JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 60, No. 8, Dec. 2025, pp. 3660–3693
© The Author(s), 2025. Published by Cambridge University Press on behalf of the Michael G. Foster School of Business, University of Washington. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (http://creativecommons.org/licenses/by/4.0), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.
doi:10.1017/S0022109025101270

Anomalies as New Hedge Fund Factors

Yong Chen
Texas A&M University Mays Business School
ychen@mays.tamu.edu

Sophia Zhengzi Li
Rutgers University Rutgers Business School, Department of Finance and Economics
zhengzi.li@business.rutgers.edu

Yushan Tang
Shanghai University of Finance and Economics Dishui Lake Advanced Finance Institute
tangyushan@sufe.edu.cn

Guofu Zhou
Washington University in St. Louis Olin Business School
zhou@wustl.edu (corresponding author)

Abstract

We identify a parsimonious set of factors from a large pool of candidates for explaining hedge fund returns, ranging from equity market, anomaly, and trend-following factors to macroeconomic factors. The resulting 9-factor model, including five anomaly factors, outperforms existing hedge fund models both in sample and out of sample, with a significant reduction in alphas while showing substantial cross sectional performance heterogeneity. Further analysis based on fund holdings confirms the model's ability to capture returns from arbitrage trading. Overall, the anomaly factors help quantify hedge fund strategies and risk exposures and improve fund performance evaluation.

> You don't have alpha. Your returns can be replicated with a value-growth, momentum, currency and term carry, and short-vol strategy. (John H. Cochrane (2011))

I. Introduction

A central concept in finance is arbitrage, defined as simultaneous long and short positions in similar assets to exploit mispricing. The arbitrage pricing theory (APT) of Ross (1976) stipulates that the trading of arbitrageurs determines expected asset returns. Numerous subsequent theories examine the interaction between

We are extremely grateful to Hendrik Bessembinder (the editor) and two anonymous referees for their detailed and insightful comments that have substantially improved the article. We thank Vikas Agarwal, Tim Bollerslev, Oleg Bondarenko, Charles Cao, Gregory Eaton, Amit Goyal, Clifton Green, Bing Liang, Alan Moreira, Sugata Ray, Andrea Rossi, Zhen Shi, seminar and conference participants at Aalto University, Texas A&M University, the 16th Annual Hedge Fund Research Conference, and the XJTLU AI and Big Data in Accounting and Finance Research Conference for helpful comments and suggestions. We also thank Vikas Agarwal, Turan Bali, Ken French, Amit Goyal, David Hsieh, Ralph Koijen, Lubos Pastor, and Grigory Vilkov for making a large amount of data available through their websites or direct sharing.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

mispricing and arbitrage activity.[1] Hedge funds, as real-world arbitrageurs as a group, have experienced fast growth over the past 3 decades.[2] Given their increasing impact on the financial market, understanding the economic drivers of hedge fund returns is important. In this article, we develop a parsimonious factor model, based on anomalies, to explain hedge fund returns.

The literature has identified many anomalous stock characteristics as return predictors, consistent with an interpretation of mispricing. These anomalies provide a fertile space to locate key factors underlying the returns of hedge funds. Indeed, Cochrane (2011) suggests that hedge fund alphas may be attributed to anomaly-based strategies. Pedersen (2015) depicts popular hedge fund strategies using well-known anomalies. Chen, Da, and Huang (2019) show that arbitrage trading, measured by the net position of hedge funds on individual stocks, predicts anomaly returns, which directly links hedge fund trades to anomalies. Therefore, it seems intuitive to use anomalies as potential economic factors for explaining hedge fund returns. While prior research proposes hedge fund factors based on trading styles and macro conditions, we are the first to develop factors for hedge funds with anomalies as potential candidates based on recent advances in anomaly studies (see, e.g., Chen and Zimmermann (2022), Jensen, Kelly, and Pedersen (2023)).

Despite the intuitive appeal, identifying hedge fund factors from anomalies is a challenging task. First, while prior studies detect numerous anomalies, our primary goal is to form a parsimonious set of systematic factors, in the spirit of the APT, capable of explaining a large fraction of the variation in hedge fund returns. Second, conventional empirical approaches such as ordinary least squares (OLS) estimator and stepwise selection often have difficulty dealing with a large number of potential factors applied to a short time series.

Using adaptive least absolute shrinkage and selection operator (LASSO)—a machine learning method—we propose a new hedge fund factor model that combines anomaly factors with market and macro factors. Based on a sample of 7,314 hedge funds, imposing regularization through adaptive LASSO produces a small set of factors that are highly informative of hedge fund returns at both the fund and portfolio levels. Our factor model shows remarkable improvement in explaining hedge fund returns over existing models. Inferred from our model, hedge fund alpha estimates reduce significantly in magnitude while still varying substantially in the cross section.

Our analysis begins with assembling a large pool of potential factors. Based on return anomalies (e.g., Asset Growth (AGR), betting against beta (BAB), momentum (MOM)), along with existing factors in hedge fund studies such as market and macro variables (e.g., equity market factor (MKT), default spread (DFLT), and term spread (TERM)) and style-based factors (e.g., trend-following factors), we compile a pool of 44 potential factors. The high dimensionality of potential factors limits the capacity of conventional statistical inference on factor loadings. Standard OLS estimator also tends to overfit in the presence of many potential factors along with

[1]For example, see Shleifer and Vishny (1997) for the argument of limits to arbitrage. Gromb and Vayanos (2010) provide a review of the related theories in the literature.

[2]According to BarclayHedge, the total assets under management in the hedge fund industry increased from about $200 billion in 2000 to over $5 trillion in 2022.

a short history of hedge fund returns. To overcome this challenge, we employ the adaptive LASSO estimator that imposes a sparsity assumption through a regularized regression approach. In prescreening potential factors, adaptive LASSO penalizes nuisance factors with smaller coefficients based on simple OLS. Compared to LASSO with constant shrinkage, adaptive LASSO performs better in uncovering the underlying model, making it more suitable for factor selection (Zou (2006)).[3]

To select factors for hedge funds, we implement the regularized regressions on individual funds and fund portfolios combined with post-selection inference to construct a factor selection framework. This framework, based on both individual funds and fund portfolios, benefits from granular information at the fund level as well as stable risk exposures and a high signal-to-noise ratio at the portfolio level. Specifically, we run a time series adaptive LASSO regression for each testing asset and record the factors with nonzero loadings. Then, we rank factors based on the fraction selected. Finally, we show that the top-ranked factors are robust across testing asset levels and identify the candidate factors based on factor rankings.

As emphasized in Belloni, Chen, Chernozhukov, and Hansen (2012) and Belloni and Chernozhukov (2013), it is important to refit an OLS model using factors identified by statistical selection algorithms for reliable inference. To that end, we conduct post-selection inference for the candidate factors. Specifically, we test the significance of alternative factors and find that a model with the top nine most-selected factors performs the best. The choice of nine factors is further justified by the number of orthogonal latent factors required for capturing the variation in hedge fund returns.

From this factor selection procedure, we obtain a 9-factor model, denoted HF9, consisting of the MKT, five anomaly-based factors (AGR factor, BAB factor, low-risk factor (LRSK), return-on-asset factor (ROA), time series momentum factor (TSMOM)), and three macro factors (the monthly change in the 10-year Treasury yield (10Y), the monthly change in credit yield spread (CRDT), and the TERM).

To evaluate model performance, we run time series regressions for both individual funds and fund portfolios to assess the explanatory power of the new model and existing models. The new model consistently outperforms the CAPM, the Fama and French (2015) 5-factor model, and the Fung and Hsieh (2004) 7-factor model in explaining hedge fund returns. In particular, the new model produces economically and statistically insignificant alphas and higher adjusted R^2 values. Switching from existing models to the new model, the reduction in the alpha estimate is at least 0.15% per month and the improvement in the adjusted R^2 exceeds 10% across testing assets. These results indicate that the model is better at capturing common factor exposures of hedge fund returns. Besides the reduction in the alpha estimate, the model produces substantial heterogeneity in performance across hedge funds, especially on the left tail. The fraction of funds deemed to underperform increases from 5% under existing models to 13% under the new model.

[3]For discussions on variable selection using LASSO, see, e.g., Fan and Li (2001) and Zou (2006). See Rapach, Strauss, and Zhou (2013) for an early study using LASSO in finance, and Kelly and Xiu (2023) for a survey of various machine learning methods in financial research.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

Lewellen, Nagel, and Shanken (2010) point out that in-sample asset pricing tests often lack sufficient testing power for model evaluation. To alleviate this concern, we conduct two out-of-sample tests. First, we perform tests using a separate sample of hedge funds that are different from those used for factor selection. Second, we validate our findings using an out-of-sample period after the main sample period used for selecting the factors. The results from both out-of-sample tests confirm the outperformance of the new model in explaining hedge fund returns relative to the existing models.

We perform a series of additional analyses and robustness checks. First, we show that the new model better explains returns from arbitrage trading (Chen et al. (2019)), which should be directly related to hedge fund strategies. Second, when evaluating alternative models that augment benchmark models with selected factors from recent studies (e.g., Ardia, Barras, Gagliardini, and Scaillet (2023)), we find that the new model effectively captures variations in hedge fund returns. Third, we examine the relation between fund flows and alphas inferred from different factor models. The results suggest that hedge fund investors rely heavily on conventional factors. Fourth, we relate alphas estimated from different models to fund failure likelihood. We find that while poor performance estimated from the new model is positively associated with fund future failure, the relationship is less pronounced compared to that inferred from conventional models. Finally, we examine the heterogeneity in fund performance and its relation with fund characteristics. Our results show that a large portion of the variation in fund alphas cannot be explained simply by fund characteristics.

This article makes several contributions to the hedge fund literature. First, given the rapid evolution of hedge funds over the past 2 decades, there is a growing need for a new factor model for hedge fund returns. Addressing this need, our article proposes a 9-factor model covering the most crucial factors in the hedge fund industry.[4] Second, the substantial reduction in the alpha estimate under the new model offers fresh evidence of hedge fund performance. This adds to the ongoing debate about the value of active asset management, particularly after accounting for anomaly-related strategies. Third, the model detects a significant fraction of underperforming hedge funds, while investors seem to confuse exotic factor exposures with true performance, suggesting the need for greater scrutiny by hedge fund investors in their capital allocation. Finally, our factor selection framework, based on shrinkage techniques, allows for periodically updating factors to accommodate evolving hedge fund strategies.

The article is organized as follows: Section II discusses both the data and the factor selection framework used in the article. Section III introduces the new hedge fund factor model and compares its performance with existing factor models. Section IV presents the out-of-sample evidence. Section V performs additional

[4]For previous papers that relate hedge fund performance to trading styles and characteristics, see, e.g., Fung and Hsieh (1997), (2004), Agarwal and Naik (2004), Getmansky, Lo, and Makarov (2004), Chen (2007), Chen and Liang (2007), Kosowski, Naik, and Teo (2007), Agarwal, Daniel, and Naik (2009), Teo (2009), Sadka (2010), Avramov, Kosowski, Naik, and Teo (2011), Chen (2011), Teo (2011), Titman and Tiu (2011), Bali, Brown, and Caglayan (2011), (2012), (2014), Cao, Chen, Liang, and Lo (2013), Chen, Cliff, and Zhao (2017), Chen, Kelly, and Wu (2020), Chen, Han, and Pan (2021), and Ardia et al. (2023), among others.

analyses and robustness checks. Section VI concludes. Auxiliary discussions and tests are provided in the Supplementary Material.

II. Data and Method

A. Hedge Fund Data

Our hedge fund sample is obtained by merging the Lipper TASS Trading Advisor Selection System (TASS) and Hedge Fund Research (HFR) databases. When merging the data, we remove redundant funds covered by both databases. Following the literature, we focus on funds that report net-of-fee returns in U.S. dollars on a monthly basis. While these databases contain records from as early as 1977, the coverage of both live and defunct hedge funds started in 1994. Thus, to mitigate survivorship bias (Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), and Liang (2000)), we exclude all monthly returns prior to 1994. To address the concern of backfill bias, for each fund, we only retain records starting from the month when the fund is first added to the database.[5]

The databases provide information on the categories of hedge fund strategies. To ensure statistical power on category-level inferences, we include 10 categories with sufficient numbers of funds, including convertible arbitrage (CA), dedicated short bias (DSB), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). Finally, we require each fund to have at least 48 monthly return observations.

Our final sample consists of 7,314 unique hedge funds over the period from January 1997 to August 2019.[6] Later in Section III, we also collect information on a different set of hedge funds from BarclayHedge to examine the performance of our factor model on this alternative group of hedge funds.

Table 1 reports for each category and all categories the descriptive statistics for net-of-fee returns (in percentage) based on fund–month observations, as well as time series mean and standard deviations of equal-weighted (EW) and value-weighted (VW) portfolios. The total number of fund–month observations in our sample is 713,737. Consistent with the literature, the most common category is LSEH with 251,141 observations and the least common one is DSB with only 2931 observations. Based on fund–month observations, the mean (median) fund return is 0.46% (0.51%) per month, and the standard deviation of monthly returns is 4.32%, suggesting great dispersion in performance across funds and over time. It is worth noting that fund performance exhibits great heterogeneity across strategy categories. Specifically, funds classified into EM and LSEH exhibit the highest mean returns, both at 0.58% per month, among all categories. In contrast, funds classified into DSB underperform the rest of the categories, with a mean return of merely 0.10% per month. Turning to the EW and VW portfolios in the last 2 columns, the

[5]Funds with better track records may have greater incentives to report to a database, which leads to an upward backfill bias. See Fung and Hsieh (2000) and Liang (2000) for more detailed discussions.

[6]We start the sample period from 1997, instead of 1994, to ensure a sufficient cross section of hedge fund observations. Early years tend to have a smaller number of funds. For instance, the number of unique funds with nonmissing fund characteristics for the year 1996 is less than 20.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 1

Descriptive Statistics for Hedge Fund Returns

Table 1 reports summary statistics of the net-of-fee returns (in percentage) for individual hedge funds as well as equal-weighted and value-weighted hedge fund portfolios. The hedge fund sample consists of 7,314 funds from the TASS and HFR databases between January 1997 and August 2019, including funds from 10 categories: convertible arbitrage (CA), dedicated short bias (DSB), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). For individual funds, the summary statistics include the number of observations, mean, standard deviation, and percentiles based on fund–month observations. For the equal-weighted and value-weighted hedge fund portfolios, the summary statistics include time series mean and standard deviations.

				Percentiles					EW Portfolio		VW Portfolio	
Category	# Obs	Mean	SD	10%	25%	Median	75%	90%	Mean	SD	Mean	SD
CA	11,957	0.51	3.88	−1.58	−0.23	0.62	1.45	2.68	0.52	2.09	0.59	1.62
DSB	2,931	0.10	6.10	−5.92	−2.98	0.00	2.70	6.69	0.01	4.03	−0.12	3.73
ED	67,308	0.51	3.62	−2.30	−0.42	0.58	1.63	3.19	0.57	1.70	0.66	1.53
EM	41,905	0.58	6.74	−5.63	−1.67	0.59	2.99	6.75	0.69	4.27	0.89	4.22
EMN	30,361	0.38	2.85	−2.14	−0.68	0.38	1.47	2.88	0.45	0.83	0.41	0.80
FIA	63,218	0.43	3.30	−1.60	−0.21	0.50	1.28	2.58	0.51	1.31	0.54	1.31
FOF	200,613	0.27	2.72	−2.15	−0.61	0.45	1.38	2.48	0.40	1.63	0.47	1.67
GM	16,537	0.45	4.69	−3.70	−1.33	0.32	2.14	4.67	0.46	1.47	0.63	1.92
LSEH	251,141	0.58	5.24	−4.38	−1.43	0.60	2.65	5.40	0.71	2.83	0.77	2.63
MS	27,766	0.54	4.60	−2.57	−0.60	0.56	1.70	3.40	0.63	1.47	0.70	2.18
All categories	713,737	0.46	4.32	−3.14	−0.83	0.51	1.82	3.94	0.56	1.97	0.62	1.73

mean returns are similar to those based on fund–month observations, while the standard deviations are lower due to portfolio diversification.

B. Potential Factors

As discussed in Pedersen (2015), while hedge funds adopt different investment tactics and have distinct risk exposures, their decisions can largely be attributed to a handful of trading strategies. This implies that a model with a relatively small set of factors should be capable of dissecting hedge fund performance. To identify these key factors, we begin by assembling a large pool of 44 potential factors widely used as trading strategies or common factors to capture hedge fund returns.

The first group of 25 factors contains the MKT and 24 anomalies: i) 11 individual anomalies drawn from Pastor and Stambaugh (2003), Stambaugh, Yu, and Yuan (2012), Moskowitz, Ooi, and Pedersen (2012), and Koijen, Moskowitz, Pedersen, and Vrugt (2018), including AGR, BAB, carry, composite equity issues, gross profitability, illiquidity, net operating assets, net stock issues, O-score, ROA, and TSMOM and ii) 13 U.S. theme factors, which consolidate information from 153 characteristics, introduced by Jensen et al. (2023), including accruals, debt issuance, investment, low leverage, low risk, MOM, profit growth, profitability, quality, seasonality, size, short-term reversal, and value.[7]

[7]The MKT and 11 individual anomalies are obtained from the data library of Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), Andrew Chen's Open Source Asset Pricing data library (https://www.openassetpricing.com/data/), AQR's online data sets (https://www.aqr.com/Insights/Datasets), Ralph Koijen's website (https://koijen.net/code-and-data.html), and Lubos Pastor's website (https://faculty.chicagobooth.edu/lubos-pastor/data). The 13 U.S. theme factors are downloaded from the Global Factor Data (https://jkpfactors.com/).

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

The second group contains five trend-following factors proposed in Fung and Hsieh (2001) to capture hedge fund returns, including the bond trend-following factor, commodity trend-following factor, currency trend-following factor, short-term interest rate trend-following factor, and stock index trend-following factor.[8]

The third group consists of 14 macroeconomic factors used in Fung and Hsieh (2004), Welch and Goyal (2008), and Bali et al. (2014), covering widely used macroeconomic risk measures: change in 10Y, book-to-market ratio for DJ Industrial Average, change in CRDT, default yield spread, dividend price ratio for S&P 500 index, earnings price ratio for S&P 500 index, real GDP per capita, inflation rate, growth rate of industrial production, net equity expansion ratio of NYSE stocks, stock variance for S&P 500 index (SVAR), 3-month Treasury bill rate, TERM, and economic uncertainty index.[9]

The complete list of these potential factors along with their acronyms is provided in Table A1 of the Appendix. Details of the factor constructions can be found in the Supplementary Material. Table 2 reports the time series mean, standard deviation, and percentiles of each factor over the entire sample period from January 1997 to August 2019.[10]

C. Method

It is reasonable to assume that not all potential factors can effectively describe hedge fund returns. To select the key factors, we proceed with the following 3 steps. In the first step, we apply adaptive LASSO, a machine learning technique, to perform factor selection based on the time series of each testing asset. We use the Akaike information criterion (AIC) to validate the choice of the shrinkage parameter λ that is crucial in variable selection. In the second step, we identify the top factors that best explain returns on testing assets as candidate factors. Finally, in the third step, we regress returns of the EW and VW hedge fund industry portfolios on all or a subset of the candidate factors to determine the final set of factors with the highest regression R^2 and the lowest alpha. We term the entire factor selection procedure "Post-Adaptive-LASSO."

We begin with a linear factor model for hedge fund returns:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i' \boldsymbol{f}_t + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the (net-of-fee) excess return for testing asset (fund or portfolio) i in month t, $\boldsymbol{\beta}_i$ is the vector of fund i's factor loadings, and vector $\boldsymbol{f}_t$ denotes the common factors.

For each testing asset, we do not expect all factors to explain its returns. Instead, we anticipate only a subset of them to be particularly informative. The LASSO estimator (Tibshirani (1996)) can sparsely estimate the coefficients by

[8]The trend-following factor data are downloaded from David Hsieh's data library: https://people.duke.edu/%7Edah7/HFData.htm.

[9]The macroeconomic factor data are obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145), the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/), and Turan Bali's website (https://sites.google.com/a/georgetown.edu/turan-bali/).

[10]In untabulated results, we find that the 44 factors tend to have low correlations with each other, suggesting that they contain different sources of risks.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 2

Descriptive Statistics for Factors

Table 2 reports the time series mean, standard deviation, and percentiles of 44 factors over the full sample period from January 1997 to August 2019.

					Percentiles				
		# Obs	Mean	SD	10%	25%	Median	75%	90%
(1)	ACC	312	0.00	0.01	−0.01	−0.01	0.00	0.01	0.01
(2)	AGR	312	1.04	4.25	−3.25	−1.56	0.56	2.46	5.43
(3)	BAB	312	0.01	0.04	−0.03	−0.01	0.01	0.02	0.05
(4)	CARRY	312	0.64	2.61	−2.08	−0.58	0.51	1.71	3.87
(5)	CEI	312	0.30	2.12	−2.13	−0.71	0.29	1.38	2.82
(6)	DTI	312	0.00	0.01	−0.01	0.00	0.00	0.01	0.01
(7)	GPF	312	0.48	2.75	−2.54	−1.30	0.33	2.25	3.95
(8)	ILL	312	0.00	0.04	−0.04	−0.02	0.00	0.03	0.04
(9)	INVEST	312	0.00	0.03	−0.02	−0.01	0.00	0.01	0.03
(10)	LLEV	312	0.00	0.04	−0.03	−0.01	0.00	0.01	0.03
(11)	LRSK	312	0.00	0.05	−0.04	−0.02	0.00	0.02	0.05
(12)	MKT	312	0.68	4.29	−5.01	−1.94	1.31	3.41	5.64
(13)	MOM	312	0.00	0.04	−0.03	−0.01	0.00	0.02	0.04
(14)	NOA	312	0.73	2.26	−1.60	−0.65	0.56	1.77	3.19
(15)	NSI	312	0.33	3.63	−3.27	−1.15	0.22	1.94	3.92
(16)	OSC	312	0.88	6.03	−6.43	−2.11	1.17	4.29	7.10
(17)	PFT	312	0.00	0.03	−0.02	−0.01	0.00	0.01	0.02
(18)	PGR	312	0.00	0.01	−0.01	0.00	0.00	0.01	0.01
(19)	QLT	312	0.00	0.02	−0.01	−0.01	0.00	0.01	0.02
(20)	ROA	312	1.02	5.96	−4.53	−1.83	1.31	4.35	7.24
(21)	SIZE	312	0.00	0.02	−0.02	−0.01	0.00	0.01	0.03
(22)	SKW	312	0.00	0.01	−0.01	0.00	0.00	0.01	0.01
(23)	SSN	312	0.00	0.01	−0.01	0.00	0.00	0.00	0.01
(24)	TSMOM	312	0.01	0.07	−0.08	−0.03	0.01	0.06	0.11
(25)	VALUE	312	0.00	0.04	−0.03	−0.01	0.00	0.02	0.04
(26)	BDTF	312	−0.01	0.16	−0.17	−0.13	−0.05	0.05	0.20
(27)	CMTF	312	0.00	0.14	−0.16	−0.10	−0.03	0.06	0.19
(28)	FXTF	312	−0.01	0.19	−0.20	−0.15	−0.05	0.08	0.23
(29)	IRTF	312	−0.02	0.25	−0.22	−0.14	−0.07	0.04	0.18
(30)	SKTF	312	−0.05	0.14	−0.20	−0.15	−0.07	0.02	0.09
(31)	10Y	312	−0.01	0.26	−0.33	−0.17	0.00	0.13	0.29
(32)	BM	312	0.27	0.07	0.16	0.23	0.28	0.32	0.35
(33)	CRDT	312	0.00	0.20	−0.18	−0.10	0.00	0.08	0.19
(34)	DFLT	312	0.01	0.00	0.01	0.01	0.01	0.01	0.01
(35)	DPR	312	−3.98	0.22	−4.29	−4.08	−3.96	−3.87	−3.74
(36)	EPR	312	−3.13	0.36	−3.48	−3.27	−3.06	−2.90	−2.79
(37)	GDP (in $1000)	312	49.17	4.96	41.11	46.40	50.35	52.12	55.11
(38)	INFL	312	0.00	0.00	0.00	0.00	0.00	0.00	0.01
(39)	INPR	312	0.00	0.01	−0.01	0.00	0.00	0.01	0.01
(40)	NTIS	312	0.00	0.02	−0.02	−0.01	0.01	0.02	0.03
(41)	SVAR	312	0.00	0.00	0.00	0.00	0.00	0.00	0.01
(42)	TBL	312	0.02	0.02	0.00	0.00	0.02	0.05	0.05
(43)	TERM	312	−0.02	0.04	−0.06	−0.04	−0.02	0.00	0.03
(44)	UNC	312	−0.26	1.78	−1.64	−1.23	−0.89	0.36	1.27

automatically setting many of them to be exactly 0, achieving the goal of factor selection. Specifically, LASSO introduces L_1 penalty to the standard least squares for regressions and minimizes the following loss function:

$$\hat{\boldsymbol{\beta}}_i^{LASSO} = \arg\min_{\beta_i} \left\| \boldsymbol{r}_i - \sum_{j=1}^{P} \beta_{i,j} \boldsymbol{f}_j \right\|^2 + \lambda_i \sum_{j=1}^{P} |\beta_{i,j}|, \tag{2}$$

where vector $\boldsymbol{f}_j$ denotes the time series of common factor j, P is the number of potential factors, and λ is the hyperparameter that controls the amount of shrinkage. In the case of $\lambda = \infty$, the objective function will be dominated by the penalty term and thus $\hat{\boldsymbol{\beta}}_i^{LASSO} = 0$. In the case of $\lambda = 0$, $\hat{\boldsymbol{\beta}}_i^{LASSO}$ corresponds to the OLS estimates.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

Because all coefficients are shrunk at a constant rate (i.e., constant shrinkage) controlled by the same λ that can be large in sparse models, LASSO tends to underestimate the magnitude of nonzero coefficients in sparse settings. To reduce such bias, we rely on the adaptive LASSO by Zou (2006), which modifies the LASSO penalty function so that larger coefficients are shrunk less severely:

$$\hat{\boldsymbol{\beta}}_i^{ALASSO} = \arg\min_{\beta_i} \left\| \boldsymbol{r}_i - \sum_{j=1}^{P} \beta_{i,j} \boldsymbol{f}_j \right\|^2 + \lambda_i \sum_{j=1}^{P} \omega_{i,j} |\beta_{i,j}|, \tag{3}$$

where ω_i is a vector of prespecified weights. In the spirit of Zou (2006), we choose the weights as $w_{i,j} = \frac{1}{|\hat{\beta}_{i,j}^{OLS}|}$, where $\hat{\beta}_{i,j}^{OLS}$ is the OLS estimate. Zou (2006) shows that the adaptive LASSO satisfies the oracle property, that is, it performs well as if the true model were known in advance (Fan and Li (2001)).

In general, using portfolios as testing assets ensures more stable risk exposures and higher signal-to-noise ratios than individual assets. However, as suggested by Harvey and Liu (2021), constructing portfolios based on characteristics or styles may overlook granular information. Accordingly, our analyses are conducted at different levels based on five sets of testing assets: individual hedge funds, 10 EW category portfolios, 10 VW category portfolios, an EW hedge fund industry portfolio, and a VW hedge fund industry portfolio. As adaptive LASSO is scale sensitive, we first standardize factors using their time series means and standard deviations before adaptive LASSO estimation.

To determine the value of λ, we use the AIC. Because factors selected by adaptive LASSO can vary across testing assets, we screen factors that are frequently selected by most assets via OLS regressions to choose the final set of factors, following the "post-estimation" approach of Belloni et al. (2012) and Belloni and Chernozhukov (2013).

III. Empirical Results

In Section III, we apply our post-adaptive-LASSO factor selection framework to the data of hedge funds and the potential factors and consequently obtain a new multifactor model for hedge fund returns. We then investigate how the new hedge fund model performs relative to existing models.

A. Model Selection

As described previously, our factor selection framework proceeds sequentially to search for a set of common risk factors that best describe hedge fund returns.

1. Adaptive LASSO

We first apply adaptive LASSO to each set of testing assets at the fund level, category level (EW and VW), and industry level (EW and VW) and record the factors with nonzero coefficients. Panel A of Table 3 reports the number of testing assets at each level, as well as the average number of factors selected by adaptive LASSO. On average, adaptive LASSO selects 7 factors for individual funds,

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 3

Factor Selection via Adaptive LASSO

Table 3 reports the results of factor selection via adaptive LASSO across different testing asset levels. The sample consists of 7,314 hedge funds from the TASS and HFR databases between January 1997 and August 2019. Panel A reports the number of time series and the average number of factors selected by adaptive LASSO at each testing asset level. Panel B lists the top factors with the highest selection rates per testing asset level. Check marks indicate the selected factors.

	Fund Level	Category Level		Industry Level	
	Individual Funds	EW Portfolios	VW Portfolios	EW Portfolio	VW Portfolio
Panel A. Summary					
Number of time series	7,314	10	10	1	1
Average number of factors selected	7.01	11.40	12.10	12	7
Panel B. Top Factors Selected					
MKT	Yes	Yes	Yes	Yes	Yes
BAB	Yes	Yes	Yes	Yes	Yes
LRSK	Yes	Yes	Yes	Yes	Yes
CRDT	Yes	Yes	Yes	Yes	Yes
TSMOM		Yes	Yes	Yes	Yes
AGR		Yes	Yes	Yes	Yes
ROA		Yes	Yes	Yes	
10Y	Yes	Yes	Yes		
TERM	Yes	Yes	Yes		
MOM			Yes		Yes
SVAR	Yes		Yes		
UNC		Yes	Yes		
IRTF		Yes		Yes	
GPF			Yes	Yes	
INVEST	Yes			Yes	
PFT	Yes				
SSN				Yes	
VALUE	Yes				
DPR				Yes	

11 factors for the EW category portfolio, and 12 factors for the VW category portfolio. For the EW and VW industry portfolios, adaptive LASSO selects 12 and 7 factors, respectively. Hence, the resulting average number of selected factors across testing-asset levels is around 10 (i.e., (7 + 11 + 12 + 12 + 7)/5 = 9.8). The last 2 columns in Panel B present the selected factors for the two hedge fund industry portfolios.

2. Candidate Factors

Given there are multiple testing assets at the fund level and category level, we calculate the fraction of each potential factor selected across assets and assign a corresponding rank to the factor.[11] In Panel B of Table 3, we report the top 10 ranked factors for individual funds. For the EW (VW) category portfolios, the top 11 (13) factors are presented instead due to tied ranks.

Among the top 10 ranked factors for individual funds, six of them (*MKT*, *BAB*, *LRSK*, investment (*INVEST)*, profitability *(PFT)*, and *VALUE*) are equity anomaly factors. The emergence of equity factors is not surprising, given that equity is one of the most important asset classes for hedge funds. The other four top factors are all macroeconomic factors (*CRDT*, *10Y*, *TERM*, and *SVAR*), indicating that hedge funds are exposed to macroeconomic risks in general.

[11]Table IA1 of the Supplementary Material provides details of the fractions and ranks for the potential factors.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

For the EW and VW category portfolios, the top-ranked factors are highly similar. Consistent with fund-level results, *MKT*, *BAB*, *LRSK*, *CRDT*, *10Y*, and *TERM* are among the top-ranked factors. Interestingly, additional equity factors (*TSMOM*, *AGR*, *ROA*, *MOM*, and gross profitability premium (*GPF)*), a macroeconomic factor (*UNC*), and a trend-following factor (*IRTF*) are also ranked as top factors to best explain category portfolio returns.

Turning to the EW and VW industry portfolios, since each of them is a single time series, we directly report factors with nonzero coefficients based on adaptive LASSO. As the results show, factors selected at the industry level are generally consistent with the fund-level and category-level results: *MKT*, *BAB*, *LRSK*, and *CRDT* remain the most important factors. Similar to category portfolios, the two industry portfolios are exposed to additional equity factors such as *TSMOM* and *AGR*. Interestingly, the EW industry portfolio is exposed to more factors than its VW counterpart. For the EW industry portfolio, *ROA*, *GPF*, *INVEST*, *SSN*, *IRTF*, and *DPR* are selected, while *MOM* is selected for the VW industry portfolio.

3. Post-Adaptive-LASSO Factor Selection

As evidenced by the above results, while the top factors selected by adaptive LASSO vary somewhat across testing assets, certain factors are consistently picked out across the board. *MKT*, *BAB*, *LRSK*, and *CRDT* emerge as top factors for assets across all five levels (one individual fund level, two category levels, two industry portfolio levels); *TSMOM* and *AGR* are top factors for four asset levels; and *ROA*, *10Y*, and *TERM* are top factors for three asset levels. Based on these nine factors, we propose the following candidate models for our post-adaptive-LASSO selection step: i) a 4-factor model including *MKT*, *BAB*, *LRSK*, and *CRDT*; ii) a 6-factor model including *MKT*, *BAB*, *LRSK*, *TSMOM*, *AGR*, and *CRDT*; and iii) a 9-factor model including *MKT*, *BAB*, *LRSK*, *TSMOM*, *AGR*, *ROA*, *CRDT*, *10Y*, and *TERM.*

Table 4 reports the OLS results by using the two industry portfolios as testing assets.[12] The estimated alpha as the intercept (i.e., the average difference between the fund portfolio return and its expected return under a model specification) is expected to be close to 0 if the factor model well captures hedge fund returns. In addition, we anticipate the estimated factor loadings to be statistically significant for useful factors. Finally, we use goodness-of-fit measures such as adjusted R^2, AIC, and BIC to illustrate the performance difference across models, and we also perform the Diebold and Mariano (1995) (DM) test on the squared errors to formally compare the models.

The first 3 columns of Table 4 report the OLS regression results for the EW industry portfolio. Moving from left to right, the 4-factor model in the first column exhibits the highest alpha of 0.16 with a significant t-statistic of 2.09, whereas both the 6-factor and 9-factor models have smaller alphas with absolute values around 0.06 and being statistically insignificant. Moreover, all nine factors appear statistically significant with t-statistics above 2.2 in absolute terms. Turning to the goodness-of-fit measures, the 9-factor model has the highest adjusted R^2 and the lowest AIC and BIC among the three models. The superiority of the 9-factor model

[12]The average third-order autocorrelation of industry portfolio returns is merely 0.05, and thus, we report Newey–West robust t-statistics with 3 lags.

TABLE 4

Nested Model Selection

Table 4 reports the results of Post-selection estimations of hedge fund industry portfolios under various candidate factor models identified by adaptive LASSO. The industry portfolios are constructed using equal-weighted (EW) and value-weighted (VW) average returns of hedge funds. The hedge fund sample consists of 7,314 funds from the TASS and HFR databases between January 1997 and August 2019. We perform time series regressions by regressing industry portfolio excess returns on candidate factors. The candidate factors include an asset growth factor (*AGR*), a betting-against-beta factor (*BAB*), a low risk factor (*LRSK*), an equity market factor (*MKT*), a return-on-asset factor (*ROA*), a time-series momentum factor (*TSMOM*), the monthly change in the 10-year treasury yield (*10Y*), the monthly change in credit yield spread (*CRDT*), and the term spread (*TERM*). We report the Diebold and Mariano (1995) (DM) *t*-statistics to assess the significance of improvement in model predictions; a negative number indicates that the model in the row has lower squared errors and thus outperforms the model in the column. Monthly excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags.

	EW Industry Portfolio			VW Industry Portfolio		
	(1) 4-Factor	(2) 6-Factor	(3) 9-Factor	(1) 4-Factor	(2) 6-Factor	(3) 9-Factor
Intercept	0.16	0.06	−0.06	0.27	0.14	0.04
	(2.09)	(0.87)	(−1.07)	(3.35)	(2.37)	(0.74)
MKT	0.24	0.25	0.25	0.16	0.16	0.16
	(11.43)	(11.95)	(13.07)	(6.43)	(8.52)	(8.78)
BAB	18.33	16.30	16.10	19.53	16.85	16.37
	(7.66)	(6.12)	(6.85)	(8.19)	(6.16)	(6.74)
LRSK	−21.74	−18.43	−16.67	−24.26	−20.78	−21.14
	(−8.32)	(−5.98)	(−5.13)	(−8.62)	(−9.76)	(−8.18)
TSMOM		3.57	3.59		5.20	5.25
		(4.81)	(5.08)		(5.00)	(5.46)
AGR		0.05	0.04		0.05	0.05
		(3.51)	(2.76)		(3.38)	(3.18)
ROA			−0.03			0.00
			(−2.27)			(0.19)
CRDT	−1.03	−1.20	−1.75	−0.37	−0.67	−1.35
	(−3.72)	(−4.94)	(−6.99)	(−1.05)	(−2.34)	(−4.83)
10Y			−1.63			−1.48
			(−3.63)			(−3.30)
TERM			−8.90			−5.86
			(−2.98)			(−2.11)
# Obs	272	272	272	272	272	272
Adj-R^2 (%)	80.76	84.05	85.34	70.79	77.91	79.16
AIC	695.49	646.49	626.30	737.09	663.03	650.11
BIC	713.52	671.73	662.36	755.12	688.28	686.17
Diebold-Mariano t-Statistic						
	(1)	(2)		(1)	(2)	
(2)	**−2.22**			**−2.29**		
(3)	**−2.81**	**−1.93**		**−2.58**	−1.64	

is further confirmed by the DM test statistics, which are reported at the bottom of the same table. A negative number indicates that the model in the row has lower squared errors and thus outperforms the model in the column. As clearly indicated by the results, the 6-factor model significantly outperforms the 4-factor model, and the 9-factor model dominates both the 4-factor and the 6-factor models.

The last 3 columns further report the results for the VW industry portfolio. Both the 4-factor and 6-factor models exhibit positive and significant alphas, whereas the alpha for the 9-factor model has the smallest magnitude and insignificant. The DM test statistics show that the 9-factor models dominate both the 4-factor model and the 6-factor model, yet only statistically significantly so for the 4-factor model. However, compared to the 6-factor model, the 9-factor model consistently delivers higher adjusted R^2 and lower AIC and BIC. Out of the nine factors, only one (*ROA*) is associated with an insignificant *t*-statistic.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

Taken together, we propose the 9-factor model, denoted as HF9, as a new hedge fund factor model. Table IA2 in the Supplementary Material provides pairwise correlations for these factors. The correlations among the nine factors are relatively low, indicating that each of them contains distinctive information about hedge fund returns. We also augment our HF9 model with additional factors that exhibit the highest selection rates under the post-adaptive-LASSO factor selection framework after the nine selected factors. The results in Table IA2 of the Supplementary Material suggest that the HF9 factors are sufficient to explain hedge fund returns and capture significant risk exposures.

B. Model Validation

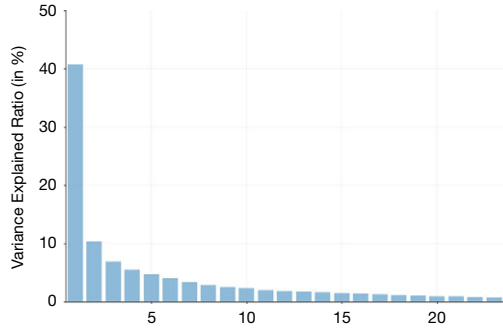
It is important to justify the number of factors in our new hedge fund model. To that end, we use the principal component analysis (PCA) to uncover the number of orthogonal latent factors required for capturing the vast majority of hedge fund return variation. PCA requires a balanced sample, yet different hedge funds enter and exit our sample at different times. To use information from as many funds as possible, we adopt a fixed-window PCA approach to retain funds in the analysis. Specifically, we divide the entire sample period into 11 2-year consecutive windows. For each window, we perform PCA on the excess returns of all hedge funds with the 2-year records. We then calculate the average variance-explained ratios by each principal component.

Figure 1 succinctly summarizes the average variance-explained ratios across principal components. Table IA4 in the Supplementary Material presents detailed PCA results for each of the 2-year windows. The first principal component alone explains more than 40% of the return variation, whereas the 10th principal component explains merely 2% of the return variation. The cumulative variance-explained ratio by the first nine components exceeds 80%, the vast majority of return variation.

FIGURE 1

Variance-Explained Ratios across Principal Components

Figure 1 illustrates the variance-explained ratios (in percentage) for the principal components, averaged across principal component analyses conducted on 11 2-year windows. Each 2-year window includes the excess returns of hedge funds that have complete 2-year histories. The average variance-explained ratio for each principal component is calculated across all 11 2-year windows.



Therefore, based on latent factors from the principal component analysis, we find evidence that strongly corroborates the choice of nine factors in our model.

C. Model Evaluation: In-Sample Evidence

In Section III.C, we evaluate and compare the in-sample performance of our model (**HF9**) with several factor models widely used in the literature.

- **CAPM**: the capital asset pricing model including an *MKT*.
- **FF5**: the Fama and French (2015) 5-factor model including an *MKT*, a small-minus-big factor (*SMB*), a high-minus-low factor (*HML*), a robust-minus-weak factor (*RMW*), and a conservative-minus-aggressive factor (*CMA*).
- **FH7**: the Fung and Hsieh (2004) 7-factor model including an *MKT*, a size factor (*SIZE*), the monthly change in the 10-year treasury yield (*10Y*), the monthly change in *CRDT*, and three trend-following hedge fund risk factors for bond (*BDTF*), commodity (*CMTF*), and currency (*FXTF*).

Panel A of Table 5 presents the time series regression results by regressing EW or VW industry portfolio returns on the factors from various models. The three benchmark models, CAPM, FF5, and FH7, generate sizable alpha estimates ranging from 0.17% to 0.31% per month, all of which are statistically significant. The adjusted R^2s of these models are between 53.02% and 72.63%, indicating that a large portion of the return variation is unexplained by those factors. In sharp contrast, our HF9 model produces insignificant alphas close to 0, as well as higher adjusted R^2s of 85.34% (EW) and 79.16% (VW), highlighting the strong explanatory power of our new factor model.

Panels B and C further compare the performance of the factor models using 10 EW and VW category portfolios. Again, the CAPM, FF5, and FH7 tend to yield alpha estimates that are both economically and statistically significant. Specifically, the average absolute alphas across the 10 EW (VW) portfolios are around 0.2% (0.3%) per month, with Gibbons, Ross, and Shanken (GRS) (1989) test statistics between 7.16 and 11.44; 6 (8) of the 10 alphas are statistically significant for EW (VW) category portfolios under these model specifications. In addition, the average adjusted R^2 across the 10 category portfolios ranges from 44.26% (36.74%) to 55.81% (46.39%) for EW (VW) portfolios, suggesting that roughly 50% of the return variations remain unexplained. In contrast, the magnitude and statistical significance of the alphas decrease remarkably when we switch to the HF9 model. For example, our new model delivers small and insignificant alphas for 9 (6) out of the 10 EW (VW) category portfolios, with the average absolute alpha of 0.06% (0.14%); its GRS statistic of 4.17 (7.05) is also lower than those from the benchmark models. The average R^2 from the HF9 model increases to 67.03% (57.52%) for the EW (VW) portfolio, echoing the early results that our 9-factor model is better at capturing hedge fund return variation than existing models.[13]

We next examine the fund alpha distribution as an alternative approach to evaluate factor models. Based on each model, we estimate alpha for each individual

[13]Our results remain robust even when we relax our requirement to include hedge funds with a minimum of 36 monthly return observations, as reported in Table IA5 of the Supplementary Material.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 5

Model Comparison

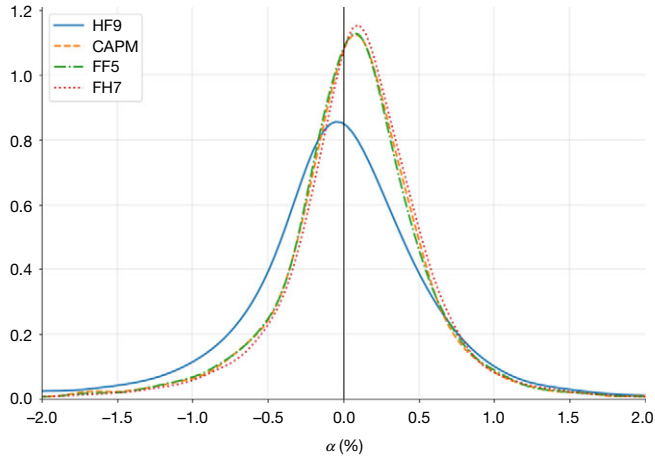
Table 5 reports the intercepts (alphas) and the adjusted R^2 values from the time series regressions of various testing assets under four alternative factor models. The sample consists of 7,314 hedge funds from the TASS and HFR databases between January 1997 and August 2019, including funds from 10 categories: convertible arbitrage (CA), dedicated short bias (DSB), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. Panel A reports the time series estimates of the industry-level portfolios constructed using equal-weighted (EW) and value-weighted (VW) averages of hedge fund excess returns. Panels B and C report the time series estimates of EW and VW category-level portfolios. Monthly excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags.

	HF9		CAPM		FF5		FH7	
	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)
Panel A. Industry-Level Portfolio								
EW portfolio	−0.06	85.34	0.17	67.37	0.19	72.63	0.18	72.51
	(−1.07)		(1.92)		(2.10)		(2.35)	
VW portfolio	0.04	79.16	0.28	53.02	0.31	60.15	0.28	56.86
	(0.74)		(3.41)		(3.73)		(3.66)	
Panel B. EW Category-Level Portfolio								
CA	−0.03	68.70	0.19	34.06	0.17	35.23	0.22	61.78
	(−0.20)		(1.14)		(0.91)		(2.20)	
DSB	0.02	77.19	0.26	61.75	0.10	76.91	0.28	62.72
	(0.13)		(1.47)		(0.67)		(1.58)	
ED	0.01	81.45	0.22	58.24	0.20	63.64	0.24	72.92
	(0.10)		(2.33)		(2.16)		(3.62)	
EM	−0.09	53.56	0.13	45.20	0.15	46.29	0.14	49.41
	(−0.45)		(0.47)		(0.55)		(0.53)	
EMN	0.04	47.28	0.21	30.90	0.18	34.09	0.21	33.20
	(0.89)		(4.54)		(3.82)		(4.95)	
FIA	0.08	74.38	0.24	30.53	0.21	32.41	0.26	64.57
	(1.04)		(2.31)		(1.91)		(4.36)	
FOF	−0.18	76.95	0.08	47.78	0.09	53.06	0.08	53.12
	(−3.11)		(0.85)		(0.96)		(1.03)	
GM	0.03	32.91	0.22	11.37	0.20	12.81	0.20	27.40
	(0.27)		(2.61)		(2.39)		(2.67)	
LSEH	−0.05	89.55	0.21	75.50	0.26	83.52	0.22	77.98
	(−0.66)		(2.05)		(2.84)		(2.28)	
MS	0.07	68.36	0.32	47.30	0.32	50.24	0.34	55.01
	(0.94)		(3.75)		(3.68)		(4.95)	
Average |alpha|	0.06		0.21		0.19		0.22	
Average Adj-R^2		67.03		44.26		48.82		55.81
F-GRS	4.17		8.35		7.16		9.30	
Panel C. VW Category-Level Portfolio								
CA	0.08	64.57	0.32	19.46	0.29	19.72	0.36	54.64
	(0.63)		(2.19)		(1.82)		(4.14)	
DSB	0.08	67.75	0.11	65.68	0.11	68.57	0.15	66.88
	(0.49)		(0.79)		(0.81)		(1.08)	
ED	0.14	77.17	0.34	50.92	0.31	55.69	0.36	66.88
	(2.01)		(3.72)		(3.35)		(5.68)	
EM	0.24	46.31	0.36	38.37	0.39	39.07	0.37	41.54
	(1.31)		(1.36)		(1.36)		(1.41)	
EMN	0.08	34.98	0.18	26.79	0.18	27.56	0.18	27.27
	(1.62)		(4.34)		(4.10)		(4.38)	
FIA	0.20	69.64	0.26	32.46	0.27	34.10	0.28	61.32
	(2.69)		(2.66)		(2.58)		(4.73)	
FOF	−0.14	72.94	0.15	42.90	0.18	48.87	0.16	47.00
	(−2.47)		(1.77)		(2.00)		(1.88)	
GM	0.45	4.34	0.44	0.31	0.41	−0.15	0.44	4.27
	(2.89)		(3.93)		(3.48)		(4.01)	
LSEH	0.01	84.70	0.32	63.25	0.38	75.23	0.31	63.93
	(0.11)		(2.96)		(3.93)		(2.92)	
MS	0.02	52.80	0.37	27.24	0.38	34.64	0.36	30.18
	(0.20)		(3.31)		(3.23)		(3.04)	
Average |alpha|	0.14		0.29		0.29		0.30	
Average Adj-R^2		57.52		36.74		40.33		46.39
F-GRS	7.05		8.64		8.71		11.44	

FIGURE 2

Distribution of Hedge Fund Alphas

Figure 2 shows the in-sample cross sectional distributions of alphas (in percentage) for 7,314 hedge funds from the TASS and HFR databases between January 1997 and August 2019. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. For each model, we estimate the time series regression of individual fund excess returns and plot the kernel density estimates for the alphas.



hedge fund in the sample. Figure 2 plots the alpha distributions under HF9 and the three benchmark models. The differences in distributions from CAPM, FF5, and FH7 are negligible, all with positive average alphas around 0.07% and standard deviations around 0.6% per month. However, the HF9 model is associated with a much lower average alpha of −0.07% per month. Interestingly, the heterogeneity in fund alpha is the greatest under HF9 as indicated by the standard deviation at 0.91% per month. In addition, both the reduction in average alpha and the increase in alpha heterogeneity based on HF9 are mainly driven by the left tail.

The top row of Table 6 further reports the fractions of significant alphas under different factor models. When using the CAPM, FF5, or FH7 to estimate alphas, we find that more than 15% of hedge funds have significantly positive alphas with t-statistic above 2, indicating outperformance. After switching to HF9, the fraction of significantly positive alphas reduces to 12%, implying that our new model is able to capture common risks of some top funds identified by other models. Turning to the fractions of negative alphas, while only around 5% of funds significantly underperform according to the CAPM, FF5, and FH7, over 13% of funds underperform after adjusted for exposures to the HF9 factors. The results suggest that HF9 is more powerful in uncovering underperforming funds than the other models.

The remaining rows of Table 6 present the fractions of underperforming and outperforming individual funds in each fund category. In general, the estimated performance of hedge funds in all categories reduces based on HF9 as the factor model. For example, more than 26% funds show underperform based on HF9.

In the Supplementary Material, we analyze changes in hedge funds' risk exposures over time by dividing the sample period into subperiods. The results in Table IA6 support the notion that hedge funds dynamically adjust portfolio

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 6

Model Comparison: Fund Alpha Distribution

Table 6 reports the fractions of the underperforming and outperforming hedge funds identified by various factor models. The sample consists of 7,314 hedge funds from TASS and HFR databases between January 1997 and August 2019, including funds from 10 categories: convertible arbitrage (CA), dedicated short bias (DSB), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model.

	HF9		CAPM		FF5		FH7	
	%($t<-2$)	%($t>2$)	%($t<-2$)	%($t>2$)	%($t<-2$)	%($t>2$)	%($t<-2$)	%($t>2$)
All funds	13.39	12.39	4.17	15.05	5.26	15.00	5.15	17.86
Category								
CA	8.89	14.44	0.00	21.11	0.00	20.00	0.00	26.67
DSB	12.90	12.90	3.23	6.45	6.45	6.45	3.23	12.90
ED	10.21	18.49	2.07	25.15	1.92	21.89	2.51	29.14
EM	4.07	8.72	4.36	8.72	4.07	10.76	4.07	9.59
EMN	8.90	17.51	2.97	22.26	4.75	23.74	4.15	22.55
FIA	6.00	31.87	2.75	30.13	3.50	29.50	3.25	36.13
FOF	26.71	5.64	5.04	9.20	6.97	8.65	6.78	11.87
GM	5.75	12.07	4.60	17.82	5.17	17.24	5.17	18.97
LSEH	8.83	9.55	5.03	11.44	6.10	12.28	6.06	13.39
MS	11.11	15.38	0.85	20.94	1.28	21.79	0.43	26.07

allocations. Notably, as shown in Figure IA1, the HF9 model consistently achieves the highest adjusted R^2 values across fund portfolios and rolling windows.

Overall, these in-sample results confirm the feature of our new HF9 model to better explain hedge fund returns and distinguish between outperforming and underperforming funds than other commonly used factor models.

IV. Out-of-Sample Analyses

In Section IV, we continue to assess the performance of the HF9 model, but with a focus on out-of-sample results. First, we compare the HF9 and benchmark models using an alternative hedge fund database that was not used in the original model training. Second, we evaluate the performance of the HF9 model over an out-of-sample period. Furthermore, in the Supplementary Material, we explore an alternative sorting dimension—fund size, which is unrelated to the portfolios used in factor selection, providing further performance validation.

A. Model Evaluation: Alternative Data

Lewellen et al. (2010) suggest that using alternative testing assets for evaluating factor models can improve the power of asset pricing tests. In this subsection, we examine two sets of alternative testing assets that are both obtained from the BarclayHedge database, a different vendor of hedge fund data. As shown in Agarwal, Fos, and Jiang (2013), most hedge funds are only covered by a single database. As a result, most of the hedge funds in the BarclayHedge database do not overlap with those in the TASS and HFR databases. To be consistent with our main sample, we focus on hedge funds in the categories examined in previous sections. The first group of testing assets consists of 10 hedge fund indices that are compiled by BarclayHedge, including one industry index and nine category

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

indices.[14] The second set of testing assets consists of individual hedge funds from BarclayHedge.

Panel A of Table 7 presents a comparison of the models using industry and category indices. In comparison to the three benchmark models (CAPM, FF5, and FH7), the HF9 model consistently produces smaller and statistically insignificant alphas and higher adjusted R^2 values across all indices, with the exception of the FOF index. For the industry index, the alpha from the HF9 model is −0.01% per month, with a t-statistic of −0.2, while the alphas from the benchmark models are around 0.28% with t-statistics above 3.0. When examining the category indices, we find that the average absolute alpha from the HF9 model across all categories is 0.08%, compared to the average alpha of around 0.25% from the other models. Moreover, the GRS F-statistics for the HF9 model is 8.58, only about half of the F-statistics for the CAPM, FF5, and FH7. Additionally, the average adjusted R^2 across the nine indices for the HF9 model is 61.84%, while the average adjusted R^2 values for the CAPM, FF5, and FH7 are at most 47.22%, indicating that the HF9 model outperforms the existing models in explaining returns of the hedge fund categories.

Finally, we repeat the fund-level analysis, focusing on the distributions of alphas under different factor models using the BarclayHedge data. Panel B of Table 7 confirms our previous in-sample analysis: the HF9 model generally reduces hedge fund alphas and identifies a larger portion of poorly performing funds compared with the existing models. Notably, the fraction of underperforming funds in the fund-of-funds (FOF) category increases from 3% under the CAPM to 31.32% under HF9, highlighting the difference in alpha distributions between conventional and new models. Figure 3 plots the cross sectional distributions of alphas for hedge funds under four alternative models using BarclayHedge funds. This figure supports our findings that the new model decreases fund performance estimates while revealing greater variation across funds.

In summary, the results using alternative testing assets are consistent with the in-sample evaluations. The HF9 model outperforms the other three models that are commonly considered in the asset pricing and hedge fund literature in terms of explaining the returns of hedge funds.

B. Model Evaluation: Out-of-Sample Period

Another approach to validate factor models is to test their performance over an out-of-sample time period. Following recent research on asset pricing that emphasizes the importance of out-of-sample model performance, we provide out-of-sample evidence for the factor models in this subsection.

To evaluate the out-of-sample performance of the models, we analyze industry and category hedge fund portfolios/indices constructed directly by TASS and BarclayHedge. Similar to Agarwal and Naik (2004), we validate the model

[14]There is no BarclayHedge index corresponding to the DSB strategy. However, we include individual funds that employ the DSB strategy and are covered by BarclayHedge in our fund-level analyses in this subsection.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 7

Model Comparison: BarclayHedge

Table 7 reports the results of model comparisons using an alternative sample consisting of 4,569 hedge funds from the BarclayHedge database between January 1997 and August 2019, including funds from nine categories: convertible arbitrage (CA), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. Panel A reports the intercepts (alphas) and the adjusted R^2 values from the time series regressions of the industry index under four factor models. Panel B reports the fractions of the underperforming and outperforming hedge funds identified by each factor model. Monthly excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags.

Panel A. Index-Level Evidence

	HF9		CAPM		FF5		FH7	
	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)
Industry index	−0.01 (−0.20)	85.81	0.27 (3.06)	68.76	0.29 (3.13)	73.83	0.28 (3.69)	73.44
Category index								
CA	0.07 (0.56)	60.86	0.29 (1.90)	19.61	0.27 (1.65)	20.02	0.32 (3.33)	53.32
ED	0.08 (1.12)	75.13	0.32 (3.29)	57.24	0.31 (3.19)	62.29	0.32 (4.08)	67.15
EM	−0.10 (−0.54)	57.83	0.16 (0.70)	49.26	0.16 (0.67)	49.94	0.18 (0.85)	53.77
EMN	−0.02 (−0.44)	35.57	0.20 (3.83)	4.42	0.17 (3.21)	6.15	0.19 (3.73)	8.50
FIA	0.10 (0.84)	49.29	0.21 (1.73)	15.56	0.20 (1.64)	15.09	0.23 (2.74)	42.88
FOF	−0.22 (−3.54)	77.82	0.09 (1.03)	45.57	0.09 (1.01)	50.46	0.10 (1.34)	51.61
GM	−0.04 (−0.51)	51.51	0.29 (3.51)	25.35	0.27 (3.27)	27.36	0.27 (3.56)	38.25
LSEH	−0.01 (−0.09)	78.35	0.32 (3.45)	56.11	0.38 (4.17)	67.23	0.33 (3.55)	56.74
MS	0.08 (1.06)	70.17	0.36 (3.69)	33.29	0.33 (3.20)	36.11	0.37 (5.33)	52.78
Average |alpha|	0.08		0.25		0.24		0.26	
Average Adj-R^2		61.84		34.04		37.18		47.22
F-GRS	8.58		16.24		15.05		17.05	

Panel B. Fund-Level Evidence

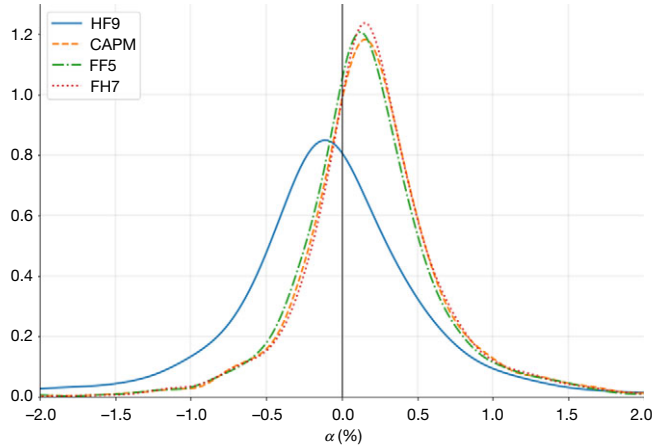
	HF9		CAPM		FF5		FH7	
	%($t<-2$)	%($t>2$)	%($t<-2$)	%($t>2$)	%($t<-2$)	%($t>2$)	%($t<-2$)	%($t>2$)
All funds	17.53	9.48	2.63	21.65	3.28	18.89	3.76	23.73
Category								
CA	9.92	16.79	3.05	35.88	3.05	35.11	0.76	43.51
DSB	13.33	13.33	6.67	10.00	6.67	10.00	10.00	20.00
ED	4.39	17.98	0.88	32.89	1.32	31.14	1.32	40.79
EM	3.84	11.38	3.70	14.79	5.69	13.51	5.97	15.65
EMN	4.19	17.96	1.20	23.95	0.60	23.35	1.20	24.55
FIA	2.56	26.92	1.28	38.46	2.56	42.31	1.28	42.31
FOF	31.32	4.44	2.98	17.95	3.58	13.92	4.34	20.42
GM	6.33	10.13	3.80	17.30	2.95	16.46	5.91	16.46
LSEH	9.79	10.16	1.36	25.15	2.11	22.06	1.86	24.29
MS	11.22	20.00	1.95	43.90	1.46	40.49	2.44	50.73

performance by comparing the monthly realized excess returns with the returns on the corresponding replicating portfolio during an unused testing period. Specifically, for each portfolio/index *i*, we begin by running a time series regression using 60 months of data from September 2014 to August 2019 (the end of the main sample

FIGURE 3

Distribution of Hedge Fund Alphas: BarclayHedge

Figure 3 shows the in-sample cross sectional distributions of alphas (in percentage) for 4,569 hedge funds from the BarclayHedge database between January 1997 and August 2019. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. For each model, we estimate the time series regression of individual fund excess returns and plot the kernel density estimates for the alphas.



for factor selection). Based on the regression coefficient estimates, we calculate the returns of the corresponding replicating portfolio for the testing period from September 2019 to December 2020. If the factor exposures accurately reflect the economic risks of the portfolio/index, the replicating portfolio, based on those estimated loadings, should closely match the out-of-sample performance. To assess the accuracy of the models, we calculate the mean squared errors (MSEs) for different factor models.

Table 8 presents the out-of-sample performance for the TASS portfolios and BarclayHedge indices under 4-factor models: the CAPM, FF5, FH7, and HF9. Our results show that i) For industry-level analysis in Panel A, the HF9 model outperforms the other three models by quite wide margins, with the MSEs only about one-third of those from the other models in most cases. ii) For category-level analyses in Panel B, the MSEs under the HF9 model are always smaller than those under the other three models across categories, indicating the benefit of including the new factors in quantifying hedge fund strategies and risk exposures.

Taken together, the results of the out-of-sample tests show that the HF9 model, consisting of the most powerful risk factors, can accurately capture hedge fund returns and therefore are useful for fund performance evaluation. These findings support the conclusion that the superior in-sample performance of the HF9 model in Section III is not simply a result of statistical artifacts in the data, but rather a result of the model's ability to model hedge fund returns. This highlights the value of the HF9 model in evaluating the performance of hedge funds and understanding their risk exposures.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 8

Model Comparison: Out-of-Sample Period

Table 8 reports the out-of-sample results of model comparisons. The testing sample consists of hedge fund portfolios/indices constructed using the TASS and BarclayHedge databases over the period from September 2019 to December 2020, including funds from nine categories: convertible arbitrage (CA), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). For each index/portfolio, we construct the replicating portfolio based on factor model coefficients estimated over a 5-year window from September 2014 to August 2019. Then, we compute the difference between the monthly realized excess returns and those on the corresponding replicating portfolio during the testing period. Finally, we report the mean squared errors for each index/portfolio. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. Panel A reports the mean squared errors for industry-level portfolio/index. Panels B and C report the mean squared errors for the category-level portfolios and indices. For each row, the minimum mean squared errors across columns are marked in bold.

	HF9	CAPM	FF5	FH7
Panel A. Industry-Level				
TASS	**1.64**	5.39	5.52	3.27
Barclay	**0.38**	2.06	2.22	0.57
Panel B. TASS Category-Level				
CA	**2.42**	6.02	5.31	2.84
ED	**3.36**	10.43	8.10	4.32
EM	4.24	14.97	15.72	**4.03**
EMN	**13.48**	14.76	16.46	14.31
FIA	**0.86**	2.00	1.84	1.19
FOF	**0.85**	1.51	2.15	1.29
GM	**8.16**	14.38	12.19	11.31
LSEH	**1.69**	2.85	3.01	2.05
MS	**1.91**	5.39	9.31	6.19
Panel C. BarclayHedge Category-Level				
CA	**1.88**	3.90	3.91	2.09
ED	2.62	6.37	6.50	**2.06**
EM	**3.21**	6.63	8.22	3.70
EMN	**0.21**	0.38	0.44	0.38
FIA	**0.66**	0.69	0.86	0.79
FOF	**0.63**	1.91	2.58	1.42
GM	2.58	1.37	1.56	**1.19**
LSEH	**0.92**	1.72	2.24	1.26
MS	**0.40**	2.04	2.01	0.80

V. Further Analyses and Robustness

A. Explaining Returns from Arbitrage Trading

So far, our factor selection and model validation have relied on hedge fund returns. To gain further insights, we perform analyses using information on hedge fund holdings. While data on short positions are unavailable at the fund level, making it infeasible to directly examine each fund's complete portfolio (including long and short positions), stock-level short interest data is available. When combined with aggregated hedge fund long positions (e.g., Cao, Chen, Goetzmann, and Liang (2018), Chen et al. (2020)), this data can provide an estimate of arbitrage trading activity in individual stocks. Thus, a factor model that more accurately captures hedge fund returns should also better explain returns derived from arbitrage trading.

In this subsection, we compare the performance of different models in explaining returns from arbitrage trading. Chen et al. (2019) show that net arbitrage trading (NAT) scores for individual stocks, as a measure of arbitrage activity, strongly

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 9

Model Comparison: Arbitrage Trading

Table 9 reports the time series regression results of spread portfolio returns formed on the net arbitrage trading (NAT) scores of Chen et al. (2019) using four models. Stocks are sorted each month into terciles or quintiles based on their NAT scores. The spread portfolio goes long in stocks with high NAT scores and short in stocks with low NAT scores. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. Annualized excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags.

	Equal Weighted		Value Weighted	
	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)
Panel A. Tercile Spread				
HF9	2.06 (1.67)	7.56	1.71 (1.41)	6.21
CAPM	6.03 (4.83)	0.88	5.19 (4.38)	0.71
FF5	5.45 (4.36)	3.78	4.66 (3.83)	3.20
FH7	5.86 (4.46)	−0.34	5.05 (4.08)	−0.16
Panel B. Quintile Spread				
HF9	4.29 (2.80)	6.54	4.72 (2.87)	3.82
CAPM	9.43 (5.81)	0.02	8.98 (5.60)	0.06
FF5	8.63 (5.41)	2.87	8.24 (5.10)	2.09
FH7	9.28 (5.54)	−1.40	8.88 (5.39)	−1.27

predict cross sectional stock returns. Following their approach, we compute the NAT score for each stock as the difference between abnormal hedge fund holdings and abnormal short interest.[15] At the end of each month, we sort stocks into tercile (or quintile) portfolios based on their NAT scores. We then compute equal- and value-weighted returns for each portfolio and form a spread portfolio that goes long stocks in the top tercile (or quintile) with high NAT scores and short stocks in the bottom tercile (or quintile) with low NAT scores.

Table 9 presents the results of time series regressions for the equal- and value-weighted spread returns across the four models. Under the three benchmark models—CAPM, FF5, and FH7—the spread returns of tercile portfolios exhibit sizable and statistically significant alpha estimates ranging from 4.66% to 6.03% per year. The adjusted R^2s of these models range between −0.34% and 3.78%. In contrast, the HF9 model produces insignificant alphas and notably higher adjusted R^2s of 7.56% (equal weighted) and 6.21% (value weighted) for the long-short portfolio, indicating superior explanatory power. Similar patterns are observed for quintile-sorted portfolios.

[15]Following Chen et al. (2019), we measure hedge fund holdings for each stock using hedge funds' 13F disclosure data and short interest using Compustat's short interest data. Abnormal hedge fund holdings and abnormal short interest are then defined as the respective values in a given quarter minus their moving averages from the past 4 quarters.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

Taken together, these analyses based on fund holdings support the effectiveness of the HF9 model in capturing hedge funds' trading strategies, further validating the model's applicability for hedge fund performance evaluation.

B. Additional Models with Recently Proposed Factors

So far, we have shown the superior performance of the HF9 model compared to three conventional factor models, which are either not tailored to hedge funds or were developed a long time ago. Recent research has introduced additional factors designed to explain hedge fund returns. In this subsection, we consider three alternative models incorporating such factors to conduct a comparative analysis with the HF9 model.

- **ABGS**: the Ardia et al. (2023) 7-factor model including an *MKT*, an *SMB*, an illiquidity factor (*ILL*), a *BAB*, a stock variance factor (*SVAR*), a carry factor (*CARRY*), and a *TSMOM*.
- **FH7EC**: the Fung and Hsieh (2004) 7-factor model augmented by an emerging market factor (*EMKT*) from Fung and Hsieh (2001) and a correlation risk factor (*CRSK*) from Buraschi, Kosowski, and Trojani (2014).[16]
- **FH7CP**: the Fung and Hsieh (2004) 7-factor model augmented by an out-of-money equity call option factor (*OTMC*) and an out-of-money equity put option factor (*OTMP*) proposed by Agarwal and Naik (2004).[17]

Table 10 reports the time series regression results using EW and VW industry and category portfolios for the alternative models, along with the HF9 model from Table 5 for easy comparison. Across the portfolios, the three alternative models—ABGS, FH7EC, and FH7CP—consistently outperform the best benchmark model, FH7 (from Table 5), as evidenced by lower absolute alpha estimates and higher adjusted R^2 values. Their GRS statistics are also lower than those from the FH7 model, collectively indicating the incremental value of the newly added factors.

In rare cases, these models appear to outperform the HF9 model; for example, the FH7EC model performs better for EM funds. However, these alternative models generally exhibit a greater tendency to produce significant alpha estimates, lower adjusted R^2 values, and larger GRS statistics when compared to the HF9 model. This suggests that our 9-factor model is more effective in capturing hedge fund return variation, even when benchmark models are augmented with recently proposed factors. These results also validate our factor selection and reaffirm the power of anomalies as hedge fund factors.

C. Flow-Performance Sensitivity

While alphas estimated from models that better capture hedge fund returns provide a more accurate measure of fund performance, investors may allocate capital based on perceived performance rather than the risk-adjusted returns

[16]We use monthly returns of the MSCI Emerging Market Index as the emerging market factor. We thank Grigory Vilkov for making the option-implied data available on his website, which we use to construct the correlation risk factor.

[17]We thank Vikas Agarwal for sharing the option-based factors with us.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 10

Model Comparison: Alternative Models

Table 10 reports the intercepts (alphas) and the adjusted R^2 values from the time series regressions of various testing assets under 4-factor models. The sample consists of 7,314 hedge funds from the TASS and HFR databases between January 1997 and August 2019, including funds from 10 categories: convertible arbitrage (CA), dedicated short bias (DSB), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The ABGS model is the Ardia et al. (2023) 7-factor model. The FH7EC is the Fung and Hsieh (2004) 7-factor model augmented by an emerging market factor (*EMKT*) of Fung and Hsieh (2001) and a correlation risk factor (*CRSK*) of Buraschi et al. (2014). The FH7CP is the Fung and Hsieh (2004) 7-factor model augmented by an out-of-money equity call option factor (*OTMC*) and an out-of-money equity put option factor (*OTMP*) of Agarwal and Naik (2004). Panel A reports the time series estimates of the industry-level portfolios constructed using equal-weighted (EW) and value-weighted (VW) averages of hedge fund excess returns. Panels B and C report the time series estimates of EW and VW category-level portfolios. Monthly excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags.

	HF9		ABGS		FH7EC		FH7CP	
	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)	Alpha	Adj-R^2 (%)
Panel A. Industry-Level Portfolio								
EW portfolio	−0.06	85.34	0.20	77.25	0.05	80.09	0.17	72.53
	(−1.07)		(1.99)		(0.81)		(2.21)	
VW portfolio	0.04	79.16	0.30	66.57	0.14	65.45	0.29	57.46
	(0.74)		(2.90)		(2.11)		(3.71)	
Panel B. EW Category-Level Portfolio								
CA	−0.03	68.70	0.47	51.69	0.08	62.97	0.23	61.60
	(−0.20)		(3.22)		(0.69)		(2.09)	
DSB	0.02	77.19	0.25	72.30	0.21	64.52	0.35	63.58
	(0.13)		(1.18)		(1.07)		(1.75)	
ED	0.01	81.45	0.31	73.08	0.11	75.28	0.22	72.89
	(0.10)		(3.73)		(1.58)		(3.32)	
EM	−0.09	53.56	0.22	49.71	0.09	75.60	0.15	49.20
	(−0.45)		(0.68)		(0.70)		(0.59)	
EMN	0.04	47.28	0.10	44.28	0.18	33.17	0.22	33.13
	(0.89)		(1.74)		(3.50)		(4.81)	
FIA	0.08	74.38	0.44	55.31	0.18	66.54	0.25	64.46
	(1.04)		(5.73)		(2.81)		(3.79)	
FOF	−0.18	76.95	0.13	65.79	−0.05	62.65	0.08	52.87
	(−3.11)		(1.31)		(−0.77)		(0.90)	
GM	0.03	32.91	−0.01	20.48	0.06	33.81	0.21	27.13
	(0.27)		(−0.08)		(0.77)		(2.76)	
LSEH	−0.05	89.55	0.19	83.73	0.05	82.72	0.20	78.28
	(−0.66)		(1.50)		(0.73)		(2.13)	
MS	0.07	68.36	0.34	59.11	0.20	60.47	0.33	54.82
	(0.94)		(4.17)		(2.78)		(4.55)	
Average |alpha|	0.06		0.25		0.12		0.22	
Average Adj-R^2		67.03		57.55		61.77		55.80
F-GRS	4.17		5.79		6.18		8.31	
Panel C. VW Category-Level Portfolio								
CA	0.08	64.57	0.60	43.74	0.26	55.60	0.38	54.41
	(0.63)		(5.75)		(2.33)		(3.92)	
DSB	0.08	67.75	0.15	68.63	0.15	67.49	0.20	67.05
	(0.49)		(0.77)		(0.82)		(1.19)	
ED	0.14	77.17	0.34	66.49	0.23	69.21	0.35	66.68
	(2.01)		(3.72)		(3.40)		(5.39)	
EM	0.24	46.31	0.39	42.93	0.36	70.42	0.42	41.49
	(1.31)		(1.14)		(2.64)		(1.59)	
EMN	0.08	34.98	0.08	35.29	0.17	26.75	0.20	27.35
	(1.62)		(1.45)		(3.52)		(4.67)	
FIA	0.20	69.64	0.46	51.11	0.20	63.60	0.28	62.52
	(2.69)		(6.09)		(3.39)		(4.46)	
FOF	−0.14	72.94	0.22	60.92	0.01	54.78	0.16	46.99
	(−2.47)		(2.02)		(0.11)		(1.82)	
GM	0.45	4.34	0.26	1.45	0.24	7.61	0.47	3.96
	(2.89)		(1.44)		(1.88)		(3.85)	
LSEH	0.01	84.70	0.25	75.62	0.16	68.93	0.30	64.37
	(0.11)		(1.70)		(1.79)		(2.83)	
MS	0.02	52.80	0.42	41.38	0.21	34.35	0.34	31.62
	(0.20)		(2.74)		(1.93)		(2.75)	
Average |alpha|	0.14		0.32		0.20		0.31	
Average Adj-R^2		57.52		48.76		51.87		46.64
F-GRS	7.05		5.57		7.51		10.72	

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

suggested by such models. Although hedge fund investors are typically considered sophisticated, recent studies such as Agarwal, Green, and Ren (2018) show that they may chase returns tied to exotic risk exposures. In this subsection, we examine the sensitivity of hedge fund flows to alpha estimates from the four models—HF9, CAPM, FF5, and FH7—to infer which risk model investors rely on when allocating capital to hedge funds.

Following Agarwal et al. (2018), at the end of each year t, we estimate yearly updated alphas for each hedge fund using the past 2 years of returns under each model. Annual net flow for each fund in the year $t+1$ is calculated as $Flow_{t+1} = \frac{AUM_{t+1}}{AUM_t} - (1+R_t)$. To assess the flow-performance sensitivity, we use both portfolio sorting and univariate sensitivity analysis. For portfolio sorting, at the end of each year, we sort hedge funds into terciles based on their alpha estimates from each model and compute fund-size-weighted annual net flows over the subsequent year for each tercile portfolio.

Next, we estimate the flow-performance sensitivity in terms of magnitudes and directions, defined as:

$$\beta^{Value} = \frac{Cov(Flow, \alpha)}{Var(\alpha)} \tag{4}$$

$$\beta^{Sign} = \frac{Cov(\Phi(Flow), \Phi(\alpha))}{Var(\Phi(\alpha))} \tag{5}$$

where Φ is a sign function that returns the sign of a real number. The intuition is that, if a model is preferred by investors, these sensitivity estimates should be more positive.[18]

Panel A of Table 11 reports the time series averages of annual net flows of tercile portfolios sorted by fund alphas under different models, along with the flow differences between the highest and lowest terciles. We observe that all flow differences are significantly positive, indicating a positive flow-performance relation across all models. However, the flow spread is largest for the CAPM alpha at 26.46% per year, closely followed by spreads of 24.87% and 23.52% for the FF5 and FH7 alphas, respectively. While the flow spread for the HF9 alpha is also significantly positive, it is smaller compared to those from the other models. Consistent with Agarwal et al. (2018), this evidence suggests that hedge fund investors mainly adjust for conventional risks when assessing fund performance. Furthermore, most of the flow spread is driven by inflows to high-alpha funds rather than outflows from low-alpha funds, likely reflecting redemption restrictions such as lock-up periods.

Panel B of Table 11 presents the results of the regression-based sensitivity analyses. For ease of interpretation, we report $(\beta^{Sign}+1)/2$, which represents the average probability that the sign of fund flow is positive (negative) conditional on

[18]We follow Agarwal et al. (2018) to perform the univariate regressions with standard errors double-clustered by fund and year.

TABLE 11

Flow-Performance Relation

Table 11 reports the results of the flow-performance relation using 4-factor models. The sample consists of 7,314 hedge funds from the TASS and HFR databases between January 1997 and August 2019. At the end of each year t, we estimate each fund's alpha using the past 2 years of returns under each model and calculate the net flow for the following year. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. Panel A reports the average annual net flows of tercile portfolios sorted by fund alphas under different models, with the "High Minus Low" row showing the difference between the highest and lowest terciles. Panel B presents the flow-alpha sensitivity estimates for each risk model. The row labeled "Value" reports the β^{Value} estimates defined in equation (4), and the row labeled "Sign" reports the β^{Sign} estimates defined in equation (5). Following Agarwal et al. (2018), we report $(\beta^{Sign}+1)/2$, which denotes the average probability that the sign of the fund flow is positive (negative) conditional on the sign of the alpha being positive (negative). If unrelated, the probability is expected to be 50%. Annual net flows are in percentage. Standard errors are clustered at both the fund and year levels, and t-statistics are reported in parentheses below coefficients.

	HF9	CAPM	FF5	FH7
Panel A. Portfolio Flows				
1 (Low)	2.87	−2.25	−0.31	−0.07
	(0.83)	(−0.81)	(−0.09)	(−0.03)
2	15.91	10.28	10.20	9.98
	(3.85)	(2.76)	(2.90)	(2.84)
3 (High)	18.27	24.21	24.56	23.45
	(5.90)	(6.57)	(6.13)	(6.57)
High minus low	15.40	26.46	24.87	23.52
	(5.86)	(10.80)	(6.90)	(8.63)
Panel B. Flow-Performance Sensitivity				
Value	0.11	0.72	0.60	0.58
	(4.60)	(7.97)	(8.21)	(7.80)
Sign	54.81%	60.15%	58.90%	58.83%
	(3.84)	(11.96)	(12.71)	(10.51)

the sign of alpha being positive (negative). Consistent with the portfolio sorting results, value sensitivity is always positive, and sign sensitivity is consistently greater than 50%. The flow-alpha relation is stronger for conventional models than for the HF9 model. Based on β^{Value}, a 1% increase in the annualized CAPM (FF5; FH7) alpha leads to a 0.72% (0.6%; 0.58%) increase in fund flow in the subsequent year, compared to only a 0.11% increase for the HF9 alpha. Similarly, according to β^{Sign}, the conditional probability of positive flows following positive CAPM (FF5; FH7) alphas is 60.15% (58.9%; 58.83%), higher than the 54.81% for the HF9 alpha. These findings further confirm that investor flows are better explained by performance measures that do not adjust for the HF9 factors, suggesting that investors may misinterpret exotic factor exposures as indicators of managerial skill.

D. Fund Failure Likelihood

Another important question regarding fund performance is whether poor performance increases the likelihood of hedge fund failure. The results from the previous subsection suggest that investors do not necessarily withdraw capital from poorly performing funds and that investor flows respond to returns driven by exotic risk exposures. In this subsection, we examine whether investors' perceptions of performance are associated with the probability of fund failure.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 12

Fund Failure Likelihood

Table 12 reports the results of the Cox proportional hazard analysis using model-implied alphas under four models. The sample consists of 7,314 hedge funds from the TASS and HFR databases between January 1997 and August 2019. "Failure" is defined as a fund becoming defunct. At the end of each year t, we estimate each fund's alpha using the past 2 years of returns under each model and construct two dummy variables, "Low alpha dummy" and "High alpha dummy," which equal 1 if the fund ranks in the lowest or highest tercile by model-implied alpha and 0 otherwise, respectively. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The CAPM is the capital asset pricing model. The FF5 model is the Fama and French (2015) 5-factor model. The FH7 model is the Fung and Hsieh (2004) 7-factor model. The control variables include fund age, fund size, management fee, incentive fee, dummy for high watermark, dummy for lockup period, and the number of months required for redemption notice. Fund style dummies are also included to capture style fixed effects. The table reports hazard ratios for each independent variable, with Z-scores in parentheses below the ratios.

	HF9	CAPM	FF5	FH7
Low alpha dummy	1.31	1.40	1.42	1.42
	(7.30)	(9.34)	(9.69)	(9.67)
High alpha dummy	0.84	0.66	0.74	0.72
	(−4.23)	(−9.48)	(−7.00)	(−7.54)
Log(fund age)	1.33	1.30	1.32	1.31
	(9.55)	(8.77)	(9.14)	(9.03)
Log(fund size)	0.79	0.80	0.80	0.80
	(−27.54)	(−25.42)	(−25.83)	(−25.80)
Management fee (%)	1.04	1.04	1.04	1.04
	(1.05)	(1.19)	(1.28)	(1.25)
Incentive fee (%)	1.02	1.02	1.02	1.02
	(6.39)	(6.63)	(6.57)	(6.62)
High watermark dummy	0.8	0.81	0.81	0.81
	(−4.51)	(−4.31)	(−4.43)	(−4.43)
Lockup period dummy	0.94	0.94	0.94	0.95
	(−1.82)	(−1.73)	(−1.62)	(−1.57)
Advance notice period (months)	1.05	1.06	1.06	1.06
	(2.86)	(3.23)	(3.39)	(3.13)
Fund style dummies	Yes	Yes	Yes	Yes

Table 12 presents the results of the Cox proportional hazard model at an annual frequency. Following the literature, we define "Failure" as a fund exiting the database. The model reports a hazard ratio for each independent variable, where a ratio greater (less) than 1 indicates a positive (negative) relation with failure risk. We include two dummy variables: "Low alpha dummy" and "High alpha dummy," which equal 1 if the fund ranks in the lowest or highest tercile by model-implied alpha, respectively, and 0 otherwise. All fund performance measures are negatively associated with failure likelihood, indicating that poorly performing funds are more likely to become defunct, while well-performing funds are less likely to fail. Additionally, we find that older funds, smaller funds, and funds with higher incentive fees and longer advance notice periods exhibit higher failure hazards.

Interestingly, funds deemed underperforming by conventional models exhibit hazard ratios of around 1.4 (with Z-scores over 9.0), which is higher than the hazard ratio of 1.31 (Z-score of 7.3) based on the HF9 model. Conversely, hazard ratios for outperforming funds are around 0.7 (Z-scores below −7.0) under the CAPM, FF5, and FH7 models, compared to a higher ratio of 0.84 (Z-score of −4.23) under the HF9 model. These results suggest that while poor performance estimated from the HF9 model is positively associated with fund future failure, the relationship is less pronounced than that inferred from conventional models. This is consistent with the

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

view that investors may place greater weight on performance measured by conventional factors when making capital allocation decisions.

E. Heterogeneity in Fund Performance

The previous analysis at the fund level reveals significant variation in hedge fund performance under the HF9 model. Among the hedge funds in our sample, around 10% significantly outperform the benchmark, while another 10% significantly underperform it. This raises the question of whether the significant performance could simply be due to pure luck. To address this question, we follow Chen and Liang (2007) and Kosowski et al. (2007) to conduct a bootstrap analysis of hedge fund performance.

The bootstrap analysis is based on the *t*-statistics of the alpha estimates rather than the alpha estimates themselves, since the *t*-statistic is a pivotal statistic. Specifically, for each fund in our sample, we resample its time series regression residuals and construct 10,000 artificial funds with alpha set to 0. These artificial funds are designed to have the same risk exposures and idiosyncratic risks as the actual fund. Since the bootstrapped funds have no alpha, any statistically significant *t*-statistic on alpha should come from pure chance. We then compare the actual *t*-statistics of alphas from the funds to the empirical distribution of *t*-statistics from the artificial funds and obtain the empirical *p*-value. A small empirical *p*-value indicates that the performance of the actual funds is unlikely to come from pure randomness.[19]

Table 13 reports the actual *t*-statistics of alphas and the corresponding bootstrapped *p*-values for the top and bottom 15 funds in the actual fund sample, ranked by their actual *t*-statistics. For the top-ranked funds, the empirical *p*-values based on 10,000 random replications are nearly 0, indicating that it is unlikely to obtain a *t*-statistic as high as the actual estimate by luck. Similarly, the bootstrapped *p*-values for the bottom 15 funds are close to 0, indicating that these underperforming funds are also unlikely due to pure randomness. Therefore, the bootstrap analysis confirms the existence of substantial heterogeneity in hedge fund performance.

Figure 4 visualizes the bootstrapped *t*-statistics distributions for the top and bottom 10% hedge funds in our sample. The shaded areas represent the kernel density of *t*-statistics under the null hypothesis of zero alpha, generated from 10,000 bootstrapped simulations. Vertical lines mark the actual *t*-statistics of the funds' alpha. For top-performing funds, the actual *t*-statistics lie substantially to the right of the bootstrapped distribution, indicating that such performance cannot be attributed to pure luck. In contrast, the actual *t*-statistics for bottom-performing funds fall far to the left, suggesting significant underperformance. This visual evidence reinforces the conclusion that the observed fund performances are unlikely due to randomness.

[19]Besides bootstrap analysis, the literature also proposes parametric and nonparametric approaches to distinguish between skill and luck and to infer the distribution of fund performance (e.g., Barras, Scaillet, and Wermers (2010), Chen et al. (2017), and Barras, Gagliardini, and Scaillet (2022)).

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 13

Bootstrap Analysis of Fund Alphas

Table 13 presents the results of a bootstrap analysis on the fund alphas estimated using the HF9 model for the top 15 and bottom 15 ranked funds based on their *t*-statistics. The hedge fund sample consists of 7,314 funds from the TASS and HFR databases between January 1997 and August 2019, including funds from 10 categories: convertible arbitrage (CA), dedicated short bias (DSB), event driven (ED), emerging markets (EM), equity market neutral (EMN), fixed income arbitrage (FIA), fund of funds (FOF), global macro (GM), long-short equity hedge (LSEH), and multi-strategy (MS). The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. For each fund, we resample its time series regression residuals and create 10,000 artificial funds with alpha set to 0. We then estimate the distribution of *t*-statistics for these artificial funds. Finally, we calculate the empirical *p*-values for the actual *t*-statistics and report them in the table. Monthly excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags.

	Bottom	2.min	3.min	4.min	5.min	10.min	15.min	15.max	10.max	5.max	4.max	3.max	2.max	Top
All funds														
t_α	−7.02	−6.17	−5.94	−5.83	−5.75	−5.54	−5.14	13.77	16.56	33.65	37.97	47.25	48.10	53.10
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Category														
CA t_α	−6.17	−3.14	−2.46	−2.30	−2.30	−1.96	−1.58	1.63	2.91	4.32	4.66	15.45	16.56	37.97
p-value	0.00	0.01	0.02	0.03	0.03	0.07	0.08	0.07	0.02	0.00	0.00	0.00	0.00	0.00
DSB t_α	−5.71	−3.04	−2.88	−2.85	−1.59	−0.66	−0.16	−0.01	1.12	1.97	2.19	2.22	2.71	3.25
p-value	0.00	0.01	0.01	0.01	0.10	0.32	0.44	0.49	0.16	0.05	0.07	0.05	0.01	0.01
ED t_α	−4.60	−4.15	−3.76	−3.76	−3.59	−3.23	−3.08	5.20	5.42	6.64	7.21	8.16	10.21	10.72
p-value	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EM t_α	−3.77	−3.60	−3.27	−2.92	−2.66	−2.18	−1.94	2.52	3.20	4.42	8.35	16.20	22.62	33.65
p-value	0.00	0.00	0.01	0.01	0.01	0.02	0.06	0.02	0.00	0.00	0.00	0.00	0.00	0.00
EMN t_α	−3.51	−3.35	−3.23	−3.11	−3.06	−2.67	−2.49	4.42	4.70	5.54	5.72	5.93	6.85	9.84
p-value	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FIA t_α	−4.36	−4.29	−3.85	−3.70	−3.48	−3.17	−2.89	10.05	12.35	16.89	17.69	22.06	47.25	48.10
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FOF t_α	−7.02	−5.94	−5.72	−5.70	−5.54	−5.14	−5.06	4.68	5.33	5.88	5.94	9.97	14.48	53.10
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GM t_α	−4.42	−3.67	−3.50	−3.01	−2.98	−2.07	−1.57	2.45	2.82	4.02	4.23	4.23	4.54	4.56
p-value	0.00	0.00	0.00	0.00	0.02	0.04	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00
LSEH t_α	−5.75	−5.61	−5.10	−5.03	−5.00	−4.43	−4.16	4.65	5.11	5.88	6.60	6.65	6.89	8.27
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MS t_α	−5.83	−4.27	−3.78	−3.47	−3.47	−3.04	−2.51	3.12	3.41	5.12	5.52	5.73	6.85	7.06
p-value	0.00	0.00	0.01	0.00	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00

F. Fund Performance and Characteristics

After showing significant differences in performance among hedge funds, we now investigate the relation between fund performance and various fund characteristics to identify which characteristics may be good indicators of fund skill. To do this, we regress fund alpha estimated from the HF9 model on one-month lagged values of fund characteristics, with estimated fund alpha as the difference between the fund's excess return and the products of its factor loadings (estimated from a 24-month rolling window) and factor realizations. We consider seven fund attributes, including fund age, fund size, management fee, incentive fee, a high-watermark dummy, a lockup period dummy, and a redemption notice period. We also include fund style dummies to control for style-specific fixed effects and capture any potential strategy-based performance over time.

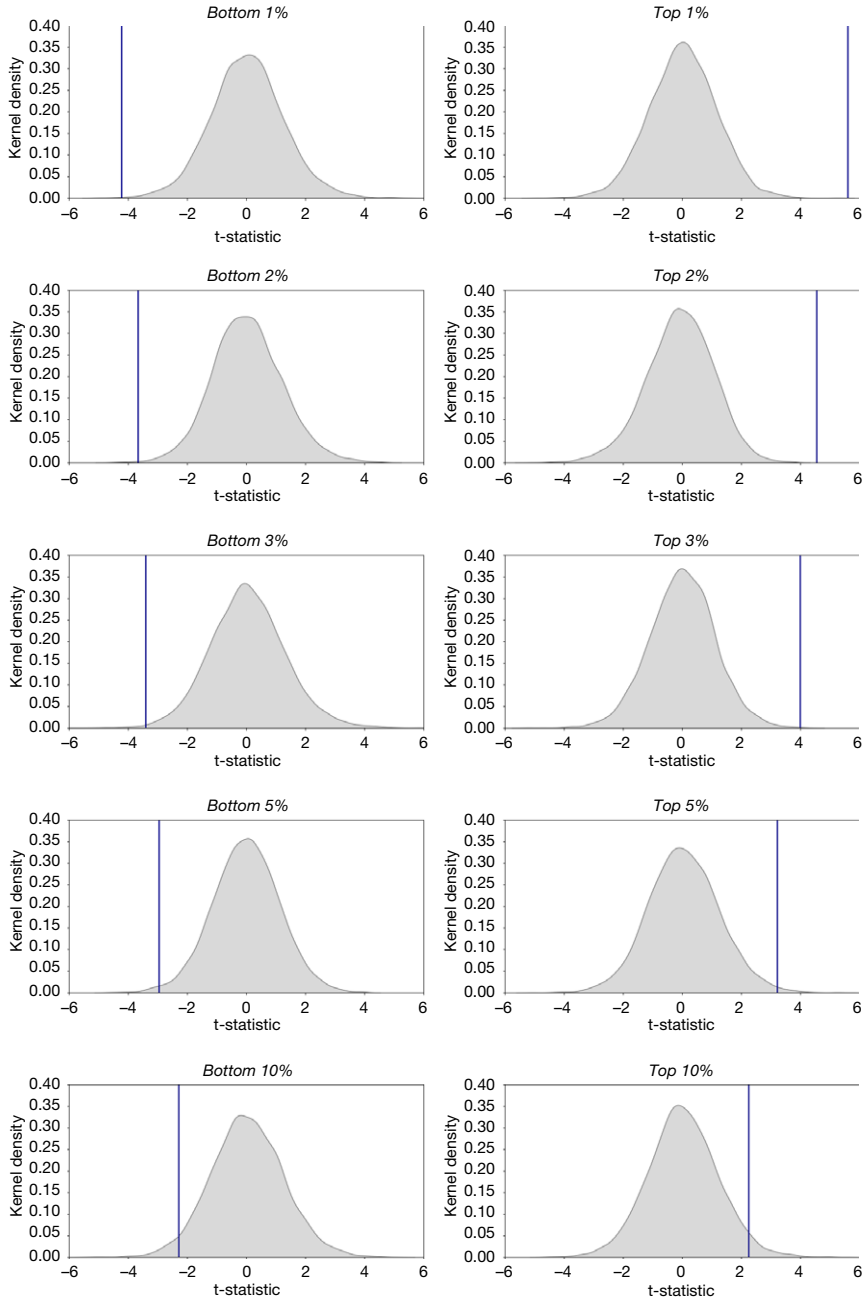
Table 14 presents the results of Fama–MacBeth regressions. There is some evidence that younger funds tend to perform better, consistent with the findings of Aggarwal and Jorion (2010). In addition, funds that use high watermark provisions and impose lockup periods seem to deliver better performance, suggesting that managerial incentives and discretion are associated with fund performance (e.g., Agarwal et al. (2009)). However, the adjusted R^2 values are relatively low, ranging from 0.53% to 3.43%.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

FIGURE 4

Distributions of Bootstrap *t*-Statistics

Figure 4 shows the kernel density distributions of bootstrapped *t*-statistics for the top and bottom 10% ranked funds based on their actual *t*-statistics using the HF9 model. The hedge fund sample consists of 7,314 funds from the TASS and HFR databases between January 1997 and August 2019. The verticle lines correspond to the actual *t*-statistics of the funds' alpha estimates.



https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

TABLE 14

Fund Alpha and Characteristics

Table 14 reports the results of Fama-MacBeth regressing hedge fund alphas from the HF9 model on fund characteristics. The hedge fund sample consists of 7,314 funds from the TASS and HFR databases between January 1997 and August 2019. The HF9 model is the 9-factor hedge fund model based on the post-adaptive-LASSO method. The regressors are seven fund characteristics including fund age, fund size, management fee, incentive fee, dummy for high watermark, dummy for lockup period, and the number of months required for redemption notice. Fund style dummies are also included to capture style fixed effects. Monthly excess returns are in percentage. *t*-statistics are based on Newey and West (1987) standard errors with 3 lags and reported in parentheses.

	(1)	(2)	(3)
Intercept	0.15	0.12	0.22
	(1.28)	(0.84)	(1.29)
Log(fund age)	−0.07	−0.06	−0.07
	(−1.91)	(−1.66)	(−2.09)
Log(fund size)	0.01	0.01	0.01
	(0.74)	(0.55)	(0.64)
Management fee (%)	−0.05	−0.04	−0.05
	(−0.97)	(−0.85)	(−1.28)
Incentive fee (%)	0.01	0.00	−0.01
	(3.35)	(0.69)	(−1.66)
High watermark dummy		0.15	0.16
		(2.65)	(2.85)
Lockup period dummy		0.13	0.10
		(2.05)	(1.91)
Advance notice period (months)		−0.03	−0.01
		(−0.90)	(−0.47)
Fund style dummies	No	No	Yes
Adj-R^2 (%)	0.53	0.89	3.43
# Obs	442,390	442,390	442,390

Therefore, while hedge fund performance is related to certain fund characteristics, a large fraction of the cross sectional difference in fund performance cannot be explained by fund characteristics alone.

VI. Conclusion

In this article, we propose a new factor model for evaluating hedge fund performance accounting for stock market anomalies. Our machine-learning-based factor selection procedure, termed post-adaptive-LASSO, systematically selects the best factors for explaining hedge fund return variation from a large pool of potential factors. We apply the procedure to different levels of testing assets, including individual hedge funds, hedge fund category portfolios, and hedge fund industry portfolios. The resulting model consists of nine factors, including the MKT, five anomaly factors (AGR factor, BAB factor, LRSK, ROA factor, TSMOM), and three macro factors (the 10Y, the CRDT, and the TERM).

Our 9-factor model outperforms existing models in explaining hedge fund returns at both the fund and portfolio levels. With the proposed factor model, we observe smaller fund alphas compared to existing models. The new model also reveals substantial performance heterogeneity across funds. Further analysis based on fund holdings confirms the model's ability to capture returns from arbitrage trading. Overall, the new factors provide valuable insights into hedge fund strategies and improve fund performance evaluation.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

Appendix

TABLE A1

Definitions of Factors

Table A1 lists all 44 potential factors including 25 MKTs and anomalies, 5 trend-following hedge fund risk factors, and 14 macroeconomic factors.

No.	Acronym	Factor	No.	Acronym	Factor
Panel A. Market and Anomaly Factor					
1	ACC	Accruals	14	NOA	Net operating assets
2	AGR	Asset growth	15	NSI	Net stock issues
3	BAB	Betting against beta	16	OSC	O-score
4	CARRY	Carry	17	PFT	Profitability
5	CEI	Composite equity issues	18	PGR	Profit growth
6	DTI	Debt issuance	19	QLT	Quality
7	GPF	Gross profitability premium	20	ROA	Return on assets
8	ILL	Illiquidity	21	SIZE	Size
9	INVEST	Investment	22	SKW	Skewness
10	LLEV	Low leverage	23	SSN	Seasonality
11	LRSK	Low risk	24	TSMOM	Time series momentum
12	MKT	Equity market factor	25	VALUE	Value
13	MOM	Momentum			
Panel B. HF Trend-Following Factor					
26	BDTF	Bond trend-following factor	29	IRTF	Short-term interest rate trend-following factor
27	CMTF	Commodity trend-following factor	30	SKTF	Stock index trend-following factor
28	FXTF	Currency trend-following factor			
Panel C. Macroeconomic Factor					
31	10Y	Monthly change in the 10-year treasury yield	38	INFL	Inflation rate
32	BM	Book-to-market ratio for DJ Industrial Average	39	INPR	Growth rate of industrial production
33	CRDT	Monthly change in credit yield spread	40	NTIS	Net equity expansion ratio of NYSE stocks
34	DFLT	Default yield spread	41	SVAR	Stock variance for S&P 500 index
35	DPR	Dividend price ratio for S&P 500 index	42	TBL	3-month Treasury bill rate
36	EPR	Earnings price ratio for S&P 500 index	43	TERM	Term spread
37	GDP	Real GDP per capita	44	UNC	Economic uncertainty index

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109025101270.

Funding statement

Li thanks the Rutgers Business School Dean's Research Seed Fund (DRSF) for financial support.

References

Agarwal, V.; N. D. Daniel; and N. Y. Naik. "Role of Managerial Incentives and Discretion in Hedge Fund Performance." *Journal of Finance*, 64 (2009), 2221–2256.

Agarwal, V.; V. Fos; and W. Jiang. "Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings." *Management Science*, 59 (2013), 1271–1289.

Agarwal, V.; T. C. Green; and H. Ren. "Alpha or Beta in the Eye of the Beholder: What Drives Hedge Fund Flows." *Journal of Financial Economics*, 127 (2018), 417–434.

Agarwal, V., and N. Y. Naik. "Risks and Portfolio Decisions Involving Hedge Funds." *Review of Financial Studies*, 17 (2004), 63–98.
Aggarwal, R. K., and P. Jorion. "The Performance of Emerging Hedge Funds and Managers." *Journal of Financial Economics*, 96 (2010), 238–256.
Ardia, D.; L. Barras; P. Gagliardini; and O. Scaillet. "Is It Alpha or Beta? Decomposing Hedge Fund Returns When Models Are Misspecified." *Journal of Financial Economics*, 154 (2023), 103805.
Avramov, D.; R. Kosowski; N. Y. Naik; and M. Teo. "Hedge Funds, Managerial Skill, and Macroeconomic Variables." *Journal of Financial Economics*, 99 (2011), 672–692.
Bali, T. G.; S. J. Brown; and M. O. Caglayan. "Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns." *Journal of Financial Economics*, 101 (2011), 36–68.
Bali, T. G.; S. J. Brown; and M. O. Caglayan. "Systematic Risk and the Cross-Section of Hedge Fund Returns." *Journal of Financial Economics*, 106 (2012), 114–131.
Bali, T. G.; S. J. Brown; and M. O. Caglayan. "Macroeconomic Risk and Hedge Fund Returns." *Journal of Financial Economics*, 114 (2014), 1–19.
Barras, L.; P. Gagliardini; and O. Scaillet. "Skill, Scale, and Value Creation in the Mutual Fund Industry." *Journal of Finance*, 77 (2022), 601–638.
Barras, L.; O. Scaillet; and R. Wermers. "False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas." *Journal of Finance*, 65 (2010), 179–216.
Belloni, A.; D. Chen; V. Chernozhukov; and C. Hansen. "Sparse Models and Methods for Optimal Instruments with an Application to Eminent Domain." *Econometrica*, 80 (2012), 2369—2429.
Belloni, A., and V. Chernozhukov. "Least Squares after Model Selection in High-Dimensional Sparse Models." *Bernoulli*, 19 (2013), 521–547.
Brown, S. J.; W. Goetzmann; R. G. Ibbotson; and S. A. Ross. "Survivorship Bias in Performance Studies." *Review of Financial Studies*, 5 (1992), 553–580.
Buraschi, A.; R. Kosowski; and F. Trojani. "When There Is No Place to Hide: Correlation Risk and the Cross-Section of Hedge Fund Returns." *Review of Financial Studies*, 27 (2014), 581—616.
Cao, C.; Y. Chen; W. N. Goetzmann; and B. Liang. "Hedge Funds and Stock Price Formation." *Financial Analysts Journal*, 74 (2018), 54–68.
Cao, C.; Y. Chen; B. Liang; and A. W. Lo. "Can Hedge Funds Time Market Liquidity?" *Journal of Financial Economics*, 109 (2013), 492–516.
Chen, A. Y., and T. Zimmermann. "Open Source Cross-Sectional Asset Pricing." *Critical Finance Review*, 11 (2022), 207–264.
Chen, Y. "Timing Ability in the Focus Market of Hedge Funds." *Journal of Investment Management*, 5 (2007), 66–98.
Chen, Y. "Derivatives Use and Risk Taking: Evidence from the Hedge Fund Industry." *Journal of Financial and Quantitative analysis*, 46 (2011), 1073–1106.
Chen, Y.; M. Cliff; and H. Zhao. "Hedge Funds: The Good, the Bad, and the Lucky." *Journal of Financial and Quantitative Analysis*, 52 (2017), 1081–1109.
Chen, Y.; Z. Da; and D. Huang. "Arbitrage Trading: The Long and the Short of It." *Review of Financial Studies*, 32 (2019), 1608–1646.
Chen, Y.; B. Han; and J. Pan. "Sentiment Trading and Hedge Fund Returns." *Journal of Finance*, 76 (2021), 2001–2033.
Chen, Y.; B. Kelly; and W. Wu. "Sophisticated Investors and Market Efficiency: Evidence from a Natural Experiment." *Journal of Financial Economics*, 138 (2020), 316–341.
Chen, Y., and B. Liang. "Do Market Timing Hedge Funds Time the Market?" *Journal of Financial and Quantitative Analysis*, 42 (2007), 827–856.
Cochrane, J. H. "Presidential Address: Discount Rates." *Journal of Finance*, 66 (2011), 1047–1108.
Diebold, F. X., and R. S. Mariano. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics*, 13 (1995), 253–263.
Fama, E. F., and K. R. French. "A Five-factor Asset Pricing Model." *Journal of Financial Economics*, 116 (2015), 1–22.
Fan, J., and R. Li. "Variable Selection via Nonconcave Penalized Likelihood and Its Oracle Properties." *Journal of the American Statistical Association*, 96 (2001), 1348–1360.
Fung, W., and D. A. Hsieh. "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds." *Review of Financial Studies*, 10 (1997), 275–302.
Fung, W., and D. A. Hsieh. "Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases." *Journal of Financial and Quantitative Analysis*, 35 (2000), 291–307.
Fung, W., and D. A. Hsieh. "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers." *Review of Financial Studies*, 14 (2001), 313–341.
Fung, W., and D. A. Hsieh. "Hedge Fund Benchmarks: A Risk-Based Approach." *Financial Analysts Journal*, 60 (2004), 65–80.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press

Getmansky, M.; A. W. Lo; and I. Makarov. "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns." *Journal of Financial Economics*, 74 (2004), 529–609.
Gibbons, M. R.; S. A. Ross; and J. Shanken. "A Test of the Efficiency of a Given Portfolio." *Econometrica*, 57 (1989), 1121–1152.
Gromb, D., and D. Vayanos. "Limits of Arbitrage." *Annual Review of Financial Economics*, 2 (2010), 251–275.
Harvey, C. R., and Y. Liu. "Lucky Factors." *Journal of Financial Economics*, 141 (2021), 413–435.
Jensen, T. I.; B. Kelly; and L. H. Pedersen. "Is There a Replication Crisis in Finance?" *Journal of Finance*, 78 (2023), 2465–2518.
Kelly, B., and D. Xiu. "Financial Machine Learning." *Foundations and Trends in Finance*, 13 (2023), 205–363.
Koijen, R. S.; T. J. Moskowitz; L. H. Pedersen; and E. B. Vrugt. "Carry." *Journal of Financial Economics*, 127 (2018), 197–225.
Kosowski, R.; N. Y. Naik; and M. Teo. "Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis." *Journal of Financial Economics*, 84 (2007), 229–264.
Lewellen, J.; S. Nagel; and J. Shanken. "A Skeptical Appraisal of Asset Pricing Tests." *Journal of Financial Economics*, 96 (2010), 175–194.
Liang, B. "Hedge Funds: The Living and the Dead." *Journal of Financial and Quantitative Analysis*, 35 (2000), 309—326.
Moskowitz, T. J.; Y. H. Ooi; and L. H. Pedersen. "Time Series Momentum." *Journal of Financial Economics*, 104 (2012), 228–250.
Newey, W., and K. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.
Pastor, L., and R. F. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.
Pedersen, L. H. *Efficiently Inefficient*. Princeton, NJ: Princeton University Press (2015).
Rapach, D. E.; J. K. Strauss; and G. Zhou. "International Stock Return Predictability: What Is the Role of the United States?" *Journal of Finance*, 68 (2013), 1633–1662.
Ross, S. A. "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory*, 13 (1976), 341–360.
Sadka, R. "Liquidity Risk and the Cross-Section of Hedge Fund Returns." *Journal of Financial Economics*, 98 (2010), 54–71.
Shleifer, A., and R. W. Vishny. "The Limits of Arbitrage." *Journal of Finance*, 52 (1997), 35–55.
Stambaugh, R. F.; J. Yu; and Y. Yuan. "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics*, 104 (2012), 288–302.
Teo, M. "The Geography of Hedge Funds." *Review of Financial Studies*, 22 (2009), 3531–3561.
Teo, M. "The Liquidity Risk of Liquid Hedge Funds." *Journal of Financial Economics*, 100 (2011), 24–44.
Tibshirani, R. "Regression Shrinkage and Selection via the LASSO." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 58 (1996), 267—288.
Titman, S., and C. Tiu. "Do the Best Hedge Funds Hedge?" *Review of Financial Studies*, 24 (2011), 123–168.
Welch, I., and A. Goyal. "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction." *Review of Financial Studies*, 21 (2008), 1455–1508.
Zou, H. "The Adaptive Lasso and Its Oracle Properties." *Journal of the American Statistical Association*, 101 (2006), 1418–1429.

https://doi.org/10.1017/S0022109025101270 Published online by Cambridge University Press