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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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There exists a wide range of portfolio performance measures for investors to assess mutual fund's managerial skills. My main research question is about investigating the main performance measure in which investors put heaviest weights on in their investment decisions. By conducting a model horse race analysis to test how sensitive the mutual fund flow is toward each competing measure, I assess the most commonly used portfolio performance measures in the literature. Consistent with previous studies, results indicate that CAPM alpha is the best predictor for fund flows, suggesting that investors tend to put most weights on it. In addition, performance measures incorporating fewer factors can also better explain the variation in fund flows.

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Table of Contents

1. Introduction

Mutual fund industry is a crucial component of the financial markets. Nowadays, mutual funds make up one-thirds of the total investment and currently there are more than 9,000 mutual funds traded in U.S., which surpass the total number of public companies traded on NASDAQ and NYSE combined (Statista). Investing money through mutual funds enables retail investors to diversify their assets, benefit from lower investment costs, and gain access to global financial instruments and markets. Since there exists numerous mutual funds which follow distinctive investment styles and are exposed to different levels of risks, the pressing challenge for investors is to identify which mutual fund can potentially offer a positive net present value and to re-allocate their assets accordingly.

If investors believe that fund managerial skills are different across funds, they would pull capitals out of a certain fund after observing negative performance, since they will interpret the fund's underperformance as an indicator, demonstrating the fact that this particular fund manager lacks skills. Nevertheless, even the least knowledgeable investors know that direct comparison of returns between each fund is meaningless, given that each fund is exposed to different levels of risks. Therefore, when assessing fund managerial skills, investors should account for different risk factors when computing adjusted returns for comparing purposes.

Previous literature has largely focused on establishing the true asset pricing models, but very few attentions have been directed toward investigating the models and factors that investors favor until Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) propose a revealed preference approach to study this question. Both papers conclude that CAPM alpha consistently beats other tested performance measures, but the range of tested measures in both papers does not go beyond alphas.

In this paper, I empirically investigate which performance measure aligns the closest to investors' fund investment decisions, thereby assessing the extent to which investors incorporate sophisticated investment tools. Building upon the methodology and findings of Barber, Huang, and Odean (2016), I intend to investigate two more classic performance measures, Sharpe ratio and information ratio, which have not been studied under this specific context previously. In total, there are seven performance measures investigated in this paper: three sets of alphas based on the capital asset pricing model (CAPM), the three-factor model (Fama and French 1993), and the four-factor model (Carhart 1997); Sharpe ratio; and three sets of information ratios based on each alpha. Inspired by previous studies, I use mutual fund flows as the outcome of investors' investment decisions and different performance measures as tools that investor rely on to make decisions. By conducting model horse race among seven competing performance measures, I more robustly address concerns about nonlinearities in the flow-return relation and investigate the question in which the fund flows are more sensitive to which performance measure. The empirical test consists of pairwise comparison of competing measures, in which I regress mutual fund flows on decile ranks of previous fund performance estimated based on each measure. In general, I find that fund flows are more sensitive towards CAPM alpha than all other competing measures and that measures incorporating fewer factors tend to generate higher flow response.

The paper is organized as the following: the next section conducts literature review to establish an overview of researches about related topics; section 3 presents data and methodology; section 4 discusses results and section 5 concludes.

2. Literature Review

2.1 Literature on mutual funds

The mutual fund industry has been extensively studied in the literature. Past researches have shown that we can learn a lot more from this industry than whether fund managers can consistently earn risk-adjusted excess return. Just as many other industries in the economy, at some point the mutual fund industry displays decreasing return to scale. Pastor et al. (2012) document that as the industry's size increases, every manager's ability to outperform passive benchmarks declines. This observation implies that all mutual funds must have enough assets under management so that they indeed face decreasing returns to scale. Investors would invest more capital in the mutual fund when they think that a mutual fund represents a positive net present value investment. Consequently, mutual fund flows react to past performance while future performance is largely unpredictable. In fact, a handful of early works establish that fund flows respond to fund returns (Ippolito 1992; Chevalier and Ellison 1997; Sirri and Tufano 1998). Furthermore, researchers find that the relation between fund flows and returns tends to be convex, meaning that positive returns generate more new flows than those lost to negative returns (Chevalier and Ellison 1997; Sirri and Tufano 1998).

The first paper to use mutual fund flows to infer investor preference is Guercio and Tkac (2002). This paper documents that flows respond to outperformance relative to the CAPM, and it focuses on contrasting the inferred behavior of retail and institutional investors. However, this paper does not consider other risk models apart from CAPM. Going beyond the simple flow-return relation, Clifford et al. (2013) focus on the impact of total risk on fund flows and separately analyze fund inflows and outflows. They document that both inflows and outflows are positively related to total risk.

2.2 Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016)

More in line with my research interest, Barber, Huang, and Odean (2016) empirically investigate which commonly used factors investors attend to by analyzing mutual fund flows as a function of recent returns decomposed into alpha and factor-related returns. First of all, they estimate mutual fund alphas using six competing empirical models. By running linear regressions of mutual fund flows on the six performance measures, they document that CAPM, among six competing performance evaluation models, best explains the variation in mutual fund flows. Furthermore, they use proxies for investor sophistication (wealth, distribution channels, and periods of high investor sentiment) and find that more sophisticated investors use more sophisticated benchmarks when evaluating mutual fund performance.

In independent work, Berk and van Binsbergen (2016) also examine mutual fund performance and flow relationships. At various horizons, they measure the percent of time that the direction of a fund's flow is the same as the sign of its alpha estimated by different asset pricing models. They find that the sign of flows is more likely to have the same sign as the alpha from the CAPM model than from the alpha calculated using competing asset pricing models. Similar to a method implemented by Barber, Huang, and Odean (2016), Berk and van Binsbergen (2016) also conduct a horse race between competing models. Both papers draw a common conclusion that fund flows are best explained by CAPM alphas than by competing models. However, these two papers disagree on the interpretation of their results. Although Berk and van Binsbergen (2016) conclude that the CAPM is closest to the "true asset pricing model", Barber, Huang, and Odean (2016) argue that both papers simply provide evidence on what factors matter to investors when assessing mutual fund performance. The second disagreement these two papers holds is about the scope to which their findings apply. Berk and van Binsbergen (2016) believe that their results also indicate behaviors of nonmutual fund investors, but Barber, Huang, and Odean (2016) argue that mutual fund flow data do not inform us about the beliefs of nonmutual fund investors and they provide a counter example where a hedge fund manager might exploit his or her belief about certain mutual fund manager by investing directly in the market instead of in the mutual fund, so that these trades will not show up in mutual fund data, and thus mutual fund flow data will not provide information about this hedge fund manager's risk model.

However, both papers only focus on one type of performance measures, which are alphas generated from different empirical factor models. Noticeably, well-recognized performance measures extend far beyond alphas, indicating that there are many other commonly used measures in the literature can be further investigated under this context. Building upon the findings of Barber, Huang, and Odean (2016) and applying their methods to other performance measures, I extend their work and investigate the extent to which investors put weights on other measures that incorporate different risk factors when assessing mutual fund performances and making investment decisions.

3. Data and Methodology

3.1 Mutual Fund Sample

The data come from the Center for Research in Security Prices (CRSP) and Morningstar. The sample contains 2,762 diversified equity mutual funds actively managed in the United States from January 1979 to December 2014. Pastor, Stambaugh, and Taylor (2014) create a cross-validated dataset of actively managed U.S. equity mutual funds. I follow closely the guidelines provided in Data Appendix to Pastor, Stambaugh, and Taylor (2014) in creating my dataset, reconciling between CRSP and Morningstar datasets for the key data items: returns and fund size. The CRSP and Morningstar merged dataset provides information about fund identifiers, monthly returns, total assets under management (AUM), inception dates, expense ratios, investment strategies classified into Morningstar Categories, and some other fund characteristics.

Table 1 presents summary information about the sample. In total, there are 390,606 fund-month observations. Specifically, funds have average total net assets (TNA) of \$1.185 million, with a standard deviation of \$4.753 million. I compute the fund age from the fund's inception date and find the typical fund has a life of 166 months. Funds earn an average net return of 0.8% per month and collect fees of 9.8 basis points per month. Monthly firm volatility is 4.64% and average fund beta is 0.98.

3.2 Mutual fund flows

Given that the direct outcome of investors' investment decision is either injecting capital in or pulling capital out of funds, I select mutual fund flows to be the dependent variable. Since the dataset of fund flow is not immediately available, I follow most of the prior literature to use the percentage change in total net assets under management as a proxy to estimate monthly mutual fund flow $F_{p,t}$:

$$F_{p,t} = \frac{AUM_{p,t}}{AUM_{p,t-1}} - \left(1 + R_{p,t}\right) \tag{1}$$

where $AUM_{p,t}$ represents the total net assets under management of fund p at the end of month t, and $R_{p,t}$ is the total return of fund p in month t.

3.3 Estimating portfolio performance measures

In total, I investigate seven performance measures: three sets of annual abnormal return estimates ("alphas") based on the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model, the Carhart four-factor model; the Sharpe ratio; and three sets of information ratios based on CAPM, three-factor and four-factor alphas.

Firstly, I compute alphas generated from three models for each fund at each time point using a rolling window estimation. Specifically, for a fund *p* at time *t*, I use all prior data points from the past sixty months up till time *t-1* to estimate alpha. Consider the four-factor model, which includes factors related to market, size, value, and momentum. In this case, I firstly estimate the following time-series regression using all prior returns data from month $\tau = t - 1$ to $\tau = t - 60$ to compute alpha:

$$R_{p,\tau} - R_{f,\tau} = \alpha_{p,t} + ß_{p,t}\left(R_{m,\tau} - R_{f,\tau}\right) + s_{p,t}SMB_{\tau} + h_{p,t}HML_{\tau} + m_{p,t}MOM_{\tau} + \varepsilon_{p,t}, \quad (2)$$

where $R_{p,\tau}$ is the mutual fund return in month τ, $R_{f,\tau}$ is the return on the risk-free rate, $R_{m,\tau}$ is the return on a value-weighted market index, SMB_{τ} is the return on a size factor (small minus big stocks), HML_{τ} is the return on a value factor (high minus low book-to-market stocks), MOM_{τ} is the return on a momentum factor (up minus down stocks). We then calculate the monthly alpha as the difference between realized return and model-fitted return:

$$\hat{\alpha}_{p,t,four} = \left(R_{p,\tau} - R_{f,\tau}\right) - \left[\,\widehat{ß}_{p,t}\left(R_{m,\tau} - R_{f,\tau}\right) + \hat{s}_{p,t}SMB_{\tau} + \hat{h}_{p,t}HML_{\tau} + \widehat{m}_{p,t}MOM_{\tau}\right]. \quad (3)$$

I repeat this procedure for all months (*t*) and all funds (*p*) to obtain a time series of monthly four-factor model alphas for each fund. Subsequently, I conduct an analogous calculation of alphas for CAPM and three-factor model. Specifically, I estimate a fund's three-factor alpha using the regression (2) but drop the independent variable *MOM*. Lastly, to estimate the CAPM alpha, I only keep the market excess return as an independent variable.

Subsequently, I calculate the Sharpe ratio using the following equation:

$$Sharpe_{p,t} = \frac{E\left(R_{p,t} - R_{f,t}\right)}{\sigma_{p,t}} \quad (4)$$

where $Sharpe_{p,t}$ is the Sharpe ratio for fund f at time t, $E(R_{p,t} - R_{f,t})$ is the fund's expected excess return, $\sigma_{p,t}$ is the standard deviation of fund excess returns over the same period. To proxy for $E(R_{p,t} - R_{f,t})$, we calculate $\bar{R}_{p,t} - \bar{R}_{f,t}$, where $\bar{R}_{p,t}$ is the fund's average return and $\bar{R}_{f,t}$ is the average return for risk-free rate. Note that I use the same rolling window to compute the average returns and their standard deviation, which means that for a rate at time *t*, all prior data points from past sixty months are used to conduct the computation.

Lastly, to calculate the information ratios, I need to incorporate previously computed alphas into the equation. Consider the four-factor model again. I compute the corresponding information ratio as below:

$$I_{p,t,four} = \frac{\hat{\alpha}_{p,t,four}}{\sigma_{p,t,four}} \tag{5}$$

where $\hat{\alpha}_{p,t,four}$ is the alpha computed using the four-factor model, and $\sigma_{p,t,four}$ is the standard deviation of $\hat{\alpha}_{p,t,four}$. Similarly, I use equation (5) to compute CAPM and three-factor information ratios using CAPM and the three-factor model alphas correspondingly.

Table 2 presents the correlation matrix of all seven performance measures. All variables are winsorized at the 1% and 99% level. Alphas and information ratios tend to have relatively high correlations since they are estimated incorporating similar factors, such as market excess return. Given that Sharpe ratio is defined quite differently from the other six performance measures, it is reasonable that its correlations with the rest six measures tend to be relatively low.

3.4 Model Horse Race Analysis

According to previous studies, the fund-performance relation tends to be convex. Therefore, I follow the pairwise approach in Barber, Huang, and Odean (2016) to address the concern of nonlinearity more robustly. The first step is to create deciles of mutual funds in each month based on the seven performance measures. Decile 10 contains the best performing funds, and decile 1 contains the worst funds. For each fund in each month, it is assigned a number indicating which decile it is in based on one of the seven performance measures. Ultimately, I have a time-series across months of seven decile ranks for each mutual fund.

Subsequently, I perform the pairwise comparison between seven performance measures. Consider the comparison between CAPM alpha and Sharpe ratio as an example. I investigate the relation between fund flows and a fund's decile ranking based on the CAPM alpha and the Sharpe ratio by estimating the following regression:

$$F_{p,t} = a + \sum_{i}\sum_{j} b_{ij}\, D_{ijpt} + cX_{p,t} + \varepsilon_{p,t} \tag{7}$$

where the dependent variable $F_{p,t}$ is the mutual fund flows for fund *p* in month *t*. D_{ijpt} is a dummy variable that takes on a value of one if fund *p* in month *t* is in decile *i* based on CAPM alpha and in decile *j* based on Sharpe ratio. I omit the dummy variable for $j = 5$ and $i = 5$. The coefficients of interest are b_{ij}, $i = 1, \ldots, 10$, and $j = 1, \ldots, 10$, which can be interpreted as the percentage flows received by a fund in decile *i* based on CAPM alpha and in decile *j* based on Sharpe ratio relative to a fund that ranks in the fifth decile on both performance measures. The matrix $X_{p,t}$ contains the control variables while $c_{p,t}$ contains a vector of associated coefficient estimates. For control variables, I include lagged fund flows from month *t-13*, lags of a fund's total expense ratio, a dummy variable for no-load funds, a fund's return standard deviation estimated over the prior 12 months, the log of fund size in month *t-1*, and the log of fund age in month *t-1*.

As specified in the regression (7), the omitted dummy variable is identified by funds with decile rank of 5 based on both measures. The empirical tests compare the coefficients of funds that have better performance based on CAPM to the coefficients of funds that have better performance based on Sharpe ratio. For example, I compare the coefficient estimate on the dummy variable for funds with a CAPM alpha in the seventh decile and Sharpe ratio in the third decile to funds with a CAPM alpha in the third decile and Sharpe ratio in the seventh decile. To determine whether investors' decisions are more sensitive to the CAPM alpha or Sharpe ratio, I test the null hypothesis that $b_{i,j} = b_{j,i}$ for all $i \neq j$. For example, I test the null hypothesis that $b_{7,3} = b_{3,7}$. If investors place more weight on CAPM alpha than Sharpe ratio, I would expect to reject the null hypothesis in favor of the alternative hypothesis, $b_{7,3} > b_{3,7}$; conversely, if investors place more weight on Sharpe ratio, I would expect to reject the null hypothesis in favor of the alternative hypothesis, $b_{7,3} < b_{3,7}$.

4. Results

The main methodology of this paper is the model horse race analysis. It is designed to address the concern of nonlinear fund-flow relations by conducting pairwise comparison of competing performance measures, following the methodology developed by Barber, Huang, and Odean (2016). Table 3 presents the results of the model horse race analysis. The table reports the sum of the differences between dummy variables' coefficients and the percentages of differences that are greater than zero. The two hypothesis tests for each model horse race reported in the table are: (1) Ho: The sum of the differences in coefficient estimates is zero and (2) Ho: The proportion of positive differences is equal to 50%.

Firstly, panel A presents comparisons in which CAPM alpha wins. In all cases that I consider, the CAPM alpha wins the horse race of flow-performance sensitivity. In other words, investors' investment decisions are best explained by the CAPM alpha which is a simple measure that adjusts for market risk while assessing the risk-adjusted performance. For example, the sum of the coefficient differences for the CAPM alpha versus the Sharpe ratio is significantly positive (0.18, t=7.39), and significantly more than half are positive (75.56% or 34 out of the 45 differences). The CAPM alpha and Sharpe ratio horse race is the closest contest for the CAPM alpha. The CAPM alpha comfortably beats all remaining performance measures. Moving down on Table 3, each panel presents results where a certain performance measure is victorious. Results in panel B suggest that the information ratio based on CAPM alpha is better able to predict fund flows than the remaining five performance measures I consider. Note that in the second set of hypothesis test, the test statistics between CAPM alpha's information ratio and Sharpe ratio are not significant. But given the significant result of the first hypothesis test, I still conclude that the CAPM alpha's information ratio is victorious. In panel C, D, E, and F, results indicate that performance measures with more simplistic forms, i.e., incorporating fewer factors, consistently provide a better prediction of fund flows.

Furthermore, results show that each alpha consistently beats its corresponding information ratio. Consider the comparison of CAPM alpha and its information ratio ("IR_CAPM" in the table), where the sum of differences is significantly positive (0.24, t=2.13), and significantly more than half are positive (80% or 36 out of the 45 differences). In addition to considering the magnitude of alpha, CAPM alpha's information ratio takes volatility into account which makes it a more comprehensive measure in theory. However, results suggest that investors do not appreciate such consideration and are more inclined toward simple alphas when assessing mutual fund performance. This finding supports a claim made by Berk and Green (2004) that investors do not take idiosyncratic volatility into account when assessing fund manager's skills.

5. Conclusion

The main purpose of this paper is to assess commonly used portfolio performance measures in the literature using mutual fund flows. Following the methodology developed by Barber, Huang, and Odean (2016), I run a horse race among seven competing performance measures to investigate each measure's flow-performance sensitivity, understanding further mutual fund investors' choices of performance measures to assess fund manager's skills. Expanding upon past studies, I investigate Sharpe ratio and information ratios in addition to alphas. Consistent with findings in the previous literature, CAPM alpha tends to generate more fund flow response than all other performance measures under consideration. Even through Sharpe ratio and CAPM alpha's information ratio are indeed better than three-factor and four-factor alphas at explaining the variation in fund flows, CAPM alpha remains the best predictor of mutual fund flows.

Most importantly, this paper contributes to the literature by expanding the research scope of recent studies on portfolio performance measures (Berk and van Binsbergen 2016; Barber, Huang, and Odean 2016) by assessing two more commonly used measures: Sharpe ratio and information ratio. Results provide more evidence to strengthen the findings of previous studies that CAPM alpha is the best predictor of fund flows and that more simplistic measures predict fund flows better. Furthermore, results provide assurance to future research that the study of portfolio performance measures can focus on the realm of alphas, given that investors in practice do not put more weights on other performance measures.

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Appendix

Table 1: Summary Statistics

This table summarizes the statistics across fund-month observations from January 1979 to December 2014. The table reports fund characteristics such as net return, percentage fund flow, fund size, etc. Percentage fund flow is percentage change TNA from month t-1 to t adjusted for the fund return in month t. Return volatility is calculated as the standard deviation of prior 12 month fund returns. All variables are winsorized at the 1% and 99% level.

Table 1
Descriptive statistics for mutual fund sample

	#Obs	Mean	SD	25th perc	Median	75th perc
Monthly net return	390,606	0.802%	4.940%	-1.906%	1.247%	3.866%
Percentage fund flow	390,606	0.436%	5.043%	-1.432%	-0.223%	1.417%
Fund size ($million)	390,606	1,267.3	2,971.2	85.5	280.6	968.6
Monthly expense ratio	390,606	1.211%	0.436%	0.948%	1.170%	1.446%
Age (months)	390,606	166.4	162.6	58.9	116.1	207.2
Return volatility	390,606	4.635%	2.093%	3.030%	4.231%	5.769%
Fund Beta	390,606	0.975	1.1	0.855	0.973	1.093

Table 2: Correlation between Performance Measures

This table presents the correlation matrix between seven portfolio performance measures. The first set of measures are alphas derived from three models: the capital asset pricing model (CAPM), a three-factor model (3F) that adds size and value factors, and a four-factor model (4F) that adds momentum factor. The second type of measure is Sharpe ratio and the last set contains information ratio that is calculated from each of the three alphas.

Table 2
Correlation between performance measures

	CAPM alpha	3F alpha	4F alpha	Sharpe	IR_CAPM	IR_3F	IR_4F
(a) CAPM alpha	1.00						
(b) 3F alpha	0.65	1.00					
(c) 4F alpha	0.62	0.89	1.00				
(d) Sharpe	0.29	0.26	0.24	1.00			
(e) IR_CAPM	0.90	0.64	0.59	0.27	1.00		
(f) IR_3F	0.60	0.90	0.79	0.23	0.72	1.00	
(g) IR_4F	0.58	0.80	0.90	0.21	0.67	0.88	1.00

Table 3: Results of Pairwise Model Horse Race

This table presents the results of a pairwise comparison of competing portfolio perofmrance measures ability to predict mutual fund flows. The table presents the results of two hypothesis tests for each model horse race: (1) Ho: The sum of the differences in coefficient estimates is zero and (2) Ho: The proportion of positive differences is equal to 50%.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3
Results of Model Horse Race
A CAPM victories

Winning model	CAPM	CAPM	CAPM	CAPM	CAPM	CAPM
Losing model	Sharpe	IR_CAPM	IR_3-factor	IR_4-factor	3-factor	4-factor
Sum of coefficient differences	0.18***	0.24***	0.21***	0.24***	0.20***	0.23***
t-stat	(7.39)	(2.13)	(16.14)	(20.21)	(15.91)	(19.36)
% of coefficient differences >0	75.56***	80.00***	95.56***	97.78***	97.78***	97.78***
Binomial p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

B IR_CAPM victories

Winning model	IR_CAPM	IR_CAPM	IR_CAPM	IR_CAPM	IR_CAPM
Losing model	Sharpe	3-factor	4-factor	IR_3-factor	IR_4-factor
Sum of coefficient differences	0.08***	0.16***	0.18***	0.16***	0.20***
t-stat	3.39	10.24	13.29	(10.66)	(15.08)
% of coefficient differences >0	53.33	82.22***	84.44***	93.33***	97.78***
Binomial p-value	>0.1	<0.01	<0.01	<0.01	<0.01

C Sharpe victories

Winning model	Sharpe	Sharpe	Sharpe	Sharpe
Losing model	3-factor	4-factor	IR_3-factor	IR_4-factor
Sum of coefficient differences	0.11***	0.14***	0.14***	0.17***
t-stat	10.03	13.10	(12.91)	(16.19)
% of coefficient differences >0	86.67***	88.89***	91.11***	95.56***
Binomial p-value	<0.01	<0.01	<0.01	<0.01

(continued)

Table 3
Continued

D 3-factor victories

Winning model	3-factor	3-factor	3-factor
Losing model	4-factor	IR_3-factor	IR_4-factor
Sum of coefficient differences	0.16***	0.14	0.21***
t-stat	（6.96）	(0.84)	(8.74)
% of coefficient differences >0	80.00***	75.56***	88.89***
Binomial p-value	<0.01	<0.01	<0.01

E IR_3-factor victories

Winning model	IR_3-factor	IR_3-factor
Losing model	4-factor	IR_4-factor
Sum of coefficient differences	0.12***	0.19***
t-stat	4.63	(4.03)
% of coefficient differences >0	66.67**	93.33***
Binomial p-value	<0.05	<0.01

F 4-factor victories

Winning model	4-factor
Losing model	IR_4-factor
Sum of coefficient differences	0.12
t-stat	1.02
% of coefficient differences >0	71.11**
Binomial p-value	<0.05