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Investor Sentiment and the Pricing of Macro Risks for Hedge Funds

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Abstract

Hedge funds with larger macroeconomic-risk betas do not earn higher returns, in contrast to the theoretically predicted risk-return trade-off. Meanwhile, high macro-beta funds deliver higher returns than low macro-beta funds following a low-sentiment period, whereas the risk-return relation is flat following a high-sentiment period. We show that the sophisticated management of hedge funds explains this pattern. The relation between funds' macro-risk betas and the timing abilities/investor flows is sentiment dependent, and such variation likely drives the contrasting beta-return tradeoffs after high and low sentiment periods. Lastly, a similar pattern is also observed in mutual funds.

Keywords: Hedge funds, Macroeconomic risks, Sentiment
JEL: G10, G11, G23

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1 Introduction

Standard economic theories predict that shocks to macroeconomic variables comove with a time-varying state and thus enter the pricing kernel (e.g., the intertemporal capital asset pricing model of Merton, 1973). Theoretically, macroeconomic risk factors should be priced in the cross section of asset returns and earn positive risk premia. Empirically, however, Shen, Yu, and Zhao (2017) find that this is not the case: stocks with large macro-risk betas earn returns similar to those with small betas, suggesting an empirical failure of macro risks in pricing stocks. Meanwhile, a positive risk-return relation does exist after periods of low investor sentiment, when the market tends to be rational. In contrast, a negative risk-return relation is observed after high-sentiment months, where high-beta stocks are more sensitive to market-wide overpricing when marginal investors are irrational.[1] The opposite risk-return trade-off observed during pessimistic and optimistic periods highlights the important role of investor sentiment plays in the pricing of macroeconomic risks.

While the two-regime phenomenon of the macro-risk-return relation has been documented among stocks, it is unclear whether hedge funds, commonly viewed as the most sophisticatedly managed portfolios, are also affected by market-wide sentiment and thus exhibit a similar pattern. If hedge funds are simply passive portfolios of stocks and their macroeconomic risk exposures are only a reflection of their holdings, we would anticipate hedge funds to exhibit the same sentiment-dependent two-regime pattern as stocks. However, hedge funds are not mere buy-and-hold portfolios; instead, they invest in alternative asset classes and employ various investment strategies, including short selling and derivative trading (see, e.g., Chen, 2011; Jiao, Massa, and Zhang, 2016; Chen, Da, and Huang, 2019). As a result, the managed nature of hedge funds may affect the macro-risk-return tradeoff during different investor sentiment periods. To see this, first, hedge fund managers, as the most sophisticated market participants, may be less susceptible to investor sentiment. Second, hedge funds are actively

[1] Antoniou, Doukas, and Subrahmanyam (2016) focus on the risk-return trade-off of the market factor and find that a positive/negative security market line is observed in pessimistic/optimistic sentiment periods. Chen, Liu, Wang, Wang, and Yu (2022b) find that the risk-return trade-off is negative/positive for characteristics-based factors after low-/high-sentiment months, implying that characteristics-based factor betas are likely to capture mispricing levels of stocks. Huang, Lou, and Polk (2021) document how sophisticated arbitrageurs affect the profitability of the beta-arbitrage strategies while taking investor sentiment into consideration.

managed, with dynamically chosen loadings on various risk factors over time (Glosten and Jagannathan, 1994), which implies that funds' macro-risk betas may reveal information about their asset management abilities. Third, fund performance is influenced by investor flows, and the impact of these fund flows can be sentiment-dependent. Overall, due to the highly dynamic nature of hedge fund strategies and the sensitivity of fund flows, existing theories do not provide a clear prescription for how macro risk exposures should be related to hedge fund returns in the cross-section and whether such a relation is sentiment-dependent. In this paper, we aim to understand this relation from an empirical perspective.

Our motivation for investigating this question is grounded in real-world observations. Despite the perception that hedge funds maintain sophisticated portfolios with time-varying macroeconomic risk exposures, they may still be subject to sentiment-induced mispricing due to strategy crowding. For instance, the Bank of America's Global Fund Manager Survey conducted in February 2021, which surveyed over 225 fund managers with $645 billion assets under management (AUM), reveals a consensus among fund managers on future economic growth. This agreement is reflected in their synchronized preference for cyclical stocks and emerging markets.[2] As a result, market-wide sentiment can have a substantial impact on hedge funds' investment decisions and, therefore, on the relation between their performance and risk exposure, particularly when considering the influence of active management and fund flows.

This paper investigates the impact of investor sentiment on the pricing of macroeconomic risks for hedge funds and explores possible underlying mechanisms. We introduce investor sentiment as a state variable to explain the time-varying risk-return tradeoff of hedge funds. Our findings suggest that even sophisticatedly managed portfolios can be influenced by investor sentiment and exhibit a different risk-return relationship during periods of high sentiment. In addition, we examine whether specific features of hedge funds, such as active management and fund flows, are correlated with market-wide sentiment and may contribute to the observed two-regime pattern.

Following Shen et al. (2017), we consider ten macroeconomic risk factors that have been

[2] Maggie Fitzgerald, "The only reason to be bearish is there is no reason to be bearish, Bank of America says", CNBC, February 16, 2021.

suggested in existing literature as elements contributing to the time-varying stochastic discount factor. These ten factors include a consumption risk factor, two production-related factors, two factors derived from bond yields, two inflation factors, a market-wide volatility factor, a stock market factor, and a labor income factor. Hedge fund portfolios are formed according to individual funds' beta loadings on these macro-risk factors. We find that, in general, hedge fund portfolios do not display a positive risk-return relation for these macro-risk factors, with the average return spread between high- and low-beta portfolios being nearly zero. After using the Baker and Wurgler (2006) sentiment index to divide our sample into two—low-sentiment and high-sentiment—subsamples, we observe a distinct two-regime macro-risk-return relation. The theoretically predicted risk-return trade-off is indeed present following low-sentiment months. However, after high-sentiment months, the risk-return relation appears nearly flat. The average return difference between the two-sentiment regimes for the high- and low-risk fund portfolios is -0.57% per month, with a t-statistic of -2.15.

Further analyses suggest that while hedge funds may partially inherit the two-regime macro-risk-return relationship from their stock holdings, other underlying mechanisms are likely at play. We identify fund managers' ability to time macroeconomic risks and the time-varying nature of fund flows as two potential explanations. Specifically, during low-sentiment periods, high-beta hedge funds demonstrate more pronounced macro-risk timing skills compared to low-beta funds, leading to better performance later on. However, this effect is not observed during high-sentiment periods. Moreover, high macro-beta funds attract greater investor inflows than low-beta funds when investor sentiment is high. The price pressures caused by these beta-sensitive inflows subsequently result in lower returns due to reversals.

The mechanisms driving the two-regime pattern can also be observed in mutual funds, another type of managed portfolios. In addition, we find that mutual fund flows exhibit greater sensitivity to sentiment: a larger amount of investor capital flows into high-macro-beta mutual funds when investor sentiment rises compared to the corresponding flows in hedge funds. This observation aligns with the widely-held belief that mutual fund investors are more retail-oriented and less sophisticated.

Our results are robust to a battery of alternatives, including different classification methods for hedge fund strategies, alternative sentiment measures, varying portfolio formation procedures, and so forth. All pieces of evidence suggest that even for sophisticatedly managed portfolios, such as hedge funds, market-wide investor sentiment can still distort the macro-risk-return relation.

Related literature. A growing strand of literature studies the effect of investor sentiment on institutional investors' investment decisions. Complementing prior research that concentrates on retail investors,[3] several recent studies examine whether and how sentiment affects professional asset managers. DeVault, Sias, and Starks (2019) find that institutional investors' demand for speculative stocks rises as market-wide sentiment increases, implying that sentiment-driven behavior among these investors underlies the return-sentiment relation. Similarly, Cornell, Landsman, and Stubben (2011) find that institutional investors increase their holdings, and analysts issue "buy" recommendations for "difficult-to-value" stocks during periods of high sentiment. On the other hand, Gao, Luo, Ren, and Zhang (2017) find that institutional investors tend to sell stocks when investor sentiment is low, leading their trades to correct mispricing across stocks. Our paper contributes to this research area by demonstrating that hedge funds are not immune to investor sentiment and by identifying new channels through which sentiment impacts their performance. Furthermore, our findings also enrich the growing body of literature on the role institutional investors play in affecting stock market efficiency.[4]

[3] Papers that examine sentiment-induced behaviors of retail investors and their consequences include, but not limited to, Lee, Shleifer, and Thaler (1991), Neal and Wheatley (1998), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Barber, Odean, and Zhu (2008), Ali and Gurun (2009), Barber, Odean, and Zhu (2009), Schmeling (2009), Ben-Rephael, Kandel, and Wohl (2012), Brown, Christensen, Elliott, and Mergenthaler (2012a), Chung, Hung, and Yeh (2012), Hribar and McInnis (2012), Mian and Sankaraguruswamy (2012), Antoniou, Doukas, and Subrahmanyam (2013), Hribar and Quinn (2013), Simpson (2013), Arif and Lee (2014), McLean and Zhao (2014), Li and Luo (2017), Chelley-Steeley, Lambertides, and Savva (2019), and Livnat and Petrovits (2019).

[4] Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) show that mutual fund flows exacerbate cross-sectional mispricing, while hedge fund flows attenuate aggregate mispricing. Cao, Chen, Goetzmann, and Liang (2018a) also find that hedge funds slowly correct mispricing by holding undervalued stocks. Edelen, Ince, and Kadlec (2016) find that institutional investors tend to buy overpriced stocks, i.e., the short leg of an anomaly, resulting in ex post negative returns. More recently, Chen, Kelly, and Wu (2020) find that hedge funds serve as the information provider after closures of brokerage firms, and their trading behaviors mitigate market inefficiency. On the theoretical side, Cong, Huang, and Xu (2019) model why financial innovations, such as ETFs and smart beta funds, become popular and encourage factor investing from the informational perspective.

Our paper is also related to studies on the cross section of hedge fund returns and the source of hedge funds' (out)performance. Some papers find that factors such as exposures to financial market and macroeconomic risk factors, funds' systematic risk levels, and their time-varying macroeconomic uncertainty betas can account for the differences in hedge funds' cross-sectional returns (Bali, Cakici, and Whitelaw, 2011; Bali, Brown, and Caglayan, 2012, 2014).[5] Chen, Han, and Pan (2021) find that hedge funds with higher sensitivity to changes in investor sentiment generate larger returns and demonstrate that sentiment timing contributes to this outperformance. Smith, Wang, Wang, and Zychowicz (2016) examine how hedge funds employ technical analysis to capitalize on increased mispricing during periods of high sentiment.[6] Several other papers focus on various aspects of timing abilities (Chen, 2007; Chen and Liang, 2007; Cao, Chen, Liang, and Lo, 2013; Cai, Cheng, and Yan, 2018; Shin, Kim, Oh, and Kim, 2019; Osinga, Schauten, and Zwinkels, 2021). To the best of our knowledge, our paper is the first to investigate how investor sentiment distorts the macro-risk-return relation of hedge funds from the perspectives of funds' timing abilities and investment capital flows.

Lastly, our paper also contributes to the extensive literature on sentiment and stock market anomalies. Building on the seminal work of Baker and Wurgler (2006, 2007), researchers have examined the impact of the Baker and Wurgler (BW) sentiment measure on various market anomalies (Stambaugh, Yu, and Yuan, 2012), the idiosyncratic volatility puzzle (Stambaugh, Yu, and Yuan, 2015), the forward premium puzzle (Yu, 2013), the mean-variance relation (Yu and Yuan, 2011), international markets (Baker, Wurgler, and Yuan, 2012), and so forth.

The remainder of the paper is organized as follows. Section 2 outlines the data used in the paper. Section 3 presents the main empirical findings. Section 4 proposes two possible

[5]Although Bali et al. (2014) find that hedge funds with greater sensitivity to a comprehensive macroeconomic uncertainty index yield higher returns unconditionally, their finding does not necessarily imply a risk-based explanation. First, the observation that high-uncertainty-beta funds generate significant returns when conditional macroeconomic uncertainty is high suggests superior management skills. Second, time-varying macroeconomic uncertainty exhibits persistence and a high autocorrelation coefficient, which does not inherently qualify as a risk factor.

[6]Other factors that affect the cross section of hedge fund returns include liquidity (Aragon, 2007; Sadka, 2010; Teo, 2011; Hu, Pan, and Wang, 2013; Jylhä, Rinne, and Suominen, 2014; Golez, Jackwerth, and Slavutskaya, 2018; Jame, 2018), managers' skill (Jagannathan, Malakhov, and Novikov, 2010; Chen, Cliff, and Zhao, 2017; Gao, Gao, and Song, 2018), and incentives (Ackermann, McEnally, and Ravenscraft, 1999; Agarwal, Daniel, and Naik, 2009; Boyson, 2010; Brown, Goetzmann, Liang, and Schwarz, 2012b; Buraschi, Kosowski, and Sritrakul, 2014; Lim, Sensoy, and Weisbach, 2016; Yin, 2016).

explanations for the observed two-sentiment-regime pattern, considering macro-risk timing and fund flows. Section 5 offers robustness results. Section 6 briefly discusses similar findings in mutual funds. Section 7 concludes.

2 Data

In this section, we describe various datasets used in the paper. We present the summary statistics for macroeconomic factors and the hedge fund dataset. In addition, we explain the construction details for the macro-factor-beta-sorted hedge fund portfolios.

2.1 Investor sentiment

We employ the Baker-Wurgler (BW) sentiment index as our measure for market participants' sentiment levels. The monthly BW sentiment index spans from July 1965 to December 2018.[7] It is constructed as the first principal component of five sentiment proxies, including the average closed-end fund discount, the number of IPOs and their average first-day returns, the dividend premium, and the equity share in new issues. All proxies are initially standardized and orthogonalized with respect to a set of macroeconomic indicators.

Figure 1 plots the BW index alongside the next-month excess returns of Hedge Fund Research Indices (HFRI) from January 1997 to December 2018. The plot clearly suggests that the BW index effectively captures the key fluctuations in investor sentiment during the given sample period. For instance, the index is high during the dot-com bubble period but low during the financial crisis. The correlation between the sentiment index and the next-month excess returns of the fund-weighted composite index is -0.11, with no statistical significance.

[7] The Baker-Wurgler sentiment index can be downloaded from Jeffrey Wurgler's website: http://people.stern.nyu.edu/jwurgler.

2.2 Hedge fund data

The data on hedge fund monthly returns and characteristics are obtained from the Lipper TASS database, which is widely used in the literature (see, e.g., Fung and Hsieh, 1997; Getmansky, Lo, and Makarov, 2004; Agarwal et al., 2009; Gao et al., 2018). We keep both live and graveyard funds that report net-of-fee returns in USD. Additional standard filters comprise a minimum AUM of $10 million as of the month of portfolio formation (Cao et al., 2013; Hu et al., 2013; Gao et al., 2018), at least 24 monthly return observations (Smith et al., 2016), and the exclusion of a fund's return observations prior to the fund's addition to the database to mitigate backfill bias (Aggarwal and Jorion, 2010). In total, our final sample consists of 8,688 funds over the period January 1997 to December 2018, with 4,957 of these being graveyard funds.

Panel A of Table 1 presents the summary statistics of hedge fund data by year, including average values of management fee, incentive fee, minimal investment, initial net asset value (NAV), AUM, as well as the mean, standard deviation, minimum, and maximum monthly returns of the average equal-weighted fund portfolio. In Panel B of Table 1, we report the same set of summary statistics for hedge funds by investment style, including equity style, non-equity style, and fund of funds (FOFs). Our classification of equity-style funds follows the definition of equity-oriented funds as described in Agarwal and Naik (2004) and Agarwal, Ruenzi, and Weigert (2017), which includes strategies such as long/short equity hedge, equity market neutral, and dedicated short bias. A detailed comparison between our strategy classification and those in previous papers can be found in Appendix Table A1.[8]

[8] Agarwal and Naik (2004) examine equity-oriented hedge fund strategies with payoffs that primarily arise from the relative mispricing of securities or taking directional bets using both the Hedge Fund Research (HFR) and CSFB/Tremont indices, including event arbitrage, restructuring, event-driven, relative value arbitrage, convertible arbitrage, long/short equity, and dedicated short bias. Agarwal et al. (2017) define equity-oriented funds as those employing strategies such as emerging markets, event-driven, equity long-short, equity market neutral, and short bias. Consequently, the intersection of the two definitions of equity-oriented funds comprises long/short equity hedge, equity market neutral, dedicated short bias, and event-driven. Due to the extensive use of distressed bonds in the event-driven strategy, we exclude event-driven funds from our final equity-style subsample. Nonetheless, the results using alternative classifications of strategy subsamples are quite similar to the main findings and available upon request.

2.3 Macroeconomic factors

Following Shen et al. (2017), we use ten macroeconomic variables to capture various aspects of macroeconomic risk: (1) CON: the monthly growth of real personal consumption expenditures on nondurable goods and services per capita; (2) TFP: the quarterly percentage change in total factor productivity; (3) IPG: the monthly growth rate of industrial production; (4) TERM: the yield spread between the 20-year and 1-year Treasury bonds; (5) DEF: the default premium measured as the monthly change in the yield spread between the BAA-rated and AAA-rated corporate bonds; (6) UI: unanticipated inflation estimated following Chen, Roll, and Ross (1986); (7) DEI: the change in monthly expected inflation estimated following Fama and Gibbons (1984); (8) VOL: the change in monthly market-wide aggregate volatility; (9) MKT: the value-weighted excess returns of the stock market; and (10) LAB: the log growth rate in nominal labor income per capita. More details on these macroeconomic risk factors can be found in Section 3.2 of Shen et al. (2017). Following the previous literature (Keim and Stambaugh, 1986; Fama and French, 1989; Shen et al., 2017), we conjecture that three factors, i.e., TERM, DEF, and VOL, have negative prices of risk. To ensure that a higher risk exposure consistently results in higher expected returns, we multiply the raw time series of these three variables by negative one.

Panel C of Table 1 presents the summary statistics of the ten macroeconomic risk factors, including their correlations with the lagged BW sentiment index, the correlations with the monthly change in the BW index, the AR(1) coefficient, as well as the mean, standard deviation, 10th percentile, median, and 90th percentile. In line with prior literature, all ten factors exhibit low persistency, supporting their capacity to capture unexpected “shocks” to market participants. Further, the correlation coefficients between macro-risk factors and the lagged investor sentiment/change in sentiment are modest, suggesting that investor sentiment does not directly influence future movements of macroeconomic factors.

2.4 Hedge fund portfolios sorted by macro-factor betas

We calculate hedge funds’ pre-ranking macro-factor betas using a 24-month rolling window with a minimum observation requirement of 18 months. Specifically, for each macro factor, we estimate individual hedge funds' betas through a univariate factor model.[9] Each month, equal-weighted decile portfolios are formed according to funds' macro-factor betas. Funds with the largest and smallest exposures to a particular macro risk factor are assigned to the 10th and 1st decile portfolio. In addition to the ten sets of decile portfolios formed based on the ten macro-risk factors, we also construct two sets of aggregate decile portfolios that encapsulate the effect of macroeconomic risk on funds across all ten individual macroeconomic variables. The first set comprises decile portfolios formed on a composite beta score (COMP), which is calculated as an arithmetic average of a fund's rank for each of the ten macro-factor betas. The second set consists of ten average portfolios (AVE) formed by taking an equal position across individual macro-factor-beta-sorted decile portfolios.

3 Sentiment-dependent relation between hedge fund performance and macro-risk exposures

Asset pricing theories predict that assets with a strong correlation to systematic risk factors should yield high returns. Although Shen et al. (2017) document a violation of this risk-return tradeoff for stocks following high-sentiment months, it remains unclear whether a similar relation also holds for hedge funds. On one hand, funds might partially adopt this two-regime pattern through their stock holdings. On the other hand, their distinct characteristics, such as active management, time-varying fund flows, and the implementation of complex trading strategies, could lead to a different pattern.

3.1 Average hedge fund returns across two sentiment regimes

Table 2 reports the average monthly excess returns of hedge fund portfolios in the highest and lowest decile of macro-factor betas, as well as the excess returns of the "High-Low" portfolios

[9]Our single-factor model specification adheres to the approach of Shen et al. (2017). In the robustness tests, we re-estimate fund betas using a two-factor model that includes the macro-related factor and the market factor, following Gao et al. (2018). Additionally, we estimate the macro-risk betas as the sum of contemporaneous and lagged factor betas in line with Asness, Krail, and Liew (2001), addressing concerns of smoothed reported returns. Results obtained through alternative beta estimation methods demonstrate consistency.

for the full sample and in months following the high- and low-sentiment periods. Following the methodology of Stambaugh et al. (2012) and Shen et al. (2017), we divide the full sample into two subsample periods based on the BW index. A month is classified as high-sentiment (low-sentiment) if the BW index for that month is above (below) the median value of the entire BW sentiment series.[10]

We find a flat risk-return relation across all macro-factor-beta-sorted hedge fund portfolios. None of the "High-Low" return spreads, sorted by the ten macro-risk-factor betas, are statistically significant. Additionally, some return spreads exhibit negative values, suggesting that high-macro-beta hedge funds may potentially yield lower returns. The two sets of summary portfolios yield similar results: the return spread of the "High-Low" composite-beta-score-sorted portfolio is 0.17% per month, while the average return across the ten "High-Low" spreads is 0.05% per month, with neither being statistically significant. This flat risk-return relationship implies that fund exposures to macro factors do not account for cross-fund return variations in an unconditional setting.[11]

Underneath the unconditional flat macro-risk and return relation, there exists a distinct two-regime pattern following high- and low-sentiment months. First, the return difference between high- and low-macro-risk fund portfolios is positive following low-sentiment months. The "High-Low" difference for the composite-macro-beta-score-sorted portfolios amounts to 0.58% per month (t-statistic = 1.59). Furthermore, the average "High-Low" return spread across the ten macro risk factors is 0.34% per month (t-statistic = 1.53). Out of the ten individual macro-risk-factor-sorted return spreads, only three—consumption growth, term spread growth, and default spread growth—yield negative return spreads, which are, however, statistically insignificant. Among the remaining seven positive "High-Low" return spreads, four are statistically significant at the 10% level. This positive risk-return relationship aligns with theoretical predictions that funds with greater macro-risk exposures should generate

[10]Throughout our hedge fund sample period from January 1997 to December 2018, 133 out of 264 months are categorized as high-sentiment, and the remaining months are considered low-sentiment. We also classify high- and low-sentiment months based on the median BW index value from the 264-month hedge fund sample. The results are quantitatively similar and available upon request.

[11]In unreported results, we demonstrate that the flat risk-return relation is not attributable to pre-ranking betas being inadequate proxies for post ranking betas. The ex-post beta spreads between the two extreme macro-beta portfolios are positive for all ten macroeconomic factors, with eight of them exhibiting statistical significance.

higher returns, provided that the market is rational.

Second, following high-sentiment months, the average return spread across high- and low-risk hedge funds exhibits a slightly negative magnitude (-0.24% per month) with no statistical significance (t-statistic $= -1.24$). This risk-return distortion is less pronounced compared to the one documented in stocks by Shen et al. (2017), where a statistically significant negative relationship is identified. Unlike stock portfolios, hedge funds are managed portfolios with fewer short-selling constraints and more investment instruments, allowing them to dynamically and flexibly adjust their exposure to macroeconomic risks. Consequently, the net effect may result in a weaker negative relationship between factor betas and fund returns.

Third, the difference between the return spreads of "High-Low" portfolios following high- and low-sentiment months is both economically and statistically significant. The average difference between the return spreads across these two regimes is -0.57% per month (t-statistic $= -2.15$), and value for the composite-beta-score-based spread is even larger at -0.82% per month (t-statistic $= -1.77$). In other words, akin to the results observed in stocks, managed hedge fund portfolios also exhibit a distinct two-regime phenomenon in the risk-return relation, conditional on market-wide investor sentiment.

Lastly, the impact of investor sentiment on the subsequent month's hedge fund return is more substantial for high-risk funds. For comparison, the return difference between high- and low-sentiment regimes is -0.94% per month (t-statistic $= -2.37$) for the high-risk fund portfolio, while the number is only -0.36% (t-statistic $= -1.71$) for the low-risk fund portfolio. In fact, as illustrated in Figure 2, the return difference between the high- and low-sentiment regimes increases almost monotonically with a fund's risk exposure. This finding suggests that even for sophisticated hedge funds, substantial exposure to macroeconomic risks could render them more susceptible to the influence of high investor sentiment when market participants tend to behave irrationally.

The last four rows of Table 2 report the Fung-Hsieh eight-factor-adjusted alphas for the "High-Low" COMP and AVE portfolios under both sentiment regimes.[12] If the model

[12]The Fung-Hsieh eight-factor model incorporates the seven hedge fund risk factors used in Fung and Hsieh (2004) and the emerging market factor used in Fung and Hsieh (2001). The seven factors consist of the bond trend-following factor, currency trend-following factor, commodity trending-following factor, equity market factor, size spread factor, bond market factor, and credit spread factor. The factor data are downloaded from

completely captures all hedge fund return variations, there should be no alpha spread between high- and low-risk portfolios, even following low-sentiment periods. We observe that the two-regime phenomena persist after risk adjustment. However, the source of the return difference following high- and low-sentiment months differs from that of raw returns. After low-sentiment months, the eight-factor adjusted alphas for the "High-Low" portfolios are reduced to nearly zero: less than -1 basis points for the COMP portfolio (t-statistic $= -0.02$) and 1 basis points for the AVE portfolio (t-statistic $= 0.10$). This reduction occurs because the risk adjustment lowers the returns of high-risk funds to levels similar to those of low-risk funds. Conversely, after high-sentiment months, the eight-factor adjusted alphas increase in magnitude and statistically significant: -0.38% for the COMP portfolio with a t-statistic of -1.77, and -0.26% for the AVE portfolio with a t-statistic of -1.95.

3.2 Results of predictive regressions

The results in the previous subsection demonstrate the existence of two regimes in the risk-return relation for macro-factor-beta-sorted hedge fund portfolios. In this section, we provide additional evidence of this sentiment-dependent risk-return relation using regression analysis. We regress the returns of the ten macro-factor-beta-sorted "High-Low" portfolios on the level of lagged BW sentiment and its change. Panel A of Table 3 presents the estimated coefficients and their associated t-statistics for the univariate regressions, in which the lagged sentiment index serves as the sole explanatory variable. All coefficients on the lagged sentiment index are all negative, with seven of them being statistically significant at a minimum significance level of 5%. The composite-beta-score-sorted "High-Low" portfolio has a coefficient of -1.34 with a t-statistic of -3.40. The coefficient for the average portfolio is -0.87 with a t-statistic of -3.27. Moreover, the estimated coefficients for high-beta portfolios are negative and exhibit a larger magnitude than those for low-beta portfolios.

Panel B of Table 3 presents the estimated coefficients for the regressions of returns of macro-factor-beta-sorted "High-Low" portfolios on the contemporaneous change in sentiment. On average, the contemporaneous change in sentiment has a stronger impact on high-risk funds

https://faculty.fuqua.duke.edu/∼dah7/HFRFData.htm.

than on low-risk funds, and the difference between the estimated coefficients is statistically significant at the 1% significance level.

In summary, the predictive regressions confirm that the macro-risk-return relation for hedge fund portfolios can be weakened due to strong mispricing induced by high-sentiment periods, particularly for funds with greater macro-risk exposure.

3.3 Evidence from hedge funds by investment styles

Table 4 displays the high-risk-minus-low-risk return spreads of hedge fund portfolios by investment styles following high- and low-sentiment subsamples, and compares their differences. Columns 2-4, 5-7, and 8-10 present the return spreads for hedge funds with the investment styles of equity, non-equity, and FOF, respectively.

The return difference between the "High-Low" equity-style hedge fund portfolios following high- and low-sentiment months is slightly larger than that using all funds, with an average monthly return of -0.66% (t-statistic $= -1.97$). Meanwhile, the two-regime effect is weaker among non-equity funds, with a monthly return spread of -0.53% that is marginal significant (t-statistic $= -1.91$). After adjusting the raw return using the Fung-Hsieh eight factors, only the alpha difference of equity hedge funds remains statistically significant, as shown in the last four rows of the table. The stronger effect in equity funds aligns with the conjecture that hedge funds may at least partially inherit the two-regime macro-risk-return relation from their stock holdings. However, the weaker but noticeable effect in non-equity funds suggests that other mechanisms might also contribute to the observed pattern. In contrast, the average return difference for the "High-Low" FOF portfolio following high- and low-sentiment months is economically smaller (-0.27%) and statistically insignificant (t-statistic $= -1.24$). We conjecture that, as FOFs aim to diversify across asset classes and strategies, an FOF's macroeconomic beta may be less representative of its exposure to macroeconomic risk in the subsequent month.[13]

[13]In untabulated results, ex post factor betas of the FOF "High-Low" spread portfolio are consistent with this conjecture: none of the ex post beta spreads for FOFs are as large as those in other style categories.

4 Possible mechanisms underlying the two-regime pattern

As our findings are not solely driven by a simple pass-on effect from stocks (Shen et al., 2017), some hedge fund specific features may also contribute to the observed pattern. In this section, we propose two possible mechanisms, namely, funds' macro-risk timing and fund flows, that could help explain the sentiment-dependent two-regime pattern.

4.1 The effect of sentiment-based macro-risk timing

Hedge funds are managed portfolios and their exposures to macroeconomic risks may reflect how fund managers actively time such risks. The time-varying relationship between a fund's macro-risk beta and its timing ability could potentially explain the contrasting macro-risk-return relations observed following low- and high-sentiment periods. Specifically, macro-risk betas may convey different information about funds' macro-risk timing abilities as investor sentiment fluctuates, and consequently, drive a sentiment-dependent risk-return relation.

To investigate how the macro-risk timing skills vary across funds with different betas and how such relation changes under different sentiment periods, we first measure hedge funds' macro-risk timing ability using the framework developed in Kacperczyk, Nieuwerburgh, and Veldkamp (2014).[14] Specifically, we define $Timing^A_{j,t}$, i.e., fund j's macro-risk timing ability with respect to a given macroeconomic risk factor A, as follows:

$$Timing^A_{j,t} = \Sigma_{i=1}^{N_{j,t}} (\omega^j_{i,t} - \omega^m_{i,t}) \beta^A_{i,t} A_{t+1}, \tag{1}$$

where the portfolio weight $\omega^j_{i,t}$ denotes the weight of stock i in fund j's portfolio at time t; the market weight $\omega^m_{i,t}$ denotes the weight of stock i in the market portfolio at time t; $\beta^A_{i,t}$ is

[14] Chen, Ferson, and Peters (2010) and Cao et al. (2013) estimate the timing ability of bond mutual funds and hedge funds based on the convex relationship between fund returns and risk factors. However, the holding-based measure is more appropriate for our study as our focus is on exploring the correlation between the time-varying timing ability and investor sentiment. Factor-regression-based approaches can be data-intensive and require a long history of fund returns. In addition, using funds' holdings directly eliminates the need to consider nonlinearities and biases unrelated to the timing ability, as pointed out by Chen et al. (2010).

stock i's exposure to macroeconomic risk A at time t, estimated using a 24-month rolling window with a minimum observation requirement of 18 months; $N_{j,t}$ is the total number of stocks held in fund j's portfolio at t; and A_{t+1} is the realization of the macro-risk shock at $t+1$, which is unknown at the time of portfolio formation.[15]

The macro-risk timing measure, expressed in terms of monthly hypothetical return as in Kacperczyk et al. (2014), captures the reward associated with having the ability to correctly adjust portfolio weights in anticipation of future change in macroeconomic conditions.[16] A fund with a better macro-risk timing ability is the one that chooses to overweight a stock that will benefit from positive shocks to its macro-risk exposure and chooses to underweight a stock when its macro-risk exposure will lead to negative returns.

We use data from Thomson Reuters Institutional Holdings Database to construct the macro-risk timing ability measure.[17] Since the database only provides holding data at the management company level, we construct and assign the macro-risk timing measure to all funds within the same management company. We exclude fund management companies that hold less than ten stocks following Chen, Liu, Wang, Wang, and Yu (2022a) and that have less than two years of record following Smith et al. (2016). Hedge funds within a management company may exhibit varying macro-risk betas. To mitigate the potential measurement error concern, we limit our sample to management companies where their member funds share the same cross-sectional decile rank in terms of macro-risk beta. By applying this restriction, we retain approximately 70% of the fund-month observations. Our sample covers the period

[15]Kacperczyk et al. (2014) also define the stock picking ability of a fund as $Picking^A_{j,t} = \Sigma_{i=1}^{N_{j,t}}(\omega^j_{i,t} - \omega^m_{i,t})(R_{i,t+1} - \beta^A_{i,t}A_{t+1})$, which captures a fund's ability to make abnormal investments in the idiosyncratic component of a stock's return that cannot be accounted for by the risk compensation for the exposure to factor A. In our paper, we focus on how a fund's dynamic timing abilities are affected by market-wide sentiment, and in turn, influence the two-regime risk-return relation.

[16]Note that the original market-risk timing measure in Kacperczyk et al. (2014) is estimated using the traded market factor, while our measures are based on non-traded factors. To highlight this difference, we use the term "hypothetical return". Despite this, our measures, estimated using the method in Kacperczyk et al. (2014), still captures macro-factor timing skills of fund managers. It is unlikely to be prone to the concern of having an unobvious sign of estimated timing coefficient, as pointed out by Chen et al. (2010), because all macro risk factors are rooted in well-established economic theories and likely to carry a positive risk premium (Shen et al., 2017).

[17]We are grateful to Charles Cao for providing data on the list of hedge fund management company names in the 13F institutional holdings database. Utilizing the quarterly institutional 13F holdings from Thomson Reuters, Cao and Petrasek (2014) and Cao et al. (2018a) manually match the names of hedge fund management companies with those that report holdings through the 13F filing.

from 1999 to 2018, as equity holding data for hedge funds are sparse prior to 1999 (see, e.g., Brunnermeier and Nagel, 2004; Griffin and Xu, 2009).[18]

We then examine whether hedge funds with different macro-risk exposures deploy timing skills differently following high- and low-sentiment regimes by estimating the following panel regression model:

$$Timing_{j,t}^{A} = b_0 + b_1\beta_{j,t}^{A} + b_2 Sent_t \times \beta_{j,t}^{A} + b_3 X_{j,t} + \gamma_t + \delta_k + \epsilon_{j,t}, \tag{2}$$

where $Timing_{j,t}^{A}$ is fund j's macro-risk timing ability at time t; $\beta_{j,t}^{A}$ is the standardized macro-risk beta with respect to the macro-risk factor A; $Sent_t$ is the standardized sentiment level; $X_{j,t}$ is a set of fund characteristics, including size, expense, fund flow, an equity-oriented fund indicator, and a fund of funds indicator; γ_t is the year-month fixed effects; and, δ_k is the fund management company fixed effects. The coefficient b_1 captures the relation between a fund's macro-risk beta and its timing ability. The coefficient b_2 is our primary parameter of interest, as it measures the impact of investor sentiment on the relation between estimated fund betas and their macro-risk timing abilities. A negative b_2 implies that when sentiment becomes lower, high-beta funds exhibit superior macro-factor timing skills, which may potentially result in higher future returns compared to low-beta funds. Standard errors are clustered at the fund management company level.

Note that the Form 13F filing only requires institutions with more than \$100 million in AUM to disclose equity long positions of more than 10,000 shares or with a market value of more than \$200,000 (for more information on the 13F filing rules, see, e.g., Cao et al., 2018a; Brunnermeier and Nagel, 2004; Gompers and Metrick, 2001). As a result, we do not have information on hedge funds' short positions, derivative positions, or holdings in other asset classes. Consequently, our timing measure only captures macro-beta dynamics through changes in equity positions and not through changes in positions in other non-equity assets.

Columns (1) to (10) in Table 5 report the panel regression results for each of the ten

[18] In the early years, hedge funds often sought to maintain confidentiality by not disclosing their holdings. However, in June 1998, the SEC issued a letter that tightened the requirements for granting confidentiality (see, e.g., SEC, 1998; Beckett, 1998). To ensure a sufficient number of observations and consistency with the SEC's 13F rule change, we follow Cao, Liang, Lo, and Petrasek (2018b) and select our sample starting from 1999.

macro-risk factors, while Column (11) presents the average effect across all ten factors. With the exception of two cases, all estimated b_1 coefficients are positive and five are significant, suggesting that hedge funds with high macro-beta exposures exhibit superior timing ability compared to those with low exposures. On average, a one standard deviation increase in a fund's macro-risk beta corresponds to a 7.1% hypothetical return per month due to better macro-risk timing abilities. Meanwhile, investor sentiment negatively influences the relation between funds' macro-risk exposures and their macro-risk timing abilities, as the estimated coefficient b_2 is negative and statistically significant. The finding implies that high-beta hedge funds demonstrate more pronounced timing skills during low-sentiment periods compared to low-beta funds, enabling them to generate higher returns in subsequent periods. On the other hand, when investor sentiment is high, the relation between macro-risk beta and timing ability weakens, resulting in a flattened or even reversed risk-return tradeoff. In general, the sentiment-dependent dynamics of funds' macro betas and their timing abilities contribute to the observed two-regime pattern documented in Section 3.1.[19]

4.2 The effect of macro-beta-sensitive fund flows

Previous literature has demonstrated that investment flows exert a significant influence on funds' performance (see, e.g., Goetzmann, Ingersoll, and Ross, 2003; Fung, Hsieh, Naik, and Ramadorai, 2008; Kosowski, Naik, and Teo, 2007; Lou, 2012). It is possible that the two-regime pattern, particularly the reversed risk-return relation observed following high-sentiment months, might be partially attributable flow variation of hedge fund investors, who resemble the behavior of retail investors in the stock market. For instance, during periods of elevated investor sentiment, "dumb money" tends to flow into high-macro-beta funds, thereby creating substantial buying pressure for stocks held by those funds. Should the positive price

[19] While the unconditional relation between funds' timing abilities and their performance is not the main focus of our paper, we do find that, on average, hedge funds with the best timing abilities outperform those with the worst timing abilities by 0.17% per month, as measured by using quintile hedge fund portfolios. These results can be found in the Internet Appendix Table IA1. In untabulated results, we also find that return predictability of timing abilities remains unchanged even when considering the influence of investor flow and past fund returns. This implies that the superior performance of skilled macro-risk hedge fund timers cannot be attributed solely to luck, different from the findings in venture capital (Cong and Xiao, 2022).

reaction of these stocks subsequently reverse, it would be expected that high-macro-beta funds experience diminished returns in the month following high sentiment.

To examine this conjecture, we explore the relation between hedge fund flows and macro-risk exposures as a function of investor sentiment, and assess the subsequent impact on fund performance. Specifically, we initiate our analysis by regressing funds' net inflows on their macro-risk betas, alongside the interaction term between macro-risk betas and investor sentiment, after controlling for fund characteristics, month fixed effects, and fund management company fixed effects, as the following (first stage):

$$FundFlow_{j,t} = c_0 + c_1\beta^A_{j,t} + c_2 Sent_t \times \beta^A_{j,t} + c_3 X_{j,t} + \gamma_m + \delta_k + \epsilon_{j,t}. \tag{3}$$

A fund's net inflow is calculated as the average value over a 24-month period, which corresponds to the time frame employed for computing the macroeconomic beta.[20] Next, we compute the predicted net fund inflows, $\widehat{FundFlow}^A_{j,t}$, that are determined by the normalized betas of macroeconomic risk factor A and the time-varying investor sentiment:

$$\widehat{FundFlow}^A_{j,t} = \hat{c}_1\beta^A_{j,t} + \hat{c}_2\beta^A_{j,t} \times Sent_t, \tag{4}$$

and then we regress next-month returns $R_{j,t+1}$ on these predicted fund flows after controlling for fund characteristics, month fixed effects, and management company fixed effects (second stage).

Panel A of Table 6 presents the results from the first-stage regressions, which explore the connection between net fund inflows and macroeconomic risk betas, contingent upon sentiment. Panel B presents results from the second-stage regressions, which investigate the relation between macroeconomic-risk-beta-predicted fund flows and corresponding fund returns in the subsequent month. Standard errors are clustered by fund management company.

A couple of observations are worth emphasizing. First, while funds with higher macro-risk betas generally exhibit lower net fund inflows, they tend to experience increased inflows

[20] Following Akbas et al. (2015), a fund j's monthly inflow in month t is computed as $(AUM_t - AUM_{t-1} \times (1 + r_t))/AUM_{t-1}$, where AUM_t and AUM_{t-1} are the fund's assets under management in month t and $t-1$, respectively, and r_t is the fund's return in month t.

when investor sentiment is high. The estimated c_2 coefficients are positive for nine out of ten macroeconomic risk measures, with all of them being statistically significant, and the overall effect is positive. Second, strong evidence supports the notion that macro-beta-predicted fund flows have a negative impact on hedge funds' returns in the subsequent month. The estimated coefficients are negative and statistically significant for all but three macro-risk factor.

In summary, the results suggest that fund flows contribute to the sentiment-dependent two-regime pattern of hedge funds' beta-return relation. When investor sentiment is high, more capital flows into high-beta funds than low-beta funds, leading to lower returns for the former group compared to the latter in the following month. Conversely, when investor sentiment is low, the situation is reversed, with capital flowing out of high-beta funds and into low-beta funds, resulting in higher future returns for the latter group.[21]

5 Robustness tests

In this section, we provide additional robustness tests and further discussions of our main results. We investigate the applicability of our results at the management company level. We also repeat the main empirical analyses using alternative classifications of hedge fund styles, different sentiment measures, and varied portfolio formation procedures.

5.1 Results at fund management company level

We also investigate whether our findings are consistent at the management company level by averaging returns of all funds managed by the same company. The two-regime phenomenon is comparable in economic magnitude and exhibits slightly larger statistical significance, which may be attributed to the smoothed returns at the company level. Hedge fund managers

[21] It is possible that the impact of sentiment on the relation between macro-risk beta and fund timing abilities (or fund flows) is stronger for equity funds, as investor sentiment holds greater importance for stocks. To investigate this possibility, we repeat the analyses in Section 4 by dividing the sample into two subsamples: equity and non-equity. We do find that the proposed mechanisms of how sentiment affect the beta-return relation are more pronounced in equity hedge funds, as indicated in the Internet Appendix Tables IA2 and IA3.

with a high level of macro-risk exposure demonstrate higher returns following low-sentiment months. On the other hand, after high-sentiment months, high macro-risk-beta managers yield negative, albeit insignificant, returns. These results can be found in Internet Appendix Table IA4.

5.2 Other classifications by hedge fund investment styles

The two-regime pattern of hedge funds' risk-return relation with respect to macro risks is more pronounced, both statistically and economically, within equity-style hedge funds. There are two commonly used fund classification methods to define equity-oriented hedge funds in the literature: the one used in Agarwal and Naik (2004) and the one used in Agarwal et al. (2017). We adopt a stricter definition for equity-oriented funds by including only those funds classified as an equity fund under both classifications. In addition, we also examine whether our findings hold for the two subsamples of equity-oriented hedge funds, as classified by each of the two methods. The results display similar economic magnitude and statistical significance, and can be found in Internet Appendix Table IA5.

5.3 Alternative investor sentiment measures

Although the BW sentiment index is arguably the most widely adopted measure for investor sentiment, our findings remain robust when using alternative sentiment indicators. The first one is the augmented BW index proposed by Huang, Jiang, Tu, and Zhou (2015), which demonstrates strong time-series predictive power for the aggregate stock market. The second one is the survey-based Michigan Consumer Sentiment Index, which may capture a broader scope of social sentiment compared to the stock-market-based BW index. We extract the sentiment component in the Michigan Consumer Sentiment Index by orthogonalizing the raw index with respect to business-cycle-related variables,including growth in the industrial production index, growth in consumer expenditure on durables, nondurables, and services, as well as a dummy variable for NBER recessions. Lastly, we construct the third investor sentiment index recursively using the raw indicators, as proposed by Baker and Wurgler (2006). For each of these three alternative sentiment measures, we classify the full sample into two subsample periods using the median value.

We find that substituting the original BW index with these alternative measures does not alter our main conclusion. The two-regime pattern of macro-factor-beta-sorted hedge fund portfolios persists, albeit with slightly reduced statistical significance and smaller alpha spreads. These results can be found in Internet Appendix Table IA6.

5.4 Other portfolio formation procedures

Our findings remain robust when considering alternative portfolio formation procedures. First, we form value-weighted hedge fund portfolios weighted by the funds' AUM in the previous month. Second, we explore two alternative models for beta estimation: a two-factor model accounting for the market factor, and another two-factor model incorporating both the contemporaneous macro factor and its lagged value. The first model follows Gao et al. (2018). The second model follows Asness et al. (2001), where the average of the contemporaneous- and lagged-factor betas is used to address the strong serial correlation in reported hedge fund returns due to stale prices and managers' incentives to smooth returns (see, e.g., Getmansky et al., 2004; Jagannathan et al., 2010). The results obtained from the three portfolio formation methods described above are consistent with our primary findings. Detailed results can be found in Internet Appendix Table IA7.

6 Evidence from equity mutual funds

Previous researchers find that equity mutual fund managers may tilt their portfolios toward high CAPM-beta stocks for various reasons, such as maintaining tracking errors (Christoffersen and Simutin, 2017) or seeking embedded leverage (Boguth and Simutin, 2018). Although the two-regime macro-risk-return relation in stocks may persist in mutual funds through their stock holdings, funds' timing skills and capital flows may also play a significant role due to their similar managed nature as hedge funds. Consequently, it is worth examining whether the theoretically predicted macro-risk-return relation is valid for mutual funds, and if this relation is influenced by market-wide investor sentiment.

As shown in Table 7, equity mutual funds exhibit a sentiment-dependent two-regime pattern in the relation between macro-risk exposures and subsequent performance, which closely resembles the pattern observed in hedge funds.[22] The composite-macro-beta-score-sorted portfolio yields a monthly return spread of 0.35% (t-statistic = 1.61) following low-sentiment months, and the figure is 0.18% (t-statistic = 1.73) when averaged across the ten spread portfolios. In contrast, the macro-risk-return relation exhibits a negative, moderate economic magnitude following high-sentiment months. Overall, there is a clear return difference in the "High-Low" macro-risk portfolios between the two sentiment subperiods: on average, the return spread is -0.54% per month (t-statistic = -2.30) lower following high-sentiment months compared to low-sentiment months, and the difference is -0.71% (t-statistic = -1.74) for the composite-score-sorted portfolio. In the last four rows of the table, we present the Carhart (1997) four-factor adjusted alphas for the COMP and AVE portfolios. The observed pattern is similar with smaller economic magnitude but no statistical significance.

Through the macro-risk timing and fund flow analyses on mutual funds, we demonstrate that mutual funds' macro-risk timing ability and influence of capital flows persist as two plausible mechanisms underlying the observed sentiment-dependent two-regime pattern. As illustrated in Table 8, investor sentiment negatively affects the relation between their macro-risk timing abilities and betas. Additionally, during periods of high sentiment, more capital flows into high-beta mutual funds compared to low-beta funds, resulting in lower returns for the former group in the subsequent month, as shown in Table 9.

Lastly, we find that the magnitude of sentiment-driven capital flows is greater for mutual funds compared to hedge funds. A one standard deviation increase of investor sentiment raises the sensitivity of mutual fund inflow to the macro-risk beta by 0.28 (t-statistic = 15.71), which is larger than that of hedge funds (0.17; t-statistic = 4.66).[23] This observation aligns with the prevailing notion that the majority of mutual fund investors are retail investors,

[22]The details on the mutual fund data construction are in Appendix A. To make it comparable with our main hedge fund analyses, the mutual fund sample is from January 1997 to December 2018. Results using the full mutual fund sample from January 1980 to December 2018 are similar and available upon request.

[23]In the fund flow analysis, the sentiment index and fund macro-risk betas utilized in the regressions are normalized. This allows for comparability of coefficient estimates across both settings.

who are generally considered to be less sophisticated.

7 Conclusion

In this paper, we find that although the unconditional risk-return trade-off is ambiguous for hedge funds with varying macroeconomic-risk exposures, a positive risk-return relation persists when market sentiment is low, and a slightly negative relation is present when the sentiment is high. We identify hedge funds' macroeconomic risk timing skills and time-varying fund flows as potential mechanisms underlying the observed two-regime pattern. Similar findings are also observed in equity mutual funds.

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Figure 1: Investor Sentiment and Next-Month Returns of Hedge Fund Indices

The figure plots the monthly time series of the Baker-Wurgler (BW) sentiment index and the subsequent month returns of various hedge fund indices. The BW sentiment index is constructed as the first principal component of five sentiment proxies, including the closed-end fund discount, the number and average of the first-day returns on IPOs, the dividend premium, and the equity share in new issues. Hedge fund indices are obtained from HFRI and encompass the fund weighted composite index (FWCI), the aggregate indices of equity hedge funds (EH), the event-driven funds (ED), the global macro funds (M), the relative value funds (RV), the emerging market funds (EM), and a composite index for the fund of funds (FOF). Correlations between the BW sentiment index and the excess returns of the indices in the following month are reported. The sample period is from January 1997 to December 2018.

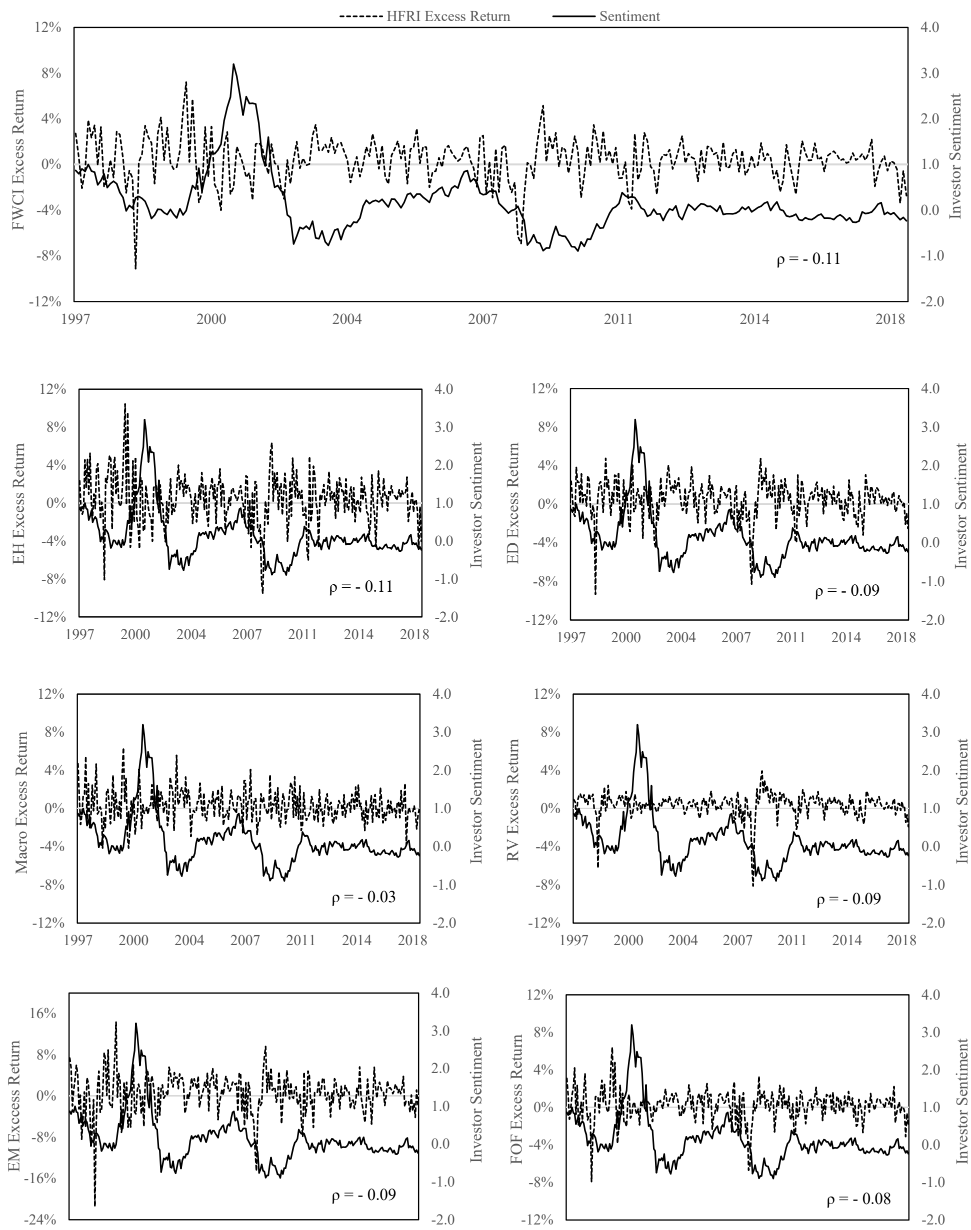

Figure 2: Investor Sentiments and Excess Returns of Beta-sorted Hedge Fund Portfolios

The figure plots the excess returns of beta-sorted hedge fund portfolios following high- and low-sentiment periods. High- and low-sentiment months are classified based on the median level of the BW sentiment index. Individual hedge funds are sorted into ten decile portfolios using betas concerning each of the ten macroeconomic risk measures. Panel A presents excess returns of portfolios sorted on the composite score, which is computed as the average value of ten macro-risk beta rankings. Panel B presents excess returns of the average portfolio across the ten macro-risk-beta-sorted portfolios. HML represents the high-minus-low portfolio. The macro-risk betas are estimated using a 24-month rolling window with a minimum observation requirement of 18 months. The figure shows the excess returns of these beta-sorted fund portfolios after high- and low-sentiment periods, as well as the difference between the two. The sample period is from January 1997 to December 2018.

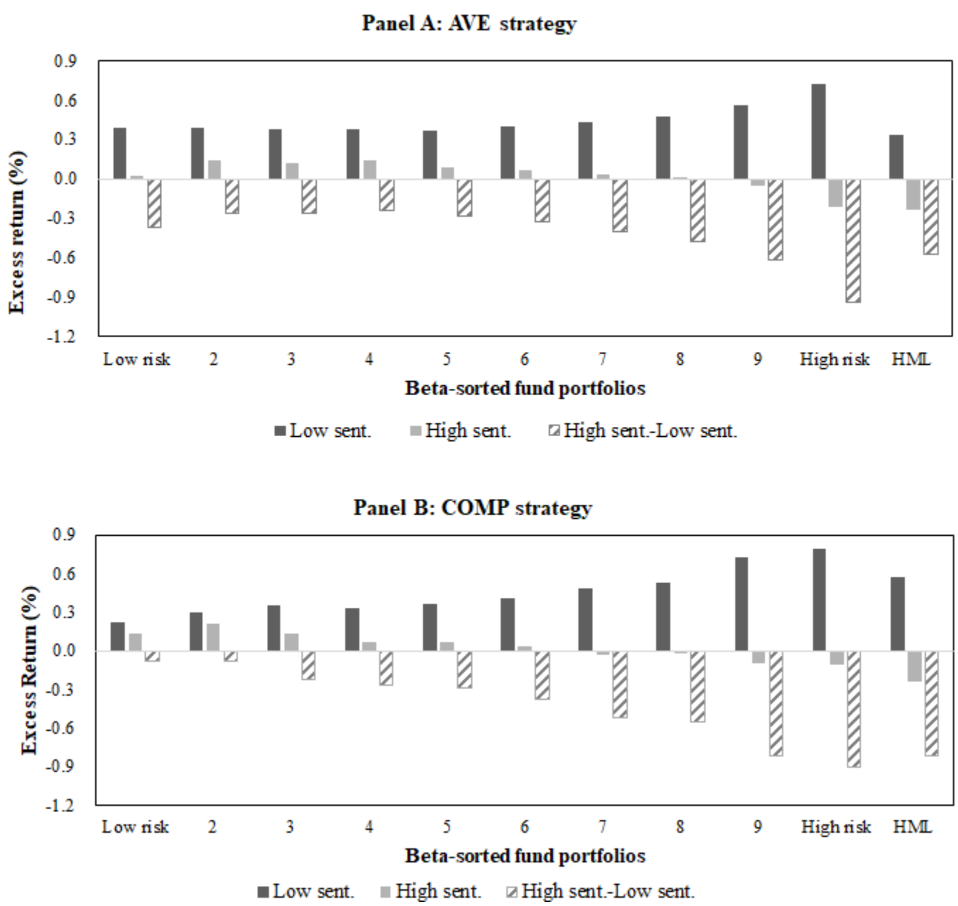

Table 1: Summary Statistics

This table presents summary statistics. Hedge funds with less than 24 months of return history in the Lipper TASS database are excluded. Panels A and B report summary statistics for hedge funds by year and by investment style, respectively. Summary statistics include the total number of funds, total number of graveyard funds, average management fee (%), average incentive fee (%), minimum investment (in thousands), average initial net asset value (NAV), average AUM (million), as well as the mean, standard deviation, minimum, and maximum of monthly equal-weighted returns of hedge fund portfolios. Panel C reports the summary statistics of ten macroeconomic risk factors. We multiply the raw time series of three variables, including TERM, DEF, and VOL, by minus one to ensure that a higher risk exposure leads to a higher expected return. The sample period is from January 1997 to December 2018.

Panel A: Summary statistics of hedge funds by year

Year	Total No.	Graveyard No.	mgt_fee (%)	inc_fee (%)	Minimum investment ($K)	Initial NAV	AUM (million)	EW fund ret (mean)	EW fund ret (std.)	EW fund ret (max)	EW fund ret (min)
1997	582	29	1.4	15.7	767.1	2043.2	85.2	0.011	0.019	0.037	-0.022
1998	787	55	1.4	16.2	911.9	1718.9	78.7	-0.001	0.026	0.032	-0.067
1999	919	56	1.3	16.3	897.3	1222.0	69.4	0.019	0.020	0.056	-0.008
2000	1003	84	1.3	16.3	946.7	1127.5	88.1	0.002	0.023	0.044	-0.027
2001	1511	93	1.3	16.9	946.8	1223.5	104.8	0.003	0.016	0.025	-0.026
2002	1738	69	1.3	17.0	952.4	1181.4	110.8	0.000	0.012	0.017	-0.022
2003	2012	100	1.3	16.8	946.2	1652.9	122.1	0.013	0.009	0.032	0.001
2004	2376	101	1.3	16.7	939.1	1518.7	163.0	0.006	0.012	0.028	-0.012
2005	2882	143	1.4	16.6	1171.2	1392.8	181.9	0.007	0.013	0.020	-0.016
2006	3063	234	1.4	16.4	1225.5	1383.2	210.2	0.010	0.013	0.033	-0.016
2007	3396	358	1.4	16.0	1432.6	1796.9	259.2	0.008	0.014	0.028	-0.018
2008	4054	540	1.4	14.3	1665.3	2135.5	227.0	-0.018	0.026	0.017	-0.062
2009	3722	471	1.4	14.2	1542.6	2385.8	144.5	0.014	0.015	0.043	-0.010
2010	3888	371	1.4	14.4	1478.3	2997.0	160.7	0.007	0.017	0.031	-0.030
2011	3644	498	1.4	14.3	1499.4	2671.7	173.5	-0.005	0.017	0.024	-0.037
2012	3233	416	1.4	14.4	1586.7	2326.2	187.7	0.006	0.013	0.026	-0.025
2013	2776	369	1.4	14.4	1075.4	2066.2	210.9	0.008	0.011	0.024	-0.016
2014	2505	249	1.4	14.5	1109.7	938.9	232.0	0.001	0.008	0.016	-0.008
2015	2197	195	1.4	14.4	1158.1	3303.3	249.6	-0.001	0.012	0.018	-0.022
2016	1841	165	1.4	14.3	1273.3	3828.1	238.7	0.003	0.012	0.018	-0.027
2017	1586	224	1.4	14.5	1271.6	4302.7	265.4	0.007	0.003	0.013	0.002
2018	1317	137	1.4	14.7	1361.3	5094.2	291.3	-0.005	0.012	0.022	-0.027
Total	8688	4957	1.4	15.4	1189.0	2195.9	175.2	0.004	0.015	0.027	-0.022

Table 1 (cont.): Summary Statistics

Panel B: Summary statistics of hedge funds by investment style

Equity funds	2853	2610	1.4	18.6	1244.4	4615.1	102.6	0.006	0.020	0.068	-0.067
Non-equity funds	3364	2964	1.5	17.3	1205.7	1832.4	213.1	0.005	0.016	0.048	-0.068
FOF	2471	2233	1.3	8.0	1591.4	579.8	120.1	0.002	0.017	0.062	-0.064

Panel C: Summary statistics of macro risk factors (%)

	Corr. S_{t-1}	Corr. ΔS_t	AR (1)	Mean	Std.	P10	Median	P90
CON	-3.21	21.16	-15.34	0.15	0.39	-0.32	0.15	0.58
TFP	-13.65	20.42	19.40	0.26	0.78	-0.64	0.23	1.25
IPG	-6.81	7.29	33.79	0.21	0.75	-0.64	0.25	1.00
TERM	-21.35	0.73	30.96	0.00	0.30	-0.30	0.01	0.28
DEF	-13.33	17.16	29.61	0.00	0.11	-0.09	0.00	0.09
UI	-6.28	20.08	40.52	0.00	0.32	-0.38	0.00	0.39
DEI	-12.10	20.07	-2.85	0.00	0.08	-0.08	0.00	0.08
VOL	-3.03	19.55	-38.74	-0.47	83.20	-101.55	0.33	97.31
MKT	-14.79	33.57	8.49	0.41	4.43	-5.07	0.87	5.17
LAB	0.43	11.47	6.81	0.44	0.51	-0.01	0.42	0.92

Table 2: Macro-Factor-Beta-Sorted Hedge Fund Portfolios Following High and Low Sentiment

This table presents the monthly excess returns of hedge fund portfolios sorted by their exposures to ten macroeconomic risk factors in the full sample and in the subsamples following high- and low-sentiment months. High- and low-sentiment months are classified based on the median level of the BW sentiment index. Individual hedge funds are sorted into ten decile portfolios based on betas with respect to each of the ten macroeconomic risk measures. Betas are estimated using a 24-month rolling window with a minimum observation requirement of 18 months. COMP indicates the portfolios sorted on the composite score across the ten macro-risk betas. AVE indicates the average portfolio across the ten macro-risk-beta-sorted portfolios. The monthly excess returns for the high-risk (Decile 10), low-risk (Decile 1) hedge fund portfolios, as well as the return differences between the high-risk and low-risk portfolios in the full sample, following high- and low-sentiment months, and their difference, are reported. The alpha of the COMP and AVE portfolios is calculated with respect to the Fung-Hsieh eight-factor model. Newey-West three-lag adjusted t-statistics are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1997 to December 2018.

	Low risk				High risk				High risk-Low risk			
	All	High Sent.	Low Sent.	High-Low	All	High Sent.	Low Sent.	High-Low	All	High Sent.	Low Sent.	High-Low
CON	0.41**	0.14	0.68***	-0.54*	0.15	-0.16	0.46	-0.62	-0.26	-0.30	-0.22	-0.08
	(2.45)	(0.59)	(3.01)	(-1.69)	(0.63)	(-0.52)	(1.57)	(-1.57)	(-1.15)	(-0.91)	(-0.76)	(-0.19)
TFP	0.12	-0.01	0.26*	-0.27	0.39	-0.12	0.91**	-1.04**	0.27	-0.11	0.65*	-0.76*
	(1.12)	(-0.07)	(1.91)	(-1.19)	(1.47)	(-0.39)	(2.38)	(-2.27)	(1.07)	(-0.37)	(1.75)	(-1.73)
IPG	0.15	-0.03	0.33	-0.36	0.26	-0.32	0.83***	-1.15***	0.11	-0.28	0.50**	-0.78**
	(0.95)	(-0.17)	(1.50)	(-1.27)	(1.07)	(-1.09)	(2.74)	(-2.94)	(0.61)	(-1.21)	(2.22)	(-2.48)
TERM	0.32*	-0.08	0.73***	-0.82**	0.15	-0.08	0.37	-0.45	-0.18	0.01	-0.36	0.37
	(1.72)	(-0.33)	(2.95)	(-2.35)	(0.65)	(-0.27)	(1.21)	(-1.12)	(-0.79)	(0.02)	(-1.10)	(0.87)
DEF	0.30**	0.02	0.58***	-0.55**	0.10	-0.31	0.51	-0.82*	-0.20	-0.33	-0.06	-0.27
	(2.29)	(0.14)	(3.14)	(-2.18)	(0.39)	(-0.89)	(1.46)	(-1.81)	(-0.82)	(-1.12)	(-0.17)	(-0.61)
UI	0.16	-0.03	0.35	-0.38	0.25	-0.26	0.77***	-1.04***	0.09	-0.24	0.42	-0.66*
	(0.86)	(-0.11)	(1.57)	(-1.17)	(1.28)	(-1.22)	(2.68)	(-3.07)	(0.50)	(-1.04)	(1.56)	(-1.94)
DEI	0.18	-0.05	0.40*	-0.45	0.36*	-0.01	0.73***	-0.74**	0.18	0.03	0.33	-0.29
	(0.96)	(-0.18)	(1.70)	(-1.35)	(1.85)	(-0.06)	(2.61)	(-2.19)	(1.00)	(0.14)	(1.23)	(-0.85)
VOL	0.05	-0.04	0.14	-0.18	0.34	-0.19	0.87**	-1.07**	0.29	-0.15	0.73**	-0.88*
	(0.60)	(-0.26)	(1.62)	(-1.08)	(1.22)	(-0.55)	(2.29)	(-2.16)	(1.12)	(-0.46)	(2.10)	(-1.90)
MKT	0.11	0.11	0.11	0.00	0.30	-0.35	0.96**	-1.31**	0.19	-0.46	0.85*	-1.31**
	(1.52)	(0.87)	(1.63)	(0.02)	(0.93)	(-0.84)	(2.19)	(-2.29)	(0.56)	(-0.98)	(1.90)	(-2.12)
LAB	0.24	0.20	0.29	-0.09	0.23	-0.34	0.80**	-1.14***	-0.02	-0.54*	0.51	-1.05**
	(1.62)	(0.89)	(1.58)	(-0.31)	(0.89)	(-1.14)	(2.25)	(-2.66)	(-0.07)	(-1.72)	(1.64)	(-2.55)
COMP	0.17***	0.13	0.22**	-0.08	0.34	-0.11	0.79**	-0.90**	0.17	-0.24	0.58	-0.82*
	(2.80)	(1.33)	(2.58)	(-0.62)	(1.29)	(-0.32)	(2.17)	(-1.98)	(0.64)	(-0.71)	(1.59)	(-1.77)
AVE	0.20*	0.02	0.39***	-0.36*	0.25	-0.21	0.72**	-0.94**	0.05	-0.24	0.34	-0.57**
	(1.79)	(0.14)	(2.75)	(-1.71)	(1.09)	(-0.76)	(2.27)	(-2.37)	(0.31)	(-1.24)	(1.53)	(-2.15)
$\text{COMP}_{\alpha}^{FH8}$	0.19***	0.15*	0.23***	-0.07	-0.00	-0.23	0.22*	-0.45**	-0.19	-0.38*	-0.00	-0.38
	(3.37)	(1.80)	(2.62)	(-0.59)	(-0.02)	(-1.23)	(1.82)	(-2.24)	(-1.37)	(-1.77)	(-0.02)	(-1.54)
$\text{AVE}_{\alpha}^{FH8}$	0.10*	-0.02	0.22**	-0.24*	-0.03	-0.28**	0.23***	-0.51***	-0.13	-0.26*	0.01	-0.27*
	(1.70)	(-0.24)	(2.46)	(-1.76)	(-0.32)	(-2.19)	(2.68)	(-3.39)	(-1.39)	(-1.95)	(0.10)	(-1.79)

Table 3: Predictive Regressions of Macro-Factor-Beta-Sorted Portfolios

This table presents the results of predictive regressions of macro-factor-beta-sorted portfolios on the BW investor sentiment index. Individual hedge funds are sorted into ten decile portfolios based on betas with respect to each of the ten macroeconomic risk measures. Betas are estimated using a 24-month rolling window with a minimum observation requirement of 18 months. The monthly excess returns of the high-risk (Decile 10), low-risk (Decile 1) hedge fund portfolios, as well as the return differences between the high-risk and low-risk portfolios, are regressed on the lagged sentiment index (Panel A) or sentiment changes (Panel B). Newey-West three-lag adjusted t-statistics are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1997 to December 2018 in Panel A, and January 1997 to December 2010 in Panel B.

Panel A: Regressions on S_{t-1}

	Low risk		High risk		High risk-Low risk	
	b (%)	t-stat	b (%)	t-stat	b (%)	t-stat
CON	-0.29	-1.34	-0.87	-2.56	-0.58	-1.43
TFP	0.04	0.35	-1.24	-3.62	-1.28	-3.92
IPG	-0.19	-1.10	-1.13	-4.25	-0.94	-4.05
TERM	-0.53	-2.54	-0.85	-2.81	-0.31	-1.03
DEF	-0.28	-1.71	-1.08	-3.01	-0.80	-2.04
UI	-0.33	-1.85	-0.96	-3.24	-0.63	-2.08
DEI	-0.29	-1.27	-0.75	-2.56	-0.46	-1.36
VOL	-0.15	-1.25	-1.11	-3.23	-0.96	-2.81
MKT	0.19	1.59	-1.45	-3.26	-1.64	-3.24
LAB	-0.06	-0.48	-1.15	-3.09	-1.09	-2.82
COMP	0.09	1.12	-1.24	-3.50	-1.34	-3.40
AVE	-0.19	-1.63	-1.06	-3.39	-0.87	-3.27

Panel B: Regressions on ΔS_t

	Low risk		High risk		High risk-Low risk	
	b (%)	t-stat	b (%)	t-stat	b (%)	t-stat
CON	0.01	0.08	1.52	6.31	1.51	6.43
TFP	0.30	1.76	1.25	5.01	0.94	3.22
IPG	0.14	0.95	1.24	4.70	1.10	4.03
TERM	0.44	2.91	0.97	3.87	0.53	2.09
DEF	0.41	2.32	1.10	3.77	0.69	1.96
UI	0.71	3.10	0.90	3.79	0.18	0.60
DEI	0.52	2.62	1.09	5.01	0.57	2.17
VOL	0.18	1.40	1.20	4.68	1.03	4.06
MKT	-0.33	-3.51	1.71	5.21	2.04	5.64
LAB	0.12	0.74	1.23	4.19	1.11	3.39
COMP	-0.10	-1.36	1.55	5.41	1.66	5.36
AVE	0.25	2.09	1.22	5.07	0.97	4.73

Table 4: Macro-Factor-Beta-Sorted Hedge Fund Portfolios Following High and Low Sentiment: by Investment Style

This table presents the monthly return differences between high and low macro-beta-sorted hedge fund portfolios for each investment style following high- and low-sentiment months. High- and low-sentiment months are classified based on the median level of the BW sentiment index. Individual hedge funds are sorted into ten decile portfolios based on betas with respect to each of the ten macroeconomic risk measures. Betas are estimated using a 24-month rolling window with a minimum observation requirement of 18 months. COMP indicates the portfolios sorted on the composite score across the ten macro-risk betas. AVE indicates the average portfolio across the ten macro-risk-beta-sorted portfolios. The return differences of high-risk (Decile 10) and low-risk (Decile 1) portfolios are reported for the equity, the non-equity, and the FOF subsamples, respectively. The alpha of the COMP and AVE portfolios is calculated with respect to the Fung-Hsieh eight-factor model. Newey-West three-lag adjusted t-statistics are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1997 to December 2018.

	Equity			Non-equity			FOF		
	High sent.	Low sent.	High -Low	High sent.	Low sent.	High -Low	High sent.	Low sent.	High -Low
CON	-0.18	-0.05	-0.14	-0.37	-0.50*	0.14	0.15	-0.22	0.37
	(-0.41)	(-0.15)	(-0.26)	(-1.23)	(-1.75)	(0.33)	(0.47)	(-1.30)	(1.06)
TFP	-0.22	0.76*	-0.98	-0.04	0.51	-0.55	-0.23	0.28	-0.51
	(-0.46)	(1.81)	(-1.65)	(-0.13)	(1.22)	(-1.18)	(-0.75)	(1.05)	(-1.30)
IPG	0.17	0.57**	-0.41	-0.18	0.67**	-0.84**	-0.47	0.26	-0.73**
	(0.45)	(2.19)	(-0.88)	(-0.73)	(2.18)	(-2.31)	(-1.62)	(1.35)	(-2.20)
TERM	-0.23	-0.23	0.01	0.20	-0.24	0.45	0.03	-0.52**	0.54
	(-0.49)	(-0.57)	(0.01)	(0.65)	(-0.72)	(1.03)	(0.10)	(-2.10)	(1.53)
DEF	-0.68	-0.13	-0.56	0.03	0.08	-0.05	-0.32	-0.19	-0.13
	(-1.57)	(-0.31)	(-0.97)	(0.11)	(0.21)	(-0.11)	(-0.88)	(-0.75)	(-0.30)
UI	-0.16	0.39	-0.55	-0.38*	0.60*	-0.98***	-0.21	0.25	-0.46
	(-0.47)	(1.28)	(-1.31)	(-1.90)	(1.88)	(-2.66)	(-0.80)	(1.27)	(-1.42)
DEI	0.13	0.18	-0.05	-0.36	0.32	-0.68*	0.13	0.07	0.06
	(0.40)	(0.58)	(-0.11)	(-1.44)	(1.04)	(-1.73)	(0.43)	(0.34)	(0.15)
VOL	-0.17	0.65	-0.82	0.11	0.87**	-0.76	-0.18	0.44*	-0.62
	(-0.34)	(1.65)	(-1.32)	(0.32)	(2.17)	(-1.50)	(-0.58)	(1.88)	(-1.61)
MKT	-0.42	1.00*	-1.41*	-0.37	0.80	-1.17*	-0.33	0.49	-0.81*
	(-0.57)	(1.96)	(-1.66)	(-0.92)	(1.63)	(-1.95)	(-0.95)	(1.56)	(-1.84)
LAB	-0.74	0.95***	-1.69***	-0.59**	0.25	-0.83**	-0.27	0.15	-0.42
	(-1.38)	(2.76)	(-2.75)	(-2.03)	(0.70)	(-2.02)	(-0.86)	(0.63)	(-1.10)
COMP	-0.50	0.68*	-1.19*	-0.33	0.53	-0.86*	-0.15	0.25	-0.40
	(-0.99)	(1.69)	(-1.93)	(-1.03)	(1.23)	(-1.74)	(-0.54)	(1.05)	(-1.20)
AVE	-0.25	0.41*	-0.66**	-0.19	0.34	-0.53*	-0.17	0.10	-0.27
	(-0.93)	(1.79)	(-1.97)	(-1.18)	(1.30)	(-1.91)	(-0.97)	(0.64)	(-1.24)
$\text{COMP}_{\alpha}^{FH8}$	-0.70*	0.04	-0.73*	-0.43**	-0.08	-0.35	-0.12	-0.11	-0.00
	(-1.93)	(0.17)	(-1.75)	(-2.10)	(-0.46)	(-1.29)	(-0.58)	(-0.84)	(-0.02)
$\text{AVE}_{\alpha}^{FH8}$	-0.31	0.07	-0.38*	-0.21*	-0.02	-0.19	-0.11	-0.12	0.01
	(-1.63)	(0.52)	(-1.72)	(-1.68)	(-0.15)	(-1.16)	(-0.84)	(-1.36)	(0.06)

Table 5: Sentiment-Dependent Relation Between Hedge Funds' Macro-Risk Timing Abilities and Macro-Risk Exposures

The table presents the relation between hedge funds' macro-risk timing skills and their macro-risk betas, as well as how this beta-ability relation varies with investor sentiment. Hedge funds' macro-timing ability is measured with respect to each of ten macroeconomic risk measures. We regress hedge funds' macro-risk timing ability of a given macroeconomic risk factor A on their macro-risk betas and the interaction term between macro-risk betas and investor sentiment, controlling for fund size, expenses, fund flow, an equity fund indicator, a fund of fund indicator, month fixed effects, and fund management company fixed effects. We present results from the panel regressions for each of the ten macroeconomic risk measures and results from a pooled panel regression to measure the average effect (AVE). The dependent variables are winsorized at 1% and 99% levels. t-statistics computed using standard errors clustered at the fund management company level are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1999 to December 2018.

	(1) CON	(2) TFP	(3) IPG	(4) TERM	(5) DEF	(6) UI	(7) DEI	(8) VOL	(9) MKT	(10) LAB	(11) AVE
β	0.077***	0.072***	0.041***	0.021	-0.016	-0.008	0.005	0.008	0.064**	0.237***	0.071***
	(3.70)	(3.46)	(3.77)	(1.36)	(-1.06)	(-0.80)	(0.60)	(1.34)	(2.33)	(5.69)	(4.07)
$\beta\times$Sentiment	0.017	-0.120***	-0.019	0.001	-0.073***	-0.079***	-0.092***	-0.026*	-0.069	0.038	-0.048**
	(0.93)	(-2.85)	(-0.71)	(0.03)	(-2.61)	(-3.40)	(-5.66)	(-1.87)	(-1.53)	(0.80)	(-2.01)
Fund size	0.024	-0.008	-0.018**	-0.013	0.006	-0.003	-0.007	0.004	0.004	0.006	0.001
	(1.61)	(-0.64)	(-2.52)	(-0.95)	(0.89)	(-0.48)	(-1.29)	(1.13)	(0.38)	(0.34)	(0.17)
Expenses	0.054	0.523	0.088	-0.015	-0.289	-0.091	-0.069	0.017	-0.237	-0.124	-0.086
	(0.17)	(0.92)	(0.53)	(-0.08)	(-1.60)	(-0.66)	(-0.53)	(0.16)	(-0.69)	(-0.30)	(-0.61)
Fund flow	-0.450*	0.586	0.124	0.418**	0.200	0.015	0.030	-0.018	0.231	-0.054	0.091
	(-1.82)	(1.62)	(1.19)	(2.30)	(1.64)	(0.10)	(0.32)	(-0.15)	(1.18)	(-0.16)	(0.99)
Equity fund	0.071	0.077	-0.070	-0.058**	0.044	0.035	0.039	-0.042	0.130	-0.141	0.002
	(0.86)	(0.73)	(-1.62)	(-2.02)	(0.96)	(1.14)	(1.10)	(-1.08)	(1.31)	(-1.18)	(0.07)
Fund of fund	-0.051	0.059	-0.008	0.017	0.085	0.043	0.058	-0.003	0.050	-0.033	0.006
	(-1.06)	(0.37)	(-0.24)	(0.36)	(1.54)	(1.24)	(0.93)	(-0.08)	(1.30)	(-0.38)	(0.22)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MGR FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.621	0.822	0.438	0.698	0.776	0.612	0.597	0.812	0.889	0.727	0.140
Observations	17,710	18,471	17,735	18,538	18,400	18,217	17,886	18,419	19,606	18,736	183,744

Table 6: Hedge Funds' Macro-Beta-Sensitive Fund Flows and Performance

The table presents the sentiment-dependent relation between hedge fund flows and macroeconomic risk exposures, as well as the subsequent performance impact of hedge funds' macro-beta-sensitive fund flows. In Panel A, we present results of regressing fund net inflow on macro-risk betas and the interaction term between macro-risk betas and investor sentiment, controlling for fund size, expenses, an equity hedge funds indicator, a fund of funds indicator, month fixed effects, and fund management company fixed effects. Panel B presents results of regressing the next-month fund returns on the macro-beta-predicted fund flows. The dependent variables are winsorized at 1% and 99% levels. t-statistics computed using standard errors clustered at the fund management company level are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1997 to December 2018.

Panel A: Sentiment-dependent relation between hedge funds' net inflow and macro-risk betas

	(1) CON	(2) TFP	(3) IPG	(4) TERM	(5) DEF	(6) UI	(7) DEI	(8) VOL	(9) MKT	(10) LAB	(11) AVE
β	-0.056	-0.095**	0.012	0.065	-0.078*	-0.086**	-0.086**	-0.112***	-0.144**	-0.036	-0.042***
	(-1.39)	(-2.24)	(0.33)	(1.61)	(-1.88)	(-2.08)	(-2.07)	(-2.65)	(-2.26)	(-0.94)	(-2.98)
$\beta\times$Sentiment	-0.010	0.433***	0.190***	0.252***	0.205***	0.104*	0.151***	0.183***	0.204***	0.186***	0.167***
	(-0.17)	(6.92)	(3.05)	(4.08)	(3.19)	(1.79)	(2.71)	(2.83)	(2.93)	(2.99)	(4.66)
Fund size	-0.114**	-0.123***	-0.116**	-0.119**	-0.117**	-0.116**	-0.116**	-0.119**	-0.119**	-0.117**	-0.116**
	(-2.46)	(-2.65)	(-2.50)	(-2.57)	(-2.52)	(-2.48)	(-2.48)	(-2.55)	(-2.57)	(-2.52)	(-2.50)
Expenses	-0.304	-0.278	-0.334	-0.380	-0.318	-0.316	-0.325	-0.285	-0.276	-0.330	-0.325
	(-0.14)	(-0.12)	(-0.15)	(-0.17)	(-0.14)	(-0.14)	(-0.14)	(-0.13)	(-0.12)	(-0.15)	(-0.14)
Equity fund	-0.071	-0.085	-0.074	-0.071	-0.072	-0.072	-0.075	-0.066	-0.059	-0.071	-0.073
	(-0.27)	(-0.33)	(-0.29)	(-0.28)	(-0.28)	(-0.28)	(-0.29)	(-0.26)	(-0.23)	(-0.28)	(-0.28)
Fund of fund	-0.375	-0.389	-0.382	-0.392	-0.379	-0.376	-0.375	-0.377	-0.381	-0.382	-0.381
	(-1.28)	(-1.32)	(-1.30)	(-1.33)	(-1.29)	(-1.28)	(-1.28)	(-1.28)	(-1.29)	(-1.30)	(-1.30)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MGR FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.251	0.253	0.252	0.252	0.252	0.252	0.252	0.252	0.252	0.252	0.259
Observations	282,304	282,304	282,304	282,304	282,304	282,304	282,304	282,304	282,304	282,304	2,823,290

Panel B: Macro-beta-sensitive net inflow and fund returns

	(1) CON	(2) TFP	(3) IPG	(4) TERM	(5) DEF	(6) UI	(7) DEI	(8) VOL	(9) MKT	(10) LAB	(11) AVE
$\widehat{\text{Fundflow}}$	2.878***	-0.936***	-0.547	0.067	-2.238**	-1.369***	-1.684**	-1.749***	-1.375**	-2.755***	-1.515***
	(3.17)	(-7.75)	(-0.75)	(0.08)	(-2.19)	(-3.39)	(-2.26)	(-6.93)	(-2.19)	(-6.31)	(-11.08)
Fund size	-0.132***	-0.125***	-0.132***	-0.134***	-0.127***	-0.131***	-0.131***	-0.125***	-0.127**	-0.126***	-0.130***
	(-2.79)	(-2.59)	(-2.71)	(-2.59)	(-2.82)	(-2.73)	(-2.79)	(-2.65)	(-2.53)	(-2.70)	(-2.73)
Expenses	0.075	-0.047	0.006	0.001	-0.022	-0.014	-0.004	-0.081	-0.082	0.002	-0.004
	(0.17)	(-0.11)	(0.01)	(0.00)	(-0.05)	(-0.03)	(-0.01)	(-0.20)	(-0.19)	(0.00)	(-0.01)
Equity fund	0.039	0.048	0.037	0.036	0.036	0.035	0.041	0.025	0.018	0.035	0.038
	(0.38)	(0.46)	(0.36)	(0.35)	(0.35)	(0.34)	(0.39)	(0.24)	(0.18)	(0.34)	(0.37)
Fund of fund	0.063	0.066	0.058	0.055	0.059	0.052	0.051	0.056	0.059	0.065	0.061
	(0.39)	(0.41)	(0.36)	(0.34)	(0.37)	(0.32)	(0.31)	(0.35)	(0.36)	(0.41)	(0.38)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MGR FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.015
Observations	280,695	280,695	280,695	280,695	280,695	280,695	280,695	280,695	280,695	280,695	2,807,220

Table 7: Macro-Factor-Beta-Sorted Mutual Fund Portfolios Following High and Low Sentiment

This table presents the monthly excess returns of domestic actual equity mutual fund portfolios sorted by their exposures to ten macroeconomic risk factors in the full sample and in the subsamples following high- and low-sentiment months. High- and low-sentiment months are classified based on the median level of the BW sentiment index. Individual hedge funds are sorted into ten decile portfolios based on betas with respect to each of the ten macroeconomic risk measures. Betas are estimated using a 24-month rolling window with a minimum observation requirement of 18 months. COMP indicates the portfolios sorted on the composite score across the ten macro-risk betas. AVE indicates the average portfolio across the ten macro-risk-beta-sorted portfolios. The monthly excess returns for the high-risk (Decile 10), low-risk (Decile 1) hedge fund portfolios, as well as the return differences between the high-risk and low-risk portfolios in the full sample, following high- and low-sentiment months, and their difference, are reported. The alpha of the COMP and AVE portfolios is calculated with respect to the Carhart four-factor model. Newey-West three-lag adjusted t-statistics are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1997 to December 2018.

	Low risk				High risk				High risk-Low risk			
	ALL	High Sent.	Low Sent.	High -Low	ALL	High Sent.	Low Sent.	High -Low	ALL	High Sent.	Low Sent.	High -Low
CON	0.64 **	0.52	0.76*	-0.24	0.39	-0.11	0.88*	-0.99	-0.25	-0.62*	0.12	-0.75*
	(2.38)	(1.62)	(1.83)	(-0.48)	(1.10)	(-0.22)	(1.90)	(-1.60)	(-1.05)	(-1.71)	(0.45)	(-1.94)
TFP	0.43 *	0.24	0.63*	-0.39	0.45	-0.03	0.93*	-0.97	0.01	-0.27	0.30	-0.57
	(1.88)	(0.80)	(1.91)	(-0.89)	(1.24)	(-0.07)	(1.96)	(-1.51)	(0.06)	(-0.80)	(1.46)	(-1.57)
IPG	0.49 *	0.28	0.71	-0.42	0.41	-0.09	0.91**	-1.00*	-0.08	-0.37	0.21	-0.57*
	(1.71)	(0.80)	(1.61)	(-0.79)	(1.25)	(-0.20)	(2.14)	(-1.76)	(-0.45)	(-1.35)	(0.98)	(-1.77)
TERM	0.42	0.10	0.75*	-0.65	0.46	0.10	0.83**	-0.73	0.04	-0.01	0.08	-0.08
	(1.44)	(0.25)	(1.83)	(-1.17)	(1.50)	(0.25)	(1.97)	(-1.35)	(0.16)	(-0.02)	(0.32)	(-0.21)
DEF	0.65 **	0.32	0.97***	-0.65	0.30	-0.16	0.77*	-0.92	-0.34 *	-0.48	-0.21	-0.27
	(2.34)	(0.87)	(2.58)	(-1.29)	(0.91)	(-0.35)	(1.69)	(-1.55)	(-1.68)	(-1.56)	(-0.88)	(-0.76)
UI	0.50 *	0.16	0.85**	-0.70	0.35	-0.08	0.78*	-0.85	-0.15	-0.23	-0.08	-0.16
	(1.67)	(0.39)	(2.11)	(-1.31)	(1.15)	(-0.20)	(1.80)	(-1.58)	(-0.90)	(-0.84)	(-0.40)	(-0.56)
DEI	0.38	0.02	0.74*	-0.71	0.47	0.04	0.91**	-0.87	0.09	0.02	0.17	-0.15
	(1.31)	(0.07)	(1.81)	(-1.35)	(1.51)	(0.10)	(2.13)	(-1.59)	(0.53)	(0.07)	(0.72)	(-0.51)
VOL	0.44 *	0.27	0.61*	-0.35	0.44	-0.08	0.96**	-1.04	0.00	-0.34	0.35*	-0.69*
	(1.87)	(0.93)	(1.80)	(-0.84)	(1.24)	(-0.15)	(2.06)	(-1.58)	(0.02)	(-1.08)	(1.78)	(-1.87)
MKT	0.36 *	0.26	0.46*	-0.21	0.49	-0.19	1.17**	-1.36*	0.13	-0.45	0.70**	-1.15**
	(1.94)	(1.22)	(1.65)	(-0.64)	(1.19)	(-0.33)	(2.29)	(-1.90)	(0.42)	(-0.94)	(2.23)	(-2.22)
LAB	0.63 **	0.53	0.73**	-0.20	0.30	-0.29	0.90**	-1.19*	-0.33	-0.82**	0.17	-0.98***
	(2.52)	(1.63)	(2.02)	(-0.43)	(0.88)	(-0.61)	(2.02)	(-1.93)	(-1.63)	(-2.54)	(0.92)	(-2.68)
COMP	0.44 **	0.26	0.63*	-0.36	0.44	-0.10	0.98**	-1.08*	-0.01	-0.36	0.35	-0.71*
	(2.02)	(0.97)	(1.90)	(-0.88)	(1.18)	(-0.19)	(2.07)	(-1.66)	(-0.03)	(-0.91)	(1.61)	(-1.74)
AVE	0.49 **	0.27	0.72**	-0.45	0.41	-0.09	0.90**	-0.99*	-0.09	-0.36	0.18*	-0.54**
	(1.98)	(0.86)	(1.99)	(-0.98)	(1.23)	(-0.20)	(2.05)	(-1.69)	(-0.67)	(-1.59)	(1.73)	(-2.30)
$\text{COMP}_{\alpha}^{FH8}$	0.03	0.05	0.00	0.04	-0.19 **	-0.24*	-0.14	-0.11	-0.21	-0.29	-0.14	-0.15
	(0.29)	(0.36)	(0.03)	(0.29)	(-2.07)	(-1.70)	(-1.48)	(-0.68)	(-1.48)	(-1.25)	(-1.00)	(-0.60)
$\text{AVE}_{\alpha}^{FH8}$	-0.00	0.03	-0.04	0.08	-0.17 **	-0.22**	-0.13*	-0.09	-0.17 **	-0.25*	-0.09	-0.16
	(-0.04)	(0.31)	(-0.44)	(0.56)	(-2.45)	(-2.05)	(-1.67)	(-0.71)	(-1.97)	(-1.86)	(-1.05)	(-1.13)

Table 8: Sentiment-Dependent Relation Between Mutual Funds' Macro-Risk Timing Abilities and Macro-Risk Exposures

The table presents the relation between domestic active equity mutual funds' macro-risk timing skills and their macro-risk betas, as well as how this beta-ability relation varies with investor sentiment. Mutual funds' macro-timing ability is measured with respect to each of ten macroeconomic risk measures. Funds' macro-risk timing abilities are regressed on macro-risk betas and the interaction term between macro-risk betas and investor sentiment, controlling for fund size, expenses, fund flow, month fixed effects, and fund fixed effects. We present results from the panel regressions for each of ten macroeconomic risk measures and results from a pooled panel regression to measure the average effect (AVE). The dependent variables are winsorized at 1% and 99% levels. t-statistics computed using standard errors clustered at the fund level are reported in parentheses. *p <0.1; **p <0.05; ***p <0.01. The sample period is from January 1997 to December 2018.

	(1) CON	(2) TFP	(3) IPG	(4) TERM	(5) DEF	(6) UI	(7) DEI	(8) VOL	(9) MKT	(10) LAB	(11) AVE
β	0.198***	0.178***	0.080***	0.042***	-0.026***	0.007***	0.012***	0.003***	0.113***	0.392***	0.099***
	(52.48)	(42.00)	(32.67)	(15.13)	(-12.16)	(5.07)	(11.46)	(3.89)	(20.87)	(70.95)	(33.10)
$\beta\times$Sentiment	-0.003	-0.133***	-0.121***	-0.175***	-0.093***	-0.036***	-0.072***	-0.038***	-0.258***	0.111***	-0.076***
	(-0.66)	(-25.67)	(-25.69)	(-34.26)	(-39.90)	(-17.74)	(-28.52)	(-27.81)	(-33.12)	(17.52)	(-26.91)
Fund size	0.011***	0.023***	-0.022***	-0.021***	-0.002	0.003***	-0.004***	0.007***	-0.011***	-0.002	0.001
	(3.53)	(5.83)	(-10.69)	(-9.63)	(-1.43)	(3.03)	(-3.32)	(8.47)	(-3.63)	(-0.51)	(0.66)
Expenses	3.412**	-1.085	-0.163	-6.122***	-0.590	0.227	-0.408	-0.113	-3.189**	-10.925***	-1.698**
	(1.96)	(-0.39)	(-0.17)	(-6.10)	(-0.53)	(0.36)	(-0.71)	(-0.22)	(-2.40)	(-3.37)	(-2.43)
Fund flow	0.001	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.000	-0.001	-0.000	-0.000
	(1.01)	(-0.07)	(-1.02)	(-0.63)	(0.36)	(0.55)	(0.87)	(-0.62)	(-1.27)	(-0.55)	(-1.09)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MF FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.729	0.823	0.584	0.708	0.790	0.665	0.687	0.813	0.893	0.726	0.127
Observations	500,181	500,181	500,181	500,181	500,181	500,181	500,181	500,181	500,181	500,181	4,997,500

Table 9: Mutual Funds' Macro-Beta-Sensitive Fund Flows and Performance

The table presents the sentiment-dependent relation between mutual fund flows and macroeconomic risk exposures, as well as the subsequent performance impact of mutual funds' macro-beta-sensitive fund flows. In Panel A, we present results of regressing fund net inflow on macro-risk betas and the interaction term between macro-risk betas and investor sentiment, controlling for fund size, expenses, month fixed effects, and fund fixed effects. Panel B presents results of regressing the next-month fund returns on the macro-beta-predicted fund flows. The dependent variables are winsorized at 1% and 99% levels. t-statistics computed using standard errors clustered at the fund level are reported in parentheses. $*p<0.1$; $**p<0.05$; $***p<0.01$. The sample period is from January 1997 to December 2018.

Panel A: sentiment-dependent relation between mutual funds' net inflow and macro-risk betas

	(1) CON	(2) TFP	(3) IPG	(4) TERM	(5) DEF	(6) UI	(7) DEI	(8) VOL	(9) MKT	(10) LAB	(11) AVE
β	-0.034**	0.042***	0.053***	0.088***	0.015	0.011	0.010	-0.106***	0.007	-0.013	0.009
	(-1.98)	(2.65)	(3.09)	(4.54)	(0.89)	(0.65)	(0.63)	(-3.33)	(0.35)	(-0.73)	(1.58)
$\beta\times$Sentiment	0.286***	0.453***	0.206***	0.306***	0.369***	0.134***	0.117***	0.424***	0.320***	0.350***	0.276***
	(10.79)	(17.30)	(7.28)	(11.47)	(12.34)	(5.15)	(4.28)	(15.14)	(11.24)	(12.62)	(15.71)
Fund size	-0.337***	-0.367***	-0.344***	-0.340***	-0.346***	-0.331***	-0.331***	-0.353***	-0.332***	-0.350***	-0.342***
	(-10.58)	(-11.54)	(-10.79)	(-10.70)	(-10.92)	(-10.40)	(-10.35)	(-11.01)	(-10.47)	(-11.06)	(-10.78)
Expenses	-164.868***	-163.120***	-164.204***	-160.502***	-161.625***	-163.063***	-162.678***	-162.698***	-164.284***	-162.260***	-164.441***
	(-8.85)	(-8.80)	(-8.92)	(-8.68)	(-8.66)	(-8.81)	(-8.79)	(-8.70)	(-8.80)	(-8.72)	(-8.79)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MF FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.323	0.328	0.323	0.325	0.325	0.321	0.321	0.327	0.324	0.325	0.329
Observations	502,654	502,654	502,654	502,654	502,654	502,654	502,654	502,654	502,654	502,654	5,022,440

Panel B: macro-beta-sensitive net inflow and fund returns

	(1) CON	(2) TFP	(3) IPG	(4) TERM	(5) DEF	(6) UI	(7) DEI	(8) VOL	(9) MKT	(10) LAB	(11) AVE
$\widehat{\text{Fundflow}}$	-1.085***	-0.705***	-1.064***	-0.368***	-0.756***	-0.875***	-0.286**	-1.184***	-1.016***	-1.211***	-0.919***
	(-23.80)	(-18.92)	(-16.59)	(-8.59)	(-19.11)	(-7.70)	(-2.34)	(-32.76)	(-23.19)	(-30.09)	(-29.37)
Fund size	-0.249***	-0.232***	-0.242***	-0.257***	-0.246***	-0.256***	-0.260***	-0.228***	-0.254***	-0.230***	-0.246***
	(-25.56)	(-23.34)	(-25.98)	(-25.50)	(-25.82)	(-26.05)	(-25.87)	(-23.73)	(-25.69)	(-24.36)	(-25.67)
Expenses	-30.766***	-32.768***	-31.515***	-33.826***	-33.884***	-32.771***	-33.011***	-33.135***	-31.499***	-33.669***	-33.071***
	(-4.05)	(-4.17)	(-4.30)	(-4.40)	(-4.35)	(-4.28)	(-4.30)	(-4.22)	(-4.12)	(-4.32)	(-4.28)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MF FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.494	0.494	0.494	0.494	0.494	0.494	0.493	0.496	0.494	0.495	0.498
Observations	502,657	502,657	502,657	502,657	502,657	502,657	502,657	502,657	502,657	502,657	5,022,470

Appendix

A Mutual fund data

This appendix provides details of the mutual fund data construction. Monthly returns and fund characteristics for mutual funds are obtained from the Center for Research in Security Prices' (CRSP) Survivor-Bias-Free Mutual Fund Database. The quarterly and semi-annual stock positions of funds are sourced from the Thomson Reuters' Mutual Fund Holdings (formerly CDA/Spectrum S12) database. These two datasets are merged using the unique identifier WFICN, as found in the Wharton Research Data Services MFLINKS file. In alignment with prior literature (see, e.g., Kacperczyk, Sialm, and Zheng, 2008; Busse, Jiang, and Tang, 2021; Dong, Feng, and Sadka, 2019; Boguth and Simutin, 2018), our sample focuses on actively managed, diversified domestic equity mutual funds.

Following the existing literature, we screen for domestic equity mutual funds within the CRSP and Thomston Reuters mutual fund data. Initially, we eliminate all funds with "policy" variable in C & I, Bal, Bonds, Pfd, B & P, GS, MM and TFM, as suggested by Kacperczyk et al. (2008) and Evans (2010). After applying the "policy" filter, we include funds with Lipper Class set to EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE. If Lipper_Class is unavailable, we include funds that use Strategic Insight Objective Code in AGG, GMC, GRI, GRO, ING, SCG. In the absence of both Lipper Objective Code nor Strategic Insight Objectives, we refer to the Wiesenberger Fund Type Code and select funds with the following objectives: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. If none of the Lipper, Strategic Insight, or Wiesenberger Fund Type Codes are available and the fund maintains a CS policy (indicating that the fund predominantly holds common stocks), the fund is included. If the "policy" variable is not available in the previous step, we exclude funds that, on average, hold less than 80% in stocks, following Kacperczyk et al. (2008).

To address the incubation bias discussed in Evans (2010), we eliminate observations prior to the fund's inception date as reported in CRSP, following the methodology of Boguth and Simutin (2018). We exclude funds that hold fewer than 10 stocks and manage less than $10 million at each month, in line with Kacperczyk et al. (2008). For funds with multiple share classes, we remove duplicates and compute portfolio-level variables by aggregating across distinct share classes. We align the sample period with that of the hedge funds, resulting in a sample comprising 5,180 funds. Subsequently, we calculate measures of mutual fund macro-risk skills, as per Kacperczyk et al. (2014), leading to our final mutual fund sample that spans from January 1997 to December 2018 and includes 4,558 unique funds.

Table A1: Classification of Hedge Fund Styles

This table showcases various classification schemes for hedge fund investment styles and the number of funds within each category. The first two columns display the Lipper TASS strategy classifications. Columns three to five exhibit the hedge fund style classification employed in the main analysis of this paper. The remaining columns illustrate the hedge fund style classification used in robustness tests: the sixth column presents the classification of equity-oriented hedge funds as defined by Agarwal and Naik (2004), while the seventh column demonstrates the classification of equity-oriented hedge funds according to Agarwal et al. (2017).

Primary Category	No. of funds	Equity HF	Non-equity HF	FoF	Equity-oriented (2004)	Equity-oriented (2017)
Convertible Arbitrage	215		✓			
Dedicated Short Bias	45	✓			✓	✓
Emerging Markets	715		✓			✓
Equity Market Neutral	379	✓			✓	✓
Event Driven	649		✓		✓	✓
Fixed Income Arbitrage	236		✓			
Fund of Funds	2,471			✓		
Global Macro	437		✓			
Long/Short Equity Hedge	2,429	✓			✓	✓
Managed Futures	7		✓			
Multi-Strategy	648		✓			
Options Strategy	43		✓			
Other	403		✓			
Undefined	11		✓			
Total	8,688	2,853	3,364	2,471	3,717	4,217

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