and fund
predinfratio	A predicted variable that relies on part of our regression analysis, predicting the next years' information ratio (in the data, this value is shifted such that the predicted information ratio for a year aligns with the year itself, rather than the year before)
weights	Treynor-Black model weights by fund, calculated according to the active portfolio method. These are calculated for the three years tested (2017, 2018, 2019)
naiveweights	Weights by fund, calculated on a simple percentage basis that depends solely on the number of hedge funds to be invested in. These are calculated for the three years tested (2017, 2018, 2019)
netweights	A net weight position calculated by a long investment in *weights* and a short of *naiveweights*
portfolioreturn	A calculated return per month, created by multiplying *monthlyret* and *netweights*
marketreturn	S&P 500 monthly return for the three years tested (2017, 2018, 2019)