The Performance of Asset Allocation Mutual Funds

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Abstract:

We analyze the performance of asset allocation funds using a best-fit multifactor model that includes both stock and bond market factors. Utilizing large samples of allocation funds from both the US and the UK, we find that, on average, asset allocation funds do not outperform their benchmarks, and there is little or weak evidence of performance persistence when examining both decile portfolios and small-size portfolios. However, asset allocation funds still demonstrate superior abilities. At the individual fund level, some funds exhibit significant positive alphas, stock market timing, and bond market timing in both the US and UK markets. Furthermore, we find that US allocation funds with low past maximum drawdowns (MDDs) outperform those with high past MDDs during periods of high stock market returns and high stock market volatility. In contrast, UK allocation funds with low past MDDs outperform those with high MDDs when bond market returns are high.

JEL Classification: G11, G12, G14, G23

Keywords: asset allocation fund, fund performance, market timing, maximum drawdown, performance persistence, bootstrap

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1 Introduction

This study examines the performance of asset allocation mutual funds. Asset allocation funds are also referred to as balanced, hybrid mutual, or multi-asset funds, as these funds combine stocks, bonds, and cash in their portfolios. Asset allocation funds have attracted relatively little attention in the literature on mutual fund performance studies. In contrast to traditional equity or bond funds, allocation funds have a wider variety of investment strategies, offering a mix of stocks and bonds to provide capital appreciation, income, diversification, or specific allocations to meet retirement objectives. Their sizeable bond holdings may offer some downside protection during financial market collapses. In 2021, asset allocation funds had total net assets of $1,869.70 billion, accounting for around 7% of US mutual fund net assets (Investment Company Institute 2022). At the same time, the Investment Association reports the assets under management by UK allocation funds totaled around £289.96 billion, representing approximately 16% of UK funds under management[1].

The performance of asset allocation funds is an important and interesting topic. Compared to traditional mutual funds, these funds claim to follow investment strategies utilizing sophisticated market timing or tactical asset allocation techniques to achieve high returns with lower volatility. Therefore, these funds serve as a good sample for testing the value of active management. In this study, we examine two samples of asset allocation funds from the US and the UK.

There is a small literature on the performance of US allocation funds (Comer 2006; Comer et al. 2009a; Comer et al. 2009b; Karoui 2013; Rodríguez 2015) and UK allocation funds (Clare et al. 2016). A possible reason for this may be the lack of a single benchmark for hybrid funds with time-varying weights and exposures. Another reason could be the challenge of estimating holding-based metrics due to the mix of bonds and

[1] UK funds under management data are available at the Investment Association. https://www.theia.org/industry-data/fund-statistics/funds-under-management/4.

stocks. Many previous studies of equity mutual fund performance include asset allocation funds as part of their overall fund sample. As a result, most studies either do not take into account the bond portion in their portfolio or include a limited number of bond indices that do not cover the wide range of bonds available in allocation funds.

Our article adds to the extant literature in many aspects. First, we propose extensions to the equity asset pricing models, which are appropriate to measure the performance of a fund that holds both stocks and bonds. Prior studies that examine the performance of allocation funds include these funds as part of the equity fund sample and apply asset-pricing models intended specifically for equity funds, even though allocation funds typically hold debt.

Next, based on the extended performance model, we estimate the abnormal return of asset allocation funds. We also evaluate the market timing performance since these funds also engage in market timing. We apply both Treynor and Mazuy (1966) (Henceforth, TM) and Henriksson and Merton (1981) (Henceforth, HM) methods to examine the stock and bond market timing ability of asset allocation funds. Then, we analyze funds' ability to handle downside risk based on their maximum drawdown (MDD) under different market conditions. Overall, these results should provide insight into whether the asset allocation can deliver better returns and/or lower losses.

After examining the ex-post performance of funds, we estimate the performance persistence of asset allocation funds using the recursive portfolio approach (Carhart 1997). Apart from reporting results for traditional decile portfolios, we test performance persistence among smaller portfolios of funds within the tail of the top decile. Following Cuthbertson et al. (2022), we construct a new nonparametric performance persistence test statistic using a bootstrap procedure, which is essential to control for non-normality in fund returns.

Our study is the first that systematically examines asset allocation funds' performance in terms of abnormal return, market timing, maximum drawdown, and performance persistence in both regions. The empirical results are robust with respect to various performance models, different market timing tests, different holding and formation periods, small versus decile persistence portfolios, and the bootstrap methodology.

Our results show that both US and UK allocation funds do not outperform their benchmarks on average. An equal-weighted portfolio of US and UK allocation funds exhibits negative annualized alphas of -1.23% and -0.68%, respectively. At the individual funds level, we find a small number of funds show positive and statistically significant alphas for both US and UK funds (around 1.5 % and 2.5%, respectively). In terms of market timing, UK and US funds show negative stock market timing on average. However, UK allocation funds show positive bond market timing while US funds do not. At the individual fund level, we find a range of funds with significant positive stock market timing and bond market timing coefficients. For example, using the TM model, 1.54% and 7.51% of US funds demonstrate positive and significant stock and bond market timing coefficients, respectively. For UK funds, 1.81% of funds show positive and significant stock market timing coefficients while 17.75% of funds exhibit positive and significant bond market timing.

We then form decile portfolios based on the funds' past MDDs and split portfolio returns into subsamples based on various market conditions. For US funds, we find that funds with low past MDDs tend to outperform funds with high past MDDs during periods of high stock market returns, high stock market volatility, and economic downturns. For UK funds, we only find evidence that funds with low past MDDs outperform funds with high MDDs when the bond market return is high. In terms of performance persistence, for the US asset allocation fund, there is little evidence of positive performance persistence for decile portfolios and small-size portfolios. The alphas of small-size portfolios are positive but not significant. We find weak evidence that small-size portfolios show performance persistence in UK allocation funds. For example, the annualized alpha of the top 2 funds portfolio is around 2.31% when we recursively form the portfolio based on the past 36-month return and hold it for one month.

The paper is organized as follows: Section 2 reviews recent related literature. Section 3 describes the empirical models used to measure abnormal performance, market timing, MDD, and performance persistence. Empirical data of our fund sample and related factors are presented in Section 4. Section 5 presents the empirical results, and Section 6 provides the robustness tests. We conclude in Section 7.

2 Related Literature

2.1 Abnormal return and performance persistence

There are fewer studies of allocation fund performance compared to studies of equity funds and studies of bond funds despite their rising importance in investor portfolios. Studies of allocation mutual funds closely resemble those of equity and bond funds in terms of evaluating risk-adjusted performance. The small number of asset allocation studies indicates a negative abnormal performance relative to benchmarks on average (Comer et al. 2009b; Comer et al. 2009a; Herrmann and Scholz 2013).

Using daily return data, Comer et al. (2009a) apply two extensions of the Carhart (1997) model to measure the performance of allocation funds that hold stocks and bonds. They find that the extended forms of the model, which incorporate a fully defined bond index model for the fund's bond component, exhibit significant negative alphas. Using similar benchmark models that incorporate different bond indices and stock risk factors, Ayadi et al. (2016) also find negative alpha for Canadian hybrid funds after fees.

Herrmann and Scholz (2013) use an innovative approach to measure quarterly total fund performance where fund returns are compared with ex-ante investable benchmarks. The empirical results indicate that these funds do not outperform their benchmarks on average. A portfolio of all hybrid funds exhibits negative and significant alpha. More than 80% of individual funds show negative alphas, although a few show positive and significant alphas.

Comer et al. (2009b) introduce monthly attribution returns to test an individual investor's preferred investment strategy. A fund's attribution return is calculated by subtracting the actual return from the indexing strategy that best reflects the fund's monthly portfolio strategy. A positive attribution return shows that the fund manager adds value by choosing specific assets or asset classes that beat the fund benchmark in effect from the previous month. They find that, as a group, hybrid funds do not add value based on a negative average attribution return.

Fund holdings are also used to test whether mutual fund managers have superior stock selection abilities that generate abnormal returns. For example, Grinblatt and Titman (1989) use the portfolio holdings of a large sample of mutual funds to construct hypothetical mutual fund returns. Using asset allocation fund holdings, Karoui (2013) further explores the impact of the stock return and bond return on changes in asset allocation across stocks, bonds, and cash. The author finds stock allocation is positively related to past stock returns and negatively related to bond returns, while bond allocation is negatively correlated to lagged stock and bond returns.

A particularly under-explored question in the asset allocation fund industry is whether past relative performance can help to predict future relative performance, i.e., the question of persistence. Herrmann and Scholz (2013) test whether the performance of individual hybrid funds persists over time using the cross-sectional regression approach of Fama and MacBeth (1973). Their results indicate that total performance and alpha are persistent only in the short term.

2.2 Market timing and MDD

A further dimension of mutual fund performance is that of market timing ability. Most studies of the market timing ability of mutual fund managers infer the ability either from fund returns (Treynor and Mazuy 1966; Henriksson and Merton 1981; Bollen and Busse 2001; Jiang 2003; Chen and Liang 2007; Clare et al. 2019; Chen et al. 2010) or fund holdings (Graham and Harvey 1996; Jiang et al. 2007; Cici and Gibson 2012; Huang and Wang 2014; Moneta 2015; Clare et al. 2016).

The holding-based methods measure whether money managers successfully allocate monies between different asset classes (for instance, equity versus cash) in order to profit from rising markets or avoid downturns. Observing mutual fund portfolio composition at the same frequency as returns would enable us to determine whether portfolio holdings anticipate market movements and determine how the funds time the market. For example, Daniel et al. (1997) use mutual fund holdings data to separate mutual funds' performance based on selections, i.e., characteristics selectivity (CS) and market timing, i.e., characteristics timing (CT). A fund's beta is calculated as a weighted average of the betas of individual securities held in a fund at the beginning of a holding period. The covariance between the fund betas and market returns during the holding period is tested. This approach does not rely on ex-post realized returns. Using this approach, Clare et al. (2016) test the market timing ability of allocation funds across the US, UK, and Canada. They find evidence of market timing ability for a tiny minority of funds. The US and UK funds show little evidence of positive equity timing but greater evidence of government bond market timing, and the Canadian asset allocation funds show a comparatively higher ability to time the equity market.

Data on changes in portfolio holdings and complete fund composition are less available in academic studies, especially in early studies. Therefore, the majority of market timing research infers timing performance using the return-based methods, which only require data on the ex-post returns of funds and benchmark portfolios. Prior studies generally add a term to standard factor regressions to capture the convexity of fund returns caused by market timing. These methods were pioneered by Treynor and Mazuy (1966) and Henriksson and Merton (1981).

Comer (2006) extends the TM model to incorporate timing variables for both bonds and stocks in the fund since the portfolio shifts assets across multiple asset categories and provides some evidence of stock timing ability for a fund sample between 1992 and 2000.[2] Using a similar approach, Rodríguez (2008) examines the stock market timing ability of global asset allocation funds. The results indicate poor stock market timing abilities when the model controls for fixed-income securities. Rodríguez (2015) further examines the market timing ability in both stock and bond markets using the sample of hybrid funds and hybrid funds of funds (FOFs). The author finds evidence of negative timing ability in both types of funds in both markets.

[2] Comer (2006) focuses on analysing the stock market timing ability of allocation funds, although they incorporate a term to capture bond market timing ability.

The market timing ability measures whether an asset allocation fund is capable of generating better returns during good times and reducing losses during bad times. In practice, investors focus more on downside risk and use the fund's MDD as a measure of fund performance relative to downside risk. The MDD represents the greatest decline in a fund's value from peak to trough in a given period. Riley and Yan (2022) find that maximum drawdown plays an important role in predicting fund performance in the equity fund industry. Low MDD funds with relatively strong past performance, on average, generate an out-of-sample alpha of 2.40% per year. As part of this study, we comprehensively evaluate this standard industry metric under different market conditions.

3 Methodology

3.1 Performance model

This section discusses the model used for the return-generating process of asset allocation funds. Since stocks, bonds, and cash assets play a significant role in the portfolios of hybrid funds, we need to capture the various investment choices that managers face. On the basis of the previous section, we define the multifactor model that represents the expected excess return for an asset allocation fund:

$$r_{i,t} = \alpha_{i,t} + \sum_{j=1}^{n} \beta_{j,t} f_{j,t} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ represents the excess return of fund i in month t. $f_{j,t}$ represents the (excess) return of factor (including stock and bond factors) j in month t. n is the total number of factors employed. The alpha $\alpha_{i,t}$ is usually interpreted as the abnormal performance earned by a fund manager in month t.

The empirical literature has not fully exploited multifactor models when it comes to examining the performance of hybrid mutual funds. Therefore, for robustness, we form several multifactor models using the various combinations of stock factor models and bond factor/index models. For a complete discussion of these factors, see the Online Appendix. Each model is estimated for individual allocation funds, and results are then averaged cross-sectionally across funds to select a "best-fit" model. This model is used in the subsequent market timing test and performance persistence analysis.

3.2 Market timing

Using the "best-fit" model from the previous subsection, we derive two appropriate tests to measure the market timing ability of allocation funds. These two models are based on Treynor and Mazuy (1966) and Henriksson and Merton (1981).

The multifactor TM model is represented by

$$r_{i,t} = \alpha_i + \sum_{j=1}^{n} \beta_{j,t} f_{j,t} + \theta_{1,t} r_{sm,t}^2 + \theta_{2,t} r_{bm,t}^2 + \varepsilon_{i,t} \tag{2}$$

where $r_{sm,t}$ and $r_{bm,t}$ are the excess return on the stock market index and bond market index, receptively.

The multifactor HM model for asset allocation funds is:

$$r_{i,t} = \alpha_i + \sum_{j=1}^{n} \beta_{j,t} f_{j,t} + \theta_{1,t} \left[r_{sm,t}\right]^+ + \theta_{2,t} \left[r_{bm,t}\right]^+ + \varepsilon_{i,t} \tag{3}$$

The $\left[r_{sm,t}\right]^+$ is equal to $\max(0, r_{sm,t})$ and $\left[r_{bm,t}\right]^+$ is equal to $\max(0, r_{bm,t})$.

In these two models, $\theta_{1,t}$ and $\theta_{2,t}$ measure market timing ability for stock and bond markets, respectively. A significant and positive coefficient indicates successful market timing.

3.3 Maximum drawdown

The maximum drawdown is quoted as the percentage difference between the peak and the trough over a specific period. We measure MDD between time t_1 and time t_2 as:

$$MDD = \frac{V_p - V_t}{V_p} \tag{4}$$

Where the V_p and V_t are the peak value and trough value of mutual funds, respectively. We calculate the MDD of each fund over the past 6 months.

We use a portfolio-sort approach to form decile portfolios based on funds' average past MDDs. At the beginning of month t, we rank funds according to the average MDDs across funds over the previous 36-month horizon and form equal-weighted decile portfolios based on rank. Decile 1 (10) contains funds with the low (high) MDDs. The monthly excess returns of the portfolios over the next year are computed after which we roll the process by one year. We also calculate the return of the long-short portfolio, i.e., Decile 1- 10.

Using the portfolios formed by past MDDs, we further explore the relationship between MDDs and market conditions. We measure the market conditions using the following variables: (i) stock market return, (ii) stock market volatility, (iii) GDP growth rate, and (iv) bond market return.

We use the market condition variables to sort our sample months and create subsamples of quintiles within each decile portfolio as well as the long-short portfolio. For example, when we use the stock market return as a market condition variable, within each decile portfolio, the lowest quintile (quintile 1) contains periods of low stock market returns while the highest quintile (quintile 5) covers periods of high market returns. Then, we estimate the performance of those quintile portfolios. The alphas of long-short quintile portfolios are also reported. Here, we hypothesize that the performance of mutual funds with low MDDs outperforms those with high MDDs.

3.4 Persistence bootstrap procedure

We apply the recursive portfolio formation approach of Carhart (1997) to examine the performance persistence of asset allocation funds, which could reveal the economic significance of persistence in addition to statistical predictability. This approach could determine if a certain ex-ante technique would have been successful for investors switching between funds. Given the non-normality in the residuals of our factor models, we use a new bootstrap procedure to test for persistence in alpha performance following Cuthbertson et al. (2022). This methodology works well for those funds in the extreme tail of the performance distribution where non-normality is greatest. The bootstrap p-values are then used to analyze the performance persistence of top decile and small-size portfolios in Section 5. The details of the bootstrap procedure are described in the Appendix. A key advantage is that our approach does not assume the estimated alpha for each fund is normally distributed. A fund's alpha can follow any distribution depending on the fund's residuals, and its distribution can vary from fund to fund.

4 Data

4.1 Fund data

Our mutual fund data for US and UK funds is from Morningstar[3]. We select the oldest share class of each fund. Duplicate funds are removed by carefully examining any merged, split, or combined funds. Fund returns are the total monthly return net of management fees but gross of income tax to account for differences in tax treatment across regions. We dismiss Target Date funds with predetermined investment targets for retirement or other goals.

Table 1 provides summary statistics on the main fund attributes. Our US sample initially includes 2,904 US funds with 546,172 fund-month observations. The US data covers the period from January 1990 to September 2021. The number of funds ranges from 299 funds (January 1990) to 1,372 (September 2021). Our UK sample initially includes 1,326 funds with 126,015 fund-month observations. The UK data covers the period from January 1998 to December 2017. The number of funds ranges from 117 funds (January 1998) to 928 (December 2017). Using Morningstar global categories, we identified five broad asset allocation categories in the US and UK: Cautious Allocation, Moderate Allocation, Aggressive Allocation, Flexible Allocation, and Allocation Miscellaneous. We only include funds with a minimum of 36 observations in our following analysis. Finally, our mutual fund data set comprises 572 US asset allocation funds and 276 UK asset allocation funds.

[3] In April 2013, Morningstar renamed its balanced fund category to asset allocation funds.

We also report summary statistics on fund total net assets (TNA), shares outstanding, age, expenses, turnover, and mean returns in Table 1. The average TNA of US and UK allocation funds are 578.69 million dollars and 50.74 million pounds, respectively. UK allocation funds have a higher net expense ratio, turnover ratio, and management fees than US allocation funds, while US allocation funds have longer fund age and average manager tenure than their UK peers. Both US and UK funds have similar average monthly returns, around 0.62%.

[Table 1 here]

Funds' maximum drawdown is obtained from Morningstar Direct, which could provide drawdowns for any horizon, such as 3-month, 6-month, 12-month, and 24-month. We use the following variables to measure US market conditions: (i) the stock market factor from the French Data Library[4] to measure stock market return, (ii) the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) to measure stock market volatility, obtained from the Federal Reserve Bank of St. Louis, (iii) the US Quarterly GDP growth rate to measure economic growth, and (iv) the Bloomberg US Aggregate Bond Index to measure bond market return.

The UK market condition variables and their data source are described below: (i) UK stock market factor from the University of Exeter Business School[5], (ii) stock market volatility based on Busse (1999), which is calculated as the monthly standard deviation of excess return on the FTSE All Share Index (from Datastream). (iii) the UK quarterly GDP growth rate, and (iv) the ICE BofA Sterling Broad Market Index to measure the bond market return.

4.2 Factor models

Our factor model combines various stock and bond factors to measure asset allocation fund performance. For a complete discussion of these factors, see the Online Appendix.

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[4] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[5] Available at http://business-school.exeter.ac.uk/about/departments/accounting-finance/famafrench/

The selected stock market models are the CAPM, 3-factor model (Fama and French 1993), 4-factor model (Carhart 1997), 5-factor model (Fama and French 2015), and 6-factor model (Fama and French 2018). We capture investment in the bond market by adding different bond risk factors or bond indices to the stock market factors. These models include (i) single factor model, which is the excess return of the bond market portfolio, (ii) 2-factor model (Fama and French 1993), (iii) 4-factor model (Elton et al. 1995), (iv) 3-index model (Blake et al. 1993), (v) 4-index model (Comer 2006), (vi) 4-index (sector) model (Comer et al. 2009a) (vii) 4-index (maturity) model (Comer et al. 2009a), and (viii) 5-index model (Comer et al. 2009b).

Table 2 Panel A provides definitions of all the stock factors, bond factors, and bond indices used in our US study. For US allocation funds, the selected stock market factors include the excess return of the market portfolio, size, book-to-market, momentum, profitability, and investment factors. All these factors are sourced from the French Data Library. We capture investment in the bond market by adding different bond risk factors or bond indices to the stock market factors. These bond factors and indices include bond market excess return, term risk factor, default risk factor, option risk factor, high-yield index (HY), MBS index (MBS), government index (GOV), credit index (CREDIT), long government & credit index, intermediate government & credit index, high-quality index, low-quality index, long-maturity index, and short-maturity index. We calculate the excess returns of bond indices to be used in bond index models. All of the bond indices used in index models measure total returns. In total, there are 40 models to measure the performance of US asset allocation funds.

In Table 2, Panel B summarizes all the stock factors, bond factors, and bond indices used in our UK study. Due to the limited data availability, we have a small number of stock and bond factors in the UK sample. In total, we have 15 models to capture the return-generating process of UK asset allocation funds.

[Table 2 here]

5 Empirical Results

5.1 US results

5.1.1 Model selection

In this section, all equilibrium models described in Section 3 are examined using the US allocation funds over the period from January 1990 to September 2021. These results are reported in Table 3 for funds with a minimum of 36-month observations. For each model, cross-sectional average (across funds) t-statistics are calculated, and all tests are conducted at a 5% significance level (two-tail test) unless stated otherwise. We only report the top 8 models in Table 3, and other results are available on request. Based on the results, a best-fit model is chosen from all models.

[Table 3 here]

The results in Table 3 suggest that all models explain US allocation fund return data reasonably well with average adjusted R^2 above 0.87. The cross-sectional average alphas of all models take on small and statistically significant negative values.

For the stock factors, the market excess return ($\mathrm{r_{sm}}$) and size (SMB) factors are consistently found to be statistically significant across eight models, whereas book-to-market (HML) and profitability (RMW) factor betas are often statistically significant at a 10% significance level. The momentum (MOM) factor is statistically significant at a 10% level for some models (models 1, 5, and 8). The investment (CMA) factor beta is found to be statistically insignificant. For the bond factors, we find that the bond market excess return (r_{bm}), default risk factor (DEF), and the excess return of the high-yield index (HY) are statistically significant. In results not tabulated we find the term risk is insignificant when the bond market factor is also included in the model, which is consistent with the findings of Elton et al. (1995).

To keep the model parsimonious, we choose model 3 as the best-fit model, although model 8 has the lowest Akaike information criterion (AIC) and Schwarz information criterion (SIC) values. Nearly all betas (except for momentum and option risk) are significant at a 10% significance level in model 3, while three variables (CMA, GOV, and MBS) are insignificant at a 10% level in model 8. Another reason is that model 3 contributes to understating the sources of risks of allocation funds as all factors are bond risk factors rather than bond indices.

In model 3, the average alpha of individual funds is -0.133% and the average cross-sectional (absolute) t-statistic of alpha is t = 2.238. Forming the equal-weighted portfolio of allocation funds yields also a statistically negative alpha of -0.103% (t = -4.593). Overall, asset allocation funds do not outperform market benchmarks on average, similar to earlier research on allocation funds (Comer et al., 2009a, 2009b; Herrmann and Scholz, 2013). The negative alpha of asset allocation funds aligns with the evidence that equity mutual funds, on average, underperform in terms of net alpha (Grinblatt and Titman 1989; Elton et al. 1993; Kosowski et al. 2006). Turning now to diagnostics, the average adjusted R^2 of model 3 is 0.883, while around 76% of funds have non-normal errors (Jarque-Bera statistic), and approximately 20% of funds exhibit serial correlation (which is the first-order LM test).

5.1.2 Abnormal return

In this section, we analyze the performance of individual allocation funds over the full data period January 1990 – September 2021 using the best-fit multifactor model (model 3 in Table 3). This model allows us to calculate multifactor alphas and provides additional information about the drivers of the returns generated by asset allocation fund managers.

Table 4 provides results for individual funds at various points in the cross-section of the performance distribution based on the t-statistic of alpha (ranging from low to high). The results indicate only the top 8 funds demonstrate statistically significant positive alpha at a 5% significance level under the null hypothesis of no abnormal performance. Around 90% of funds demonstrate negative alpha (60% are statistically significant).

The stock market, r_{sm}, and bond market factor, r_{bm}, exhibit strong statistical significance for individual funds. Specifically, 99.2% and 86.7% of funds show positive and statistically significant betas for stock and bond factors, respectively. The HML risk factor plays a more important role in stock returns than the SMB and MOM risk factors, where 44.7% of funds show positive and significant coefficients for the HML factor (compared with 16.2% for the SMB factor and 26.4% for the MOM factor). For the bond portion, there is some evidence that the default risk factor has a stronger role to play in fund returns compared to the option risk, where 65.9% of these funds have positive and significant loadings (betas) on default risk while 1.9% of funds show significant positive betas for option risk.

[Table 4 here]

Overall, we find little evidence that asset allocation funds show abnormal performance. Only 1.5% of funds show positive and significant alpha after controlling for additional explanatory risk factors. Most recent studies (Kosowski et al. 2006; Barras et al. 2010; Fama and French 2010) find similar evidence for equity mutual funds. Barras et al. (2010) find that the proportion of truly positive-alpha US equity funds has declined since the mid-1990s, while the proportion of statistically significant negative net-alpha funds has increased.

5.1.3 Market timing

This section examines the allocation funds' ability to time the market return. We examine whether allocation fund managers predict market fluctuations to increase (decrease) their fund's market exposure in advance of higher (lower) market returns. We adopt the testing methods originally proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981) augmented by additional risk factors (model 3 Table 3). In these models, a positive and significant value of the timing coefficient indicates that the manager has timing ability, i.e., increasing (reducing) exposure to market risk as the market return rises (falls).

[Table 5 here]

Panel A of Table 5 presents our findings on stock market timing ability. We find that a small number of funds have stock market timing ability. Using the TM (HM) test, under the column heading "All", 1.54% (1.92%) of funds show significant positive stock market timing, while 41.04% (33.71%) of funds demonstrate significant negative market timing. In both TM and HM tests, the average timing coefficients, θ_1, are negative, indicating that, on average, the stock market timing decisions of managers tend to subtract rather than add value for investors. The percentage of significant positive stock market timers is less than the percentage of significant negative ones in both TM and HM measures. In terms of analysis by fund type categories, Flexible Allocation (FA) funds demonstrate the strongest stock market timing ability, where about 5% of these funds show significant positive market timing skills. The negative timing ability of the stock market is consistent with the evidence of perverse stock market timing ability of equity funds[6].

Panel B of Table 5 shows the results on bond market timing ability. There is some evidence that a number of asset allocation fund managers successfully time the bond market. Using the TM (HM) test under the column heading "All", 7.51% (5.00%) of funds show significant positive bond market timing, while 7.12% (5.78%) of funds demonstrate significant negative market timing. The cross-sectional averages of the timing coefficients, θ_2, are negative in both TM and HM tests, suggesting allocation fund managers negatively time the bond market on average. The negative performance of bond market timing is consistent with the finding of Boney (2009) for US corporate bond funds. There is evidence that some Cautious Allocation (CA) and Flexible Allocation (FA) funds are able to time aggregate bond market fluctuations, where 7.93% (5.55%) of Cautious Allocation funds and 10.52% (5.26%) of Flexible Allocation have positive and statistically significant bond timing coefficients in TM (HM) measure.

Overall, we find evidence of only a minority of funds with market timing ability. There is more evidence of bond market timing than stock market timing for asset allocation funds at the individual fund level. On average, the evidence suggests that market timing within the US asset allocation mutual fund industry has generally detracted value from fund performance over time.

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[6] Studies that find no or negative timing abilities of equity mutual funds include Treynor and Mazuy (1966), Henriksson and Merton (1981), Chang and Lewellen (1984), Ferson and Schadt (1996), Graham and Harvey (1996), Becker et al. (1999), Jiang (2003), and Elton et al. (2012).

5.1.4 Maximum drawdown analysis

In order to perform MDD analysis, we first need to consider the size of MDDs in our sample. Figure 1 plots the average maximum drawdown in each month for the full sample of mutual funds and subsamples of allocation funds based on the investment style. As expected, there are significant fluctuations in the average maximum drawdown from 1990 to 2021 for the US sample. Full sample averages range from 2.12% in August 2015 to 24.33% in February 2009. There are also significant fluctuations between styles. The average maximum drawdown of aggressive funds is higher than other styles most of the time. For equity mutual funds, Riley and Yan (2022) find the average maximum drawdown ranges from 4.5% to 50.5% during the period from 1999 to 2019. Compared with equity mutual funds, US asset allocation funds demonstrate a lower average maximum drawdown.

[Figure 1 here]

We then explore the maximum drawdown during different market conditions. After sorting each decile portfolio into quintile portfolios based on market conditions, we estimate the alphas of those quintile portfolios and long-short spread portfolios. We report these results in Table 6, where Panels A, B, C, and D report the alphas of the high and low quintiles sorted by stock market return, stock market volatility, GDP growth rate, and bond market return, respectively. In Panels A and B, we find that low MDD funds outperform high MDD funds when the market return and market volatility are high. In panel A, during the periods of high stock market returns (Quintile 5), the monthly alpha of spread portfolios is 0.76% (t=2.06), while Panel B shows a statistically significant alpha of 0.32% (t = 2.18) for spread portfolio when the market volatilities are high (Quintile 5). Panel C suggests that low MDD funds could provide downside protection during the economic downturn. The low MDD funds outperform the high MDD funds during the low GDP growth rate periods. In Quintile 1, the alpha of the spread portfolio is 0.33% with a t-statistic of 3.07. In Panel D, there is little evidence of the outperformance of low MDD funds regardless of whether the bond market return is high or low.

[Table 6 here]

In summary, we find the low average MDD funds outperform high average MDD funds during the (i) high stock return periods, (ii) high stock market volatility periods, and (iii) economic downturn periods.

5.1.5 Performance persistence

This section reports performance persistence results for decile-sorted and small-size portfolios over the full data period from January 1990 to September 2021. Since persistence findings are sensitive to the length of the formation and holding periods, we report the results with various combinations of formation and holding periods for robustness.

Table 7 provides results for our best-fit model after sorting funds into deciles based on past t-alpha. We find no persistence for the top decile portfolio for all combinations of (f, h), where f = portfolio formation period and h = portfolio holding period. Top decile portfolio alphas are insignificant by both conventional t-statistic (denoted "t-alpha") as well as by bootstrap p-value (denoted "p-value"). Only three decile portfolios exhibit positive alpha out of 10 combinations of (f, h). For a 3-year formation period and holding periods that are less than three months (h = 1, 2, 3), the forward-looking alphas of the top deciles are generally positive, although not statistically significant at a 5% significance level according to the t-statistics and bootstrap p-values. When we extend the formation period to 5 years, it is evident that all holding period alphas decline: all the top deciles alphas are negative and not significant. This indicates that over the sample period, following a strategy of investing in the past top-performing funds would not have yielded a positive holding period abnormal return. For the bottom decile, the holding period alphas are negative and statistically significant (using the standard t-test) for all combinations of formation and holding periods, indicating poor performance persistence at the bottom end of the performance distribution. Our results fail to provide evidence in support of the proposition that economically significant performance persistence exists for the top decile among US asset allocation mutual funds.

[Table 7 here]

Table 8 reports the results for portfolios of a small number of funds. We examine the persistence of performance within the tail of the top decile portfolios because it may be difficult to detect persistence in large decile portfolios. When sorting into small-size portfolios, there are 8 size portfolios x 10 combinations of (f, h), giving 80 combinations for the model. We see positive alphas (but not significant) across many combinations in the performance of small-size portfolios. It is evident that there are only a small number of combinations that show significant positive performance persistence. From the full set of combinations, only two combinations have positive and significant alpha at a 10% significance level according to the bootstrapped p-values. For a size-3 portfolio, (f, h) = (60, 6) and (f, h) = (60, 12) have statistically significant alphas of 0.11% and 0.16%, respectively, at the 10% level. Overall, there is little evidence of positive performance persistence for small-size portfolios.

[Table 8 here]

Herrmann and Scholz (2013) find that US allocation funds exhibit short-term persistence in abnormal performance. Compared with them, we find less evidence of performance persistence in the short term. Overall, we fail to find evidence of positive performance persistence for top decile portfolios. There is also little evidence that small-size portfolios have positive performance persistence that is not purely due to luck.

5.2 UK results

5.2.1 Model selection

In this section, the equilibrium models described in Section 3 are examined using the UK allocation funds over the period from January 1998 to December 2017. These results are reported for funds with a minimum of 36-month observations. For each model, cross-sectional average statistics are calculated, and all tests are conducted at a 5% significance level unless stated otherwise. We only report the top 8 models in Table 9, and other results are available on request. Based on the results, a best-fit model is chosen from all models.

The results in Table 9 suggest that all models explain UK allocation fund returns data reasonably well with average adjusted R^2 above 0.75. The cross-sectional average alphas of all models take on small negative values. For the stock factors, the market excess return (r_{sm}) and SMB factors are consistently found to be statistically significant across eight models, while HML and MOM betas are statistically insignificant at a 5% significance level. For the bond factors, we find that the bond market excess return (r_{bm}), and default risk factors (DEF) are statistically significant at a 10% significance level across models. In model 2 and model 6, the excess return of the high-yield index (HY) is statistically significant. The excess return of the credit index (CREDIT) is found to be statistically significant in model 4 and model 8. Similar to US results, we find the term risk factor is insignificant when the bond market factor is also included in the model (results are not tabulated in Table 9), which is consistent with the findings of Elton et al. (1995).

To keep the model parsimonious, we choose model 3 as the baseline model, although model 8 has the lowest Akaike information criterion (AIC) and Schwarz information criterion (SIC) values on average. Most variables are significant at a 10% significance level in model 3 except for HML and Option risk factor, while five variables are insignificant in model 8 (including HML, MOM, HY, MBS, and GOV). Another reason is that model 3 contributes to understating the sources of risks of allocation funds as all factors are risk factors rather than indices.

In model 3, the cross-sectional average alpha is -0.084% (t = 1.202). The alpha of the equal-weighted portfolio of allocation funds is -0.057% (t = -1.213). Overall, asset allocation funds do not outperform the market benchmark, similar to the negative performance of UK equity funds (Blake and Timmermann 1998; Cuthbertson et al. 2008). Turning now to diagnostics, the average adjusted R^2 of model 3 is 0.770, while around 54% of funds have non-normal error terms (Jarque-Bera statistic), and approximately 37% of funds have serial correlation (which is the first order LM test).

[Table 9 here]

5.2.2 Abnormal return

In this section, we analyze the performance of individual allocation funds over the full data period January 1998 – December 2017 using our baseline multifactor model (model 3 in Table 9). This model allows us to calculate multifactor alphas but also provides additional information about the drivers of the returns generated by asset allocation fund managers.

Table 10 provides results for individual funds at various points in the cross-section of performance ranging from lowest to highest t-statistic of alpha. The results indicate the top 7 funds demonstrate statistically significant positive alpha at a 5% significance level under the null hypothesis of no abnormal performance, comprising around 2.5% of the sample. The number of funds with positive alphas is greater than those with negative alphas, with around 32% of funds showing negative alpha (50 funds are statistically significant). Overall, there is evidence of positive alpha for top asset allocation funds.

[Table 10 here]

The stock market factor (r_{sm}) exhibits strong statistical significance for all individual allocation funds. Specifically, 97.5% of funds show positive and statistically significant betas for the stock market factor. The SMB risk factor plays a more important role in stock returns than the HML risk factor, where 40.6% of funds show positive and significant coefficients for the SMB factor (compared with 12.3% for the HML factor). For the bond portion, there is evidence that the bond market (r_{bm}) and default risk (DEF) factors have a strong role to play in fund returns compared to the option risk. A large number of funds exhibit statistically significant betas for the bond market factor (53.3%) and default risk factor (38.4%), while 1.8% of funds have significant positive betas for option risk.

Overall, we find some evidence that top asset allocation funds show abnormal performance. Broadly similar results of abnormal performance for top funds are found for UK equity funds. For example, Cuthbertson et al. (2008) find that a number of top equity funds (around 20) show positive alpha in the UK.

5.2.3 Market timing

We adopt testing methods originally proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981) augmented by additional risk factors (model 3 Table 9).

Panel A of Table 11 presents our findings on the UK stock market timing ability. In the TM and HM tests, the average timing coefficients, θ_1, are negative, suggesting allocation fund managers negatively time the stock market. The percentage of significant positive stock market timers is less than the percentage of significant negative ones in both TM and HM measures. More specifically, in the TM (HM) measure, 1.81% (1.08%) of funds show significant positive stock market timing, while 38.76% (39.13%) of funds demonstrate significant negative market timing. In terms of categories, Flexible Allocation funds (FA) demonstrate the strongest stock market timing ability in both TM and HM measures, where 4.76% of these funds show significant positive market timing skills. The finding of negative stock market timing ability is broadly consistent with the evidence that UK equity funds show negative market timing ability on average (Cuthbertson et al. 2010).

Panel B of Table 11 shows the results on bond market timing ability. There is evidence that asset allocation fund managers successfully time the bond market. The averages of the timing coefficients (θ_2) are positive for both TM and HM tests, suggesting allocation fund managers positively time the bond market on average. The percentage of funds found to significantly positively time the market is greater than the percentage found to significantly negatively time the market in both TM and HM measures. In terms of categories, Allocation Miscellaneous (AM) funds demonstrate the strongest bond market timing ability in the TM measure, while Moderate Allocation (MA) funds show the strongest significant positive market timing skills in the HM measure.

Overall, we find more evidence of bond market timing than stock market timing for UK asset allocation funds, which is consistent with the previous findings of Clare et al. (2016). On average, the bond market timing has generally added value for fund performance over time.

[Table 11 here]

5.2.4 Maximum drawdown analysis

To begin our maximum drawdown analysis in the UK, we look at its size within the sample. Figure 2 plots the average maximum drawdown in each month for the full sample of UK allocation funds and subsamples based on the investment style. There are significant fluctuations in the average maximum drawdown from 1998 to 2017 for the UK sample. Full sample averages range from 2.22% in November 2014 to 19.56% in November 2008. There are also significant fluctuations between styles. The average MDDs of aggressive and miscellaneous funds are higher than other styles most of the time.

We then sort UK allocation funds into decile portfolios and split these portfolios' returns into quintiles based on the market conditions. In Table 12, we report the alpha of these quintile portfolios with respect to different market conditions, including stock market return, stock market volatility, GDP growth rate, and bond market return. In Panel A, we do not find evidence that low MDD funds outperform high MDD funds either in low return periods or high return periods. Panel B suggests that low MDD funds underperform high MDD funds when stock market volatility is low. The alpha of the spread portfolio in the low stock market volatility period is -0.43% with a t-statistic of -4.43. In terms of GDP growth rate (Panel C), we find little evidence of the outperformance of low MDD funds compared to high MDD funds. Panel D shows that the low MDD decile outperforms the high MDD decile when the bond market return is high. During the high bond market return periods, the alphas (1.00%) of the spread portfolio is statistically significant at the 5% level (t =3.09). This result aligns with the evidence presented in Section 5.2.4 that UK allocation funds exhibit positive bond market timing on average.

[Table 12 here]

5.2.5 Performance persistence

In this section, we report performance persistence results for decile-sorted and small-size portfolios over the full data period from January 1998 to December 2017. The persistence findings are sensitive to the length of the formation and holding periods. Therefore, we report the results with various combinations of formation and holding periods.

Table 13 provides results for the best-fit model after sorting funds into deciles based on past t-alpha. From Table 13, we only find one top decile exhibits performance persistence over ten combinations of (f, h): for a 3-year formation period and a 6-month holding period (f, h) = (36, 6), the forward-looking alpha of the top decile is positive and statistically significant at a 10% significance level according to the t-value and bootstrap p-value. It is evident that the holding period alphas of the top deciles are positive for all combinations of (f, h). However, these forward-looking alphas are not significant.

There is poor performance persistence at the bottom end of the performance distribution. Past poor-performing allocation funds perform relatively poorly in the following period. For the bottom decile, the holding period alphas are negative and statistically significant at least at a 10% significance level (using the t-test) for all combinations of formation and holding periods.

[Table 13 here]

Table 14 reports the results for portfolios of a small number of funds. We examine the persistence of performance *within* the tail of the top decile portfolio, which may not be revealed in larger decile portfolios. Overall, we find some weak evidence of positive performance persistence for small-size portfolios. When sorting into small-size portfolios, there are 8-size portfolios x 10 combinations of (f, h), giving 80 combinations for the model. It is evident that there is a small number of combinations showing significant positive performance persistence. From the full set of combinations, there are 8 (11) positive and significant alphas at the 5% (10%) significance level. For example, for size-2 and size-3 portfolios, we see that for a 3-year formation period and holding periods less than six months (h = 1, 2, 3, 6), the forward-looking alphas are positive and statistically significant at a 5% significance level (using bootstrap p-value). However, considering that only size-2 and size-3 portfolios show significant positive persistence, our result is likely to show a false positive result since there are only a few funds selected from the entire sample for short-term periods.

[Table 14 here]

Overall, we find weak evidence that top decile and small-size portfolios show positive and significant alphas that are not purely due to luck. Compared with UK equity funds (Cuthbertson et al. 2023), we find less evidence of performance persistence for decile portfolios as well as small-size portfolios.

6 Robustness Tests

6.1 Market timing

In the previous section, we do not find evidence of stock market timing ability in both US and UK allocation funds. Then, we are interested in whether asset allocation funds use the stock market timing strategy. If asset allocation funds do time the stock market, fund managers would at least adjust their exposure based on the past stock market return (though it is public information). To answer this question, we create equally weighted portfolios of all funds and different styles and measure those portfolios' stock market betas over the previous 36 months recursively using the best-fit model. As a result, we obtain the time series of portfolios' stock market betas, which reflects those portfolios' sensitivity to the stock market and hence could be used as proxies for portfolios' stock allocation. We hypothesize that fund managers increase (decrease) their stock allocation after good (bad) equity market conditions.

We rely on the following regressions to test our hypotheses:

$$\Delta\beta = \beta_0 + \lambda_1 stock_{t-1} + \lambda_2 bond_{t-1} + \varepsilon_{i,t} \qquad (5)$$

Where $\Delta\beta$ is the beta difference between month t and $t-1$, and $stock_{t-1}$ and $bond_{t-1}$ are the stock and bond market returns at time $t-1$, respectively.

Table 15 exhibits the result of the regression. We find evidence that the stock allocation is positively correlated with lagged stock returns. For US funds, we find that Aggressive Allocation funds and Flexible Allocation funds show positive and significant (at the 10% level) coefficients of λ_1. For UK funds, we find more evidence of positive and significant coefficients, λ_1, of all funds, Cautious Allocation, Moderate Allocation, Aggressive

Allocation, and Flexible Allocation funds. These results suggest that both US and UK allocation funds use past stock returns to adjust their portfolios' exposure to the stock market, which supports our hypothesis that fund managers attempt to use the market timing strategy based on lagged stock market returns.

[Table 15 Here]

6.2 Further MDD analysis

To ensure that our MDD results are not sensitive to the length of MDD, we consider using alternative lengths of MDDs to re-run our analysis. We choose to use 3-month, 12-month, 18-month, and 24-month to check the robustness of our MDD results in Section 5.

Similarly, we sort funds into decile portfolios based on these alternative MDDs over the previous 36 months and hold these deciles for 12 months. After that, we roll the process by 12 months. We then split each decile into quintile portfolios based on the market conditions, such as stock market return, stock market volatility, GDP growth rate, and bond market return.

We estimate the out-of-sample alpha of these quintile portfolios. These results are broadly consistent with our findings in previous sections. To save space, these tables are not tabulated here and upon request. In general, for US funds, low MDD funds tend to outperform the high MDD funds when the market return and market volatility are high, and when the GDP growth rate is low. For UK funds, low MDD funds tend to outperform high MDD funds when the bond market return is high while low MDD funds underperform high MDD funds when the stock market volatility is low.

6.3 Performance persistence

To make sure that our persistence results are not driven by the performance model, We consider using the Comer et al. (2009a) 4-index (sector) model (model 8 in Table 3 and Table 9) to measure the performance persistence of both US and UK allocation funds.

In untabulated results, for US allocation funds, no top deciles show positive and significant alpha at the 5% level using t-statistics and bootstrap p-values, which is similar to the result from Table 7. We find similar evidence for small portfolios that only one combination, (f,h)= (60,6) for size-2 portfolio, has positive and statistically significant alpha at the 10% level (using bootstrap p-values).

For UK allocation funds, we find some weak evidence of performance persistence in decile portfolios and small-size portfolios. For a 3-year formation period and holding period up to three months (h) = (1, 2, 3), the forward-looking alphas of the top deciles are positive and statistically significant at a 5% significance level according to the t-values and the bootstrap p-values. We also find similar evidence of persistence for small portfolios of 2 funds or 3 funds. From the full set of combinations, five combinations have positive alpha at a 5% significance level according to the t-test and bootstrap p-values.

Overall, there is little evidence of performance persistence for US allocation funds. We find some evidence of performance persistence for UK allocations, but this evidence is weak.

7 Conclusion

In this study, we specifically focus on allocation funds that hold a substantial number of fixed-income securities within their portfolios. Despite their growth in popularity, the performance of these funds has received little attention in academic literature.

Using monthly return data on the US and UK asset allocation funds, we estimate ex-post performance using the best-fit model that we believe is appropriate to measure the performance of allocation funds that hold both stocks and bonds. We measure allocation fund performance from three perspectives: security selection, market timing, and maximum drawdown. Then, we examine whether abnormal performance can be identified ex-ante and how long it persists. We have examined the robustness of positive persistence in fund performance using the monthly data for different decile and size portfolios, formation and holding periods, and alternative performance models by a bootstrap procedure.

Using a comprehensive data set over the period 1990 to 2021, we first examine the ex-post performance of US asset allocation mutual funds. We find a small number of funds have security selection skills (positive alpha). As a group, asset allocation funds underperform the benchmarks. In terms of market timing, we find a small number of funds with stock and bond market timing at the individual fund level, and US asset allocation funds exhibit more bond market timing ability than stock market timing ability. The more prevalent bond market timing suggests it is easier to time the bond market movement. Overall, the evidence suggests that market timing within the US asset allocation mutual fund industry has generally detracted value from fund performance over time, which is consistent with previous US studies (Clare et al., 2016). We find that low MDD funds tend to outperform high MDD funds during periods of high stock market returns, high stock market volatility, and economic downturns. We examine the performance persistence using decile portfolios and small-size portfolios. It is difficult to find positive alpha persistence in funds for most combinations of formation and holding periods, no matter what model is used, which is broadly consistent with recent US empirical evidence (Herrmann and Scholz, 2013).

For UK allocation funds over the recent period 1998 to 2017, we find positive abnormal returns for top-performing funds. However, forming an equal-weighted portfolio of allocation funds yields a negative alpha. As a group, asset allocation funds do not outperform their benchmarks. We find more evidence of bond market timing rather than stock market timing for UK asset allocation funds, and fund managers positively time the bond market on average. In terms of maximum drawdown analysis, we only find low MDD funds outperform high MDD funds when the bond market return is high. After sorting funds into decile and small-size portfolios, there is weak evidence of positive persistence with statistically significant positive alphas for some combinations.

Overall, our results provide support for positive abnormal return, and market timing ability though only for a relatively small number of top asset allocation funds. The maximum drawdown analysis also suggests top funds with low MDDs (a signal of managerial skills) could provide better returns and/or downside protections. The overall result may help us understand why investors continue to seek to invest in top-performing funds despite the consensus that the fund industry as a whole underperforms and despite the wide availability of low-cost index funds.

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Statements and Declarations

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript.

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Appendices:

Appendix 1: Bootstrap procedure

The bootstrap procedure is described as follows. We consider the following model to estimate the abnormal return for each fund: $r_{i,t} = \alpha_{i,t} + \beta_i' F_t + \varepsilon_{i,t}$ [7], where β_i is a vector of factor loadings and F_t is a vector of selected risk factors. Using data on all individual fund return $r_{i,t}$ at time t, our first step is to estimate the alphas over the previous f-month formation period and form equally weighted portfolios based on the t-statistic of alpha. Here, the equally weighted portfolio could be the top decile portfolio or small-size portfolio. Each portfolio is held for h months, and the process is repeated every h months. Then, we obtain a time series of actual holding period return $r_{p,t} (t = 1, 2, 3 \ldots \mathrm{T})$ and estimate the t-statistic of alpha $\hat{t}_p$ for each portfolio from our factor model.

The next step is to simulate returns $\tilde{r}_{i,t}^{B=1} (i = 1, 2, 3 \ldots n, and\ t = 1, 2, 3 \ldots T_i)$ for each fund-i under the null hypothesis of zero alphas. First, we regress the factor model and save the vectors $\{\hat{\beta}_i, \varepsilon_{i,t}\}$ for each fund over the full sample period. Next, we bootstrap residuals $\tilde{\varepsilon}_{i,t}$ with replacement of length T_i to simulate the return series $\tilde{r}_{i,t}^{B=1}$ under the null hypothesis $\alpha_i = 0$ for fund-i, that is, $\tilde{r}_{i,t}^{B=1} = 0 + \hat{\beta}_i' F_t + \tilde{\varepsilon}_{i,t}$. As a result, the simulated returns for each fund-i have zero alphas and exhibit no alpha persistence.

Next, using the simulated returns data, we sort funds into a persistence portfolio with formation period f and roll over the portfolio every-h period, which generates a single

[7] Note that the equation is equal to $r_{i,t} = \alpha_{i,t} + \sum_{j=1}^{n} \beta_{\mathrm{j},t} f_{j,t} + \varepsilon_{i,t}$.

time series of simulated holding period returns $\tilde{r}_{p,t}^{B=1}(t = 1, 2, 3 \ldots T)$. For each portfolio, we estimate a simulated alpha $\tilde{\alpha}_p^{B=1}$ and t-statistic of alpha $\tilde{t}_p^{B=1}$ using our factor model. That is, we test the simulated returns data for persistence. By construction with zero alpha, the simulated alpha $\tilde{\alpha}_p^{B=1}$ represents sampling variation around a true alpha of zero and is entirely due to "luck". This process is repeated B=1000 times which gives a "luck distribution" $f(\tilde{t}_p)$ for each sorted persistence portfolio of funds under the null hypothesis of no alpha persistence.

Our bootstrap analysis mainly focuses on the luck distribution using the t-statistic of alpha as suggested by Kosowski et al. (2006) and Fama and French (2010) because the t-statistic of alpha controls for the difference in risk-taking across funds. If the t-statistic of alpha for a portfolio of funds is consistently higher than the corresponding bootstrap value, this portfolio is said to exhibit performance persistence that is not purely due to luck. We calculate the actual ex-post and bootstrap t-statistics using the Newey and West (1987) heteroscedasticity and autocorrelation adjusted standard errors. Bootstrap p-values are calculated as follows. We compare the actual t-statistic of alpha $\hat{t}_p$ from the actual returns with its "luck distribution" $f(\tilde{t}_p)$ from simulated returns. We reject the null of no performance persistence at a 95% confidence level if $\hat{t}_p$ is greater than the 5% upper tail cut-off point of $f(\tilde{t}_p)$, that is, the sorting rules give a true positive alpha persistence. Therefore, the distribution under the null hypothesis zero alpha-persistence $f(\tilde{t}_p)$, contained the luck distribution of each individual fund.

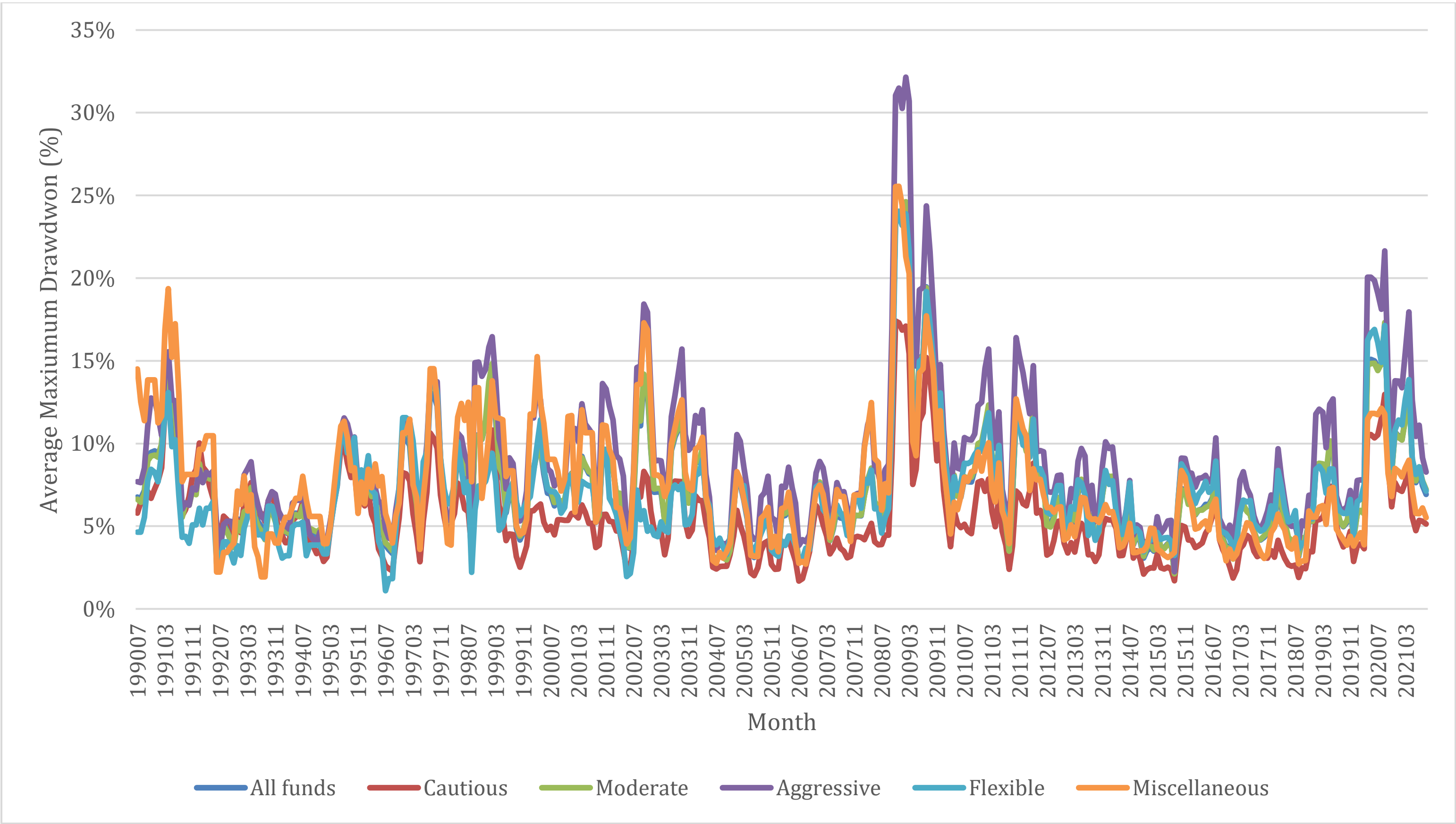

Figure 1 Maximum drawdowns of US allocation funds

This figure shows the average maximum drawdown for all US allocation funds in each month from July 1990 to March 2021. It also presents the averages for subsamples of cautious, moderate, aggressive, flexible and miscellaneous funds.

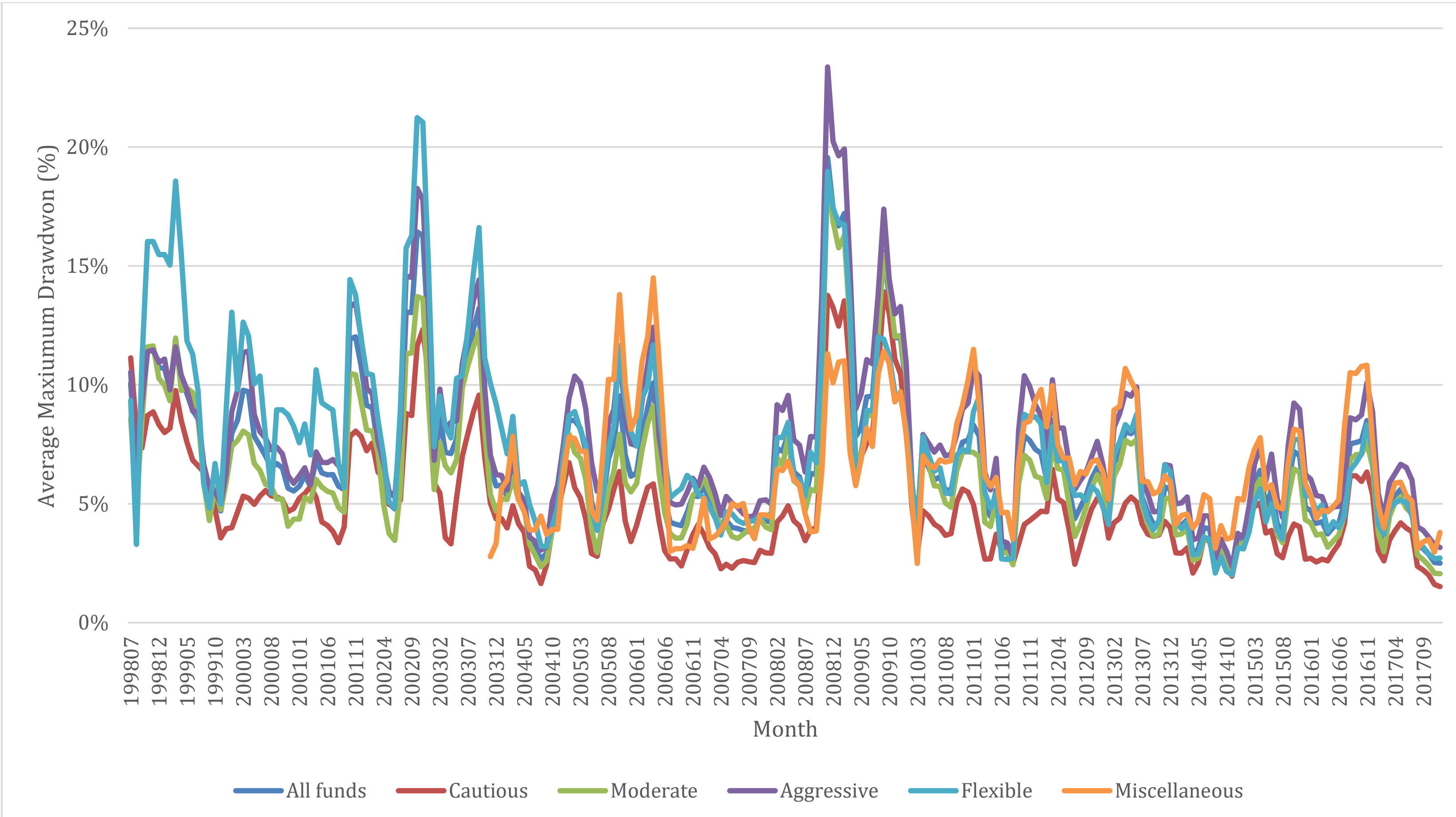

Figure 2 Maximum drawdowns of UK allocation funds

This figure shows the average maximum drawdown for all UK allocation funds in each month from July 1998 to September 2017. It also presents the averages for subsamples of cautious, moderate, aggressive, flexible and miscellaneous fun.

Table 1 Summary statistics of mutual funds

This table presents the summary statistics for the US and UK asset allocation funds. The US sample covers the period from January 1990 to September 2021, and the UK data covers the period from January 1998 to December 2017.

	Mean	Median	Standard deviation
Panel A: US Allocation Funds			
Number of distinct allocation funds	2,904		
Number of fund-month observation	546,172		
Number of funds per month	1,428	1,466	
Total net assets (in millions)	578.69	14.36	4,258.33
Shares outstanding (in millions)	74.22	0.81	754.87
Net asset value (in millions)	315.50	12.82	9,173.75
Annual net expense ratio(%)	0.95	0.88	0.64
Turnover ratio(%)	66.54	40.00	93.64
Age (in years)	15.67	16.00	9.44
Morningstar rating	3.29	3.00	1.08
Average manager tenure (in years)	7.13	6.71	4.12
Management fee(%)	0.40	0.30	0.35
Average monthly return (%)	0.62	0.96	2.67
Panel B: UK Allocation Funds			
Number of distinct allocation funds	1,326		
Number of fund-month observation	126,015		
Number of funds per month	525	550	
Total net assets (in millions)	50.74	4.22	212.61
Shares outstanding (in millions)	41.65	3.39	123.93
Net asset value (in millions)	3.91	1.30	16.27
Annual net expense ratio (%)	1.62	1.65	0.60
Turnover ratio (%)	89.43	55.00	129.16
Age (in years)	8.31	6.25	6.60
Morningstar rating	2.80	3.00	1.09
Average manager tenure (in years)	6.91	5.54	5.00
Management fee (%)	0.91	0.85	0.44
Average monthly return (%)	0.62	0.81	2.57

Table 2 Description of stock and bond factors and relevant data source

	Description	Data source
Panel A: US		
Risk-free rate	US one-month Treasury Bill rate	Kenneth R. French – Data Library
Stock market factor	The return on value-weighted market portfolio minus risk-free rate	Kenneth R. French – Data Library
Size factor (SMB)	The average return on diversified portfolios of small stocks minus the average return on diversified portfolios of big stocks	Kenneth R. French – Data Library
Book-to-market factor (HML)	The average return on diversified portfolios of value stocks minus the return on diversified portfolios of growth stocks	Kenneth R. French – Data Library
Momentum factor (MOM)	The average return on diversified portfolios of stocks with high prior returns minus the average return on diversified portfolios of stocks with low prior returns.	Kenneth R. French – Data Library
Profitability factor (RMW)	The average returns on diversified portfolios of stocks with robust profitability minus the average return on diversified portfolios of stocks with weak profitability	Kenneth R. French – Data Library
Investment factor (CMA)	The average returns on diversified portfolios of stocks with conservative investment minus the average return on diversified portfolios of stocks with aggressive investment	Kenneth R. French – Data Library
Bond market factor	Total return on the Bloomberg US Aggregate Bond Index minus risk-free rate	Morningstar
Term risk factor (TERM)	Total return on the Bloomberg US Government Long Index minus total return on the Bloomberg US Government Intermediate Index.	Morningstar
Default risk factor (DEF)	Total return on the Bloomberg US Corporate High-Yield Index minus the total return on the Bloomberg US Government Intermediate Index	Morningstar
Option risk factor (OPTION)	Total return on the Bloomberg US MBS Index minus the total return on the Bloomberg US Government Intermediate Index	Morningstar
High-Yield index (HY)	Total return on the Bloomberg US Corporate High-Yield Index minus risk-free rate	Morningstar
MBS index (MBS)	Total return on the Bloomberg US MBS Index minus risk-free rate	Morningstar
Government index (GOV)	Total return on the Bloomberg US Government Index minus risk-free rate	Morningstar
Credit index (CREDIT)	Total return on the Bloomberg US Credit Index minus risk-free rate	Morningstar
Long government & credit index	Total return on the Bloomberg US Government & Credit Long Index minus risk-free rate	Morningstar
Intermediate government & credit index	Total return on the Bloomberg US Government & Credit Intermediate Index minus risk-free rate	Morningstar
High-quality index	Total return on the Bloomberg US Government & Credit Index minus risk-free rate	Morningstar
Low-quality index	Total return on the Bloomberg US Corporate High-Yield Index minus risk-free rate	Morningstar
Long-maturity index	Total return on the Bloomberg US Government & Credit Long Index minus risk-free rate	Morningstar

Short-maturity index	Total return on the Bloomberg US Government & Credit 1-3 Years Index minus risk-free rate	Morningstar
Panel B: UK		
Risk-free rate	Monthly return on three-month UK Treasury Bills.	University of Exeter Business School
Stock Market factor	The return on value-weighted market portfolio minus risk-free rate	University of Exeter Business School
Size factor (SMB)	The average return on diversified portfolios of small stocks minus the average return on diversified portfolios of big stocks	University of Exeter Business School
Book-to-market factor (HML)	The average return on diversified portfolios of value stocks minus the return on diversified portfolios of growth stocks	University of Exeter Business School
Momentum factor (MOM)	The average return on diversified portfolios of stocks with high prior returns minus the average return on diversified portfolios of stocks with low prior returns.	University of Exeter Business School
Bond market factor	Total return on the ICE BofA Sterling Broad Market Index minus risk-free rate	Morningstar
Term risk factor (TERM)	Total return on the ICE BofA 10+ Years UK Gilt minus total return on the ICE BofA Sterling 1-10 years UK Gilt Index	Morningstar
Default risk factor (DEF)	Total return on the ICE BofA Sterling High-Yield Index minus total return on the ICE BofA Sterling 1-10 Years UK Gilt Index	Morningstar
Option risk factor (OPTION)	Total return on the IBoxx UK MBS Index minus total return on the ICE BofA Sterling 1-10 Years UK Gilt Index	Morningstar
High-Yield index (HY)	Total return on the ICE BofA Sterling High-Yield Index minus risk-free rate	Morningstar
MBS index (MBS)	Total return on the Markit iBoxx UK MBS Index minus risk-free rate	Morningstar
Government index (GOV)	Total return on the ICE BofA UK Gilt Index minus risk-free rate	Morningstar
Credit index (CREDIT)	Total return on the ICE BofA Sterling Non-Gilt Index minus risk-free rate	Morningstar

Table 3 US model selection: cross-sectional results of model estimates

The table shows results from estimating the various performance models using individual mutual funds. All betas shown are cross-sectional averages. T-statistics are reported in parentheses and are calculated as the cross-sectional averages of the absolute values of funds' t-statistics (Newey-West adjusted). The percentiles of adjusted R^2, Akaike information criterion (AIC), and Schwarz information criterion (SIC) are presented. The table shows statistics on the percentage of funds that reject the null hypothesis of no serial correlation in residuals at lag 1 to 6 (LM test) and reject normality in the residuals (Jarque-Bera test)-both at a 5% significance level. The table also shows alphas, adjusted R^2, AIC, SIC, Jarque-Beta test, and LM tests for equal-weighted portfolios of all mutual funds.

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Regression Coefficients								
Average Alpha	-0.130 (1.969)	-0.131 (2.180)	-0.132 (2.222)	-0.124 (2.127)	-0.134 (2.039)	-0.140 (2.292)	-0.140 (2.330)	-0.130 (2.206)
Stock Factor								
r_{sm}	0.602 (31.441)	0.550 (26.885)	0.549 (26.685)	0.547 (26.535)	0.603 (31.467)	0.555 (26.806)	0.554 (26.593)	0.552 (26.508)
SMB	0.012 (2.141)	-0.009 (2.157)	-0.008 (2.156)	-0.007 (2.160)	0.022 (2.149)	0.002 (2.025)	0.002 (2.025)	0.003 (2.051)
HML	0.038 (2.636)	0.037 (2.606)	0.037 (2.615)	0.038 (2.664)	0.035 (1.713)	0.029 (1.701)	0.030 (1.712)	0.034 (1.784)
MOM	-0.009 (1.773)	0.012 (1.596)	0.010 (1.590)	0.011 (1.601)	-0.009 (1.814)	0.010 (1.634)	0.010 (1.627)	0.010 (1.645)
RMW					0.011 (1.823)	0.017 (1.875)	0.016 (1.871)	0.013 (1.866)
CMA					-0.025 (1.583)	-0.001 (1.546)	-0.003 (1.522)	-0.010 (1.572)
Bond Factor								
r_{bm}	0.356 (5.558)	0.332 (2.616)	0.359 (6.449)		0.356 (5.682)	0.334 (2.717)	0.357 (6.522)	
DEF			0.136 (3.631)				0.133 (3.640)	
OPTION			-0.056 (0.822)				-0.057 (0.836)	
HY		0.142 (3.568)		0.105 (2.206)		0.139 (3.598)		0.100 (2.169)
MBS		-0.103 (0.930)		0.051 (0.920)		-0.106 (0.991)		0.056 (0.915)
GOV				-0.015 (1.267)				-0.019 (1.293)
CREDIT				0.196 (2.380)				0.198 (2.413)
Model Selection Criteria								
Adjusted R^2								
Min 1%	0.356	0.352	0.355	0.350	0.351	0.344	0.348	0.342
Min 5%	0.614	0.634	0.637	0.646	0.622	0.645	0.649	0.656

Min 10%	0.715	0.745	0.745	0.749	0.729	0.754	0.753	0.762
Min 25%	0.850	0.868	0.868	0.871	0.856	0.871	0.871	0.873
Median	0.911	0.924	0.924	0.926	0.913	0.927	0.927	0.929
Max 25%	0.942	0.951	0.950	0.953	0.945	0.952	0.953	0.955
Max 10%	0.960	0.969	0.969	0.970	0.963	0.971	0.970	0.971
Max 5%	0.969	0.974	0.973	0.974	0.970	0.975	0.974	0.976
Max 1%	0.978	0.982	0.982	0.983	0.978	0.982	0.982	0.983
Average	0.870	0.883	0.883	0.886	0.874	0.887	0.887	0.889
AIC								
Min 1%	71.50	55.93	51.92	57.42	65.93	48.46	51.86	57.07
Min 5%	156.84	131.10	133.82	122.57	154.50	132.22	132.29	122.41
Min 10%	200.51	172.21	173.66	175.07	194.80	170.45	171.64	173.00
Min 25%	353.11	312.33	313.63	306.63	352.31	306.62	309.30	305.30
Median	577.12	548.21	549.11	541.40	569.70	537.10	536.91	535.12
Max 25%	807.28	782.78	780.57	775.37	796.60	770.07	769.99	765.64
Max 10%	1024.73	998.98	999.09	985.81	1005.97	978.91	978.91	975.77
Max 5%	1179.88	1172.05	1171.93	1171.31	1176.68	1165.11	1165.84	1165.34
Max 1%	1474.59	1469.37	1467.20	1466.09	1469.25	1463.66	1461.34	1460.84
Average	604.61	574.54	574.64	570.65	597.26	567.46	567.71	563.69
SIC								
Min 1%	88.97	86.58	83.02	82.08	89.36	80.53	78.56	86.61
Min 5%	173.59	149.47	152.10	151.23	177.31	155.01	154.90	156.16
Min 10%	219.62	199.30	199.55	200.75	220.85	203.15	201.63	201.99
Min 25%	376.02	339.73	340.34	337.64	380.38	341.84	343.13	340.40
Median	600.70	578.02	578.67	575.64	601.18	574.00	574.20	575.43
Max 25%	832.44	817.21	814.55	811.64	831.42	811.56	811.23	807.31
Max 10%	1051.91	1034.15	1034.20	1025.24	1041.19	1018.07	1018.07	1020.03
Max 5%	1205.49	1206.51	1204.28	1207.25	1208.93	1208.28	1208.96	1211.09
Max 1%	1501.95	1504.55	1502.37	1505.17	1504.42	1506.65	1504.33	1507.73
Average	627.98	604.59	604.69	604.03	627.31	604.18	604.43	603.75
Normality and LM tests								
Rejection of Normality (% of funds)	83.2	76.3	75.9	71.7	81.7	74.0	72.4	71.5
LM (1) statistic (% of Funds)	36	20.4	20.2	17.5	32.2	19.3	20.6	16.8
LM (6) statistic (% of Funds)	29.9	24.7	25.2	27	28.7	24.5	25.4	27.4
Equal Weighted Portfolio								
Alpha	-0.094 (-3.406)	-0.097 (-4.257)	-0.103 (-4.593)	-0.091 (-4.273)	-0.106 (-3.780)	-0.110 (-4.727)	-0.116 (-5.017)	-0.104 (-4.793)
Adjusted R^2	0.975	0.980	0.980	0.982	0.975	0.980	0.981	0.982
JB(p)	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
LM (1) test	0.000	0.010	0.018	0.086	0.001	0.006	0.011	0.061
LM (6) test	0.025	0.247	0.042	0.010	0.015	0.031	0.042	0.012
AIC	436.91	346.93	345.34	320.02	434.11	342.80	341.84	316.78
SIC	464.51	382.41	380.83	359.45	469.60	386.18	385.21	364.09

Table 4 US allocation fund performance

This table shows results for selected points in the cross-sectional distribution of the full sample of asset allocation funds using the best-fit multifactor model. The first row reports the fund's alpha for each regression. r_{sm}, SMB, HML, and MOM refer to the stock market, size, value, and momentum risk factors for the stock market, respectively. r_{bm}, DEF and Option refer to the bond market, default, and option risk factors for the bond market, respectively. Newey-West adjusted t-statistics are reported. The table shows the adjusted R-squared, number of observations, and p-values of the Jarque-Bera (JB) test statistic in the last three rows. The null hypothesis of the JB test is that the regression residuals follow a normal distribution. Results relate to the sample period January 1990 – September 2021. Funds with a minimum of 36 observations are used, leaving 519 funds in the sample.

	Min	5 min	min 5%	min 10%	min 40%	max 30%	max 10%	max 5%	20 max	15 max	12 max	10 max	7 max	5 max	3 max	2 max	1 max
alpha	-0.197	-0.098	-0.788	-0.423	-0.167	-0.141	0.001	0.053	0.091	0.082	0.068	0.069	0.229	0.129	0.196	0.140	0.224
t(alpha)	-7.094	-5.476	-4.472	-4.070	-2.608	-1.165	0.009	0.510	0.789	1.072	1.251	1.479	2.352	2.432	2.471	2.531	2.849
r_{sm}	0.749	0.206	0.428	0.945	0.947	0.885	0.641	0.491	0.356	0.569	0.635	0.572	0.492	0.544	0.530	0.553	0.516
t($r_s m$)	70.934	32.969	8.884	21.420	49.007	23.936	30.028	12.566	8.237	24.383	38.178	38.350	14.440	28.415	20.898	25.547	19.662
SMB	-0.012	-0.050	0.141	0.292	0.024	-0.027	0.051	0.172	-0.045	0.056	-0.011	-0.097	0.102	-0.011	0.079	-0.014	0.001
t(SMB)	-0.876	-9.302	2.950	2.968	0.876	-0.636	1.480	3.566	-1.623	1.945	-0.491	-5.520	1.999	-0.609	2.900	-0.719	0.037
HML	0.040	-0.007	0.071	0.073	-0.025	-0.269	-0.053	0.275	0.051	0.050	0.280	0.167	0.175	-0.070	0.243	-0.070	0.189
t(HML)	3.359	-0.756	1.193	1.517	-0.995	-4.884	-2.098	5.942	1.107	1.728	10.097	9.165	3.505	-3.603	6.394	-3.227	4.710
MOM	-0.001	-0.002	0.079	0.048	0.053	-0.076	0.064	-0.054	0.020	-0.087	-0.072	-0.033	-0.091	0.054	0.007	0.054	-0.056
t(MOM)	-0.133	-0.481	2.523	1.561	3.539	-2.118	3.517	-1.925	0.655	-3.066	-4.069	-2.316	-2.151	4.172	0.309	3.785	-2.396
r_{bm}	0.331	0.784	1.235	0.379	0.648	-0.360	-0.158	0.208	0.997	-0.379	0.823	0.395	0.845	0.712	0.838	0.803	0.518
t(r_{bm})	4.599	8.611	3.402	1.424	4.180	-1.193	-0.579	0.832	3.619	-1.918	5.165	3.867	3.270	5.571	4.077	6.182	2.824
DEF	-0.051	-0.094	-0.427	-0.086	-0.186	0.135	0.129	-0.065	-0.218	0.225	-0.221	-0.022	-0.269	-0.174	-0.282	-0.201	-0.069
t(DEF)	-2.061	-2.014	-3.174	-1.064	-4.169	1.311	1.085	-0.650	-2.518	3.365	-4.089	-0.563	-2.987	-3.883	-3.835	-4.412	-1.036
Option	0.181	-0.205	0.200	0.282	0.061	-0.110	-0.128	0.404	-0.340	0.409	-0.127	0.025	0.015	-0.161	-0.293	-0.323	0.323
t(Option)	2.186	-2.423	0.535	1.047	0.340	-0.366	-0.647	1.357	-0.966	2.200	-0.839	0.217	0.056	-1.060	-1.144	-2.014	1.460
Adj R^2	0.985	0.968	0.662	0.895	0.964	0.842	0.930	0.708	0.721	0.842	0.913	0.901	0.737	0.873	0.833	0.871	0.794
JB(p)	0.000	0.000	0.002	0.000	0.408	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Nobs	246	165	101	225	204	249	114	381	189	291	381	381	339	348	310	336	381

Table 5 US Market timing ability of asset allocation funds

This table presents market timing results using the TM and HM tests. Panel A shows results on stock market timing, while Panel B presents results on bond market timing. Columns headings All, CA, MA, AA, FA, and AM represent the full set of funds, Cautious Allocation, Moderate Allocation, Aggressive Allocation, Flexible Allocation, and Allocation Miscellaneous funds, respectively. Mean represents the cross-sectional average of timing coefficients, and Std represents the standard deviation. "% +" and "% -" represent the proportion of funds with positive or negative timing coefficients, respectively; "% sig +" and "% sig -" represent the proportion of funds that produce positive significant and negative significant timing coefficients at the 5% significance level, respectively.

	TM test						HM test					
Panel A: Stock Market Timing												
θ_1	All	CA	MA	AA	FA	AM	All	CA	MA	AA	FA	AM
Mean	-0.003	-0.003	-0.002	-0.005	-0.003	-0.005	-0.053	-0.051	-0.041	-0.077	-0.053	-0.061
Std	0.005	0.004	0.005	0.004	0.006	0.007	0.090	0.071	0.095	0.079	0.125	0.156
% +	18.30%	17.46%	23.10%	7.01%	26.31%	22.22%	22.73%	19.84%	28.68%	11.40%	31.57%	22.22%
% sig +	1.54%	2.38%	1.19%	0.87%	5.26%	0.00%	1.92%	2.38%	1.59%	1.75%	5.26%	0.00%
% -	81.69%	82.53%	76.89%	92.98%	73.68%	77.77%	77.26%	80.15%	71.31%	88.59%	68.42%	77.77%
% sig -	41.04%	47.61%	34.26%	50.00%	21.05%	66.66%	33.71%	38.88%	27.09%	42.10%	31.05%	66.66%
Panel B: Bond Market Timing												
θ_2	All	CA	MA	AA	FA	AM	All	CA	MA	AA	FA	AM
Mean	-0.003	-0.010	-0.003	0.002	-0.010	0.024	-0.055	-0.048	-0.046	-0.058	-0.214	-0.030
Std	0.079	0.074	0.076	0.064	0.162	0.111	0.344	0.295	0.338	0.319	0.579	0.333
% +	44.89%	35.71%	46.61%	52.63%	26.31%	66.66%	38.15%	37.30%	38.24%	38.59%	26.31%	66.66%
% sig +	7.51%	7.93%	6.77%	6.14%	10.52%	33.33%	5.00%	5.55%	4.78%	2.63%	5.26%	33.33%
% -	55.10%	64.28%	53.38%	47.36%	73.68%	33.33%	61.84%	62.69%	61.75%	61.40%	73.68%	33.33%
% sig -	7.12%	10.31%	7.96%	2.63%	5.26%	0.00%	5.78%	4.76%	7.17%	3.50%	10.52%	0.00%
Nobs	519	126	251	114	19	9	519	126	251	114	19	9

Table 6 Maximum drawdown and US allocation fund performance

We use a portfolio-sort approach to form decile portfolios based on funds' average past 6-month MDDs. At the beginning of month t, we rank funds according to the average MDDs across funds over the previous 36-month horizon and form equal-weighted decile portfolios based on rank. The Decile 1 (10) contains funds with the low (high) MDDs. The monthly excess returns of the portfolios over the next year are computed after which we roll the process by one year. We also calculate the return of the long-short portfolio, i.e., Decile 1- 10. We then use the market condition variables to sort our sample month and create sub-samples of quintiles for each decile portfolio and long-short portfolio. These market conditions variables include (i) stock market return, (ii) stock market volatility (iii) GDP growth rate and (iv) bond market return. After sorting each decile portfolio into quintile portfolios based on market conditions, we estimate the alphas of those quintile portfolios. The alphas of long-short quintile portfolios are also estimated. T-statistics are reported in parentheses.

	Quintile				
Panel A: stock market return					
Decile	1 (low)	2	3	4	5 (high)
1	0.20	-0.06	0.06	0.27	0.79
	(0.56)	(-1.07)	(0.66)	(0.83)	(5.01)
10	0.32	-0.26	-0.26	-0.23	0.03
	(1.36)	(-2.44)	(-1.28)	(-0.90)	(0.09)
1-10	-0.13	0.20	0.32	0.50	0.76
	(-0.25)	(2.39)	(1.86)	(1.64)	(2.06)
Panel B: VIX index					
Decile	1 (low)	2	3	4	5 (high)
1	-0.01	-0.20	-0.01	-0.07	-0.03
	(-0.10)	(-4.40)	(-0.25)	(-0.96)	(-0.34)
10	0.09	-0.31	-0.08	-0.06	-0.35
	(1.10)	(-4.53)	(-0.98)	(-0.43)	(-2.71)
1-10	-0.09	0.10	0.06	-0.01	0.32
	(-0.94)	(1.88)	(0.68)	(-0.08)	(2.18)
Panel C: GDP growth rate					
Decile	1 (low)	2	3	4	5 (high)
1	-0.19	-0.12	-0.05	-0.02	-0.18
	(-3.25)	(-1.93)	(-0.76)	(-0.39)	(-1.19)
10	-0.52	-0.21	0.03	-0.08	-0.02
	(-4.28)	(-1.93)	(0.36)	(-1.21)	(-0.19)
1-10	0.33	0.09	-0.08	0.06	-0.16
	(3.07)	(0.86)	(-0.86)	(0.72)	(-0.85)
Panel D: bond market return					
Decile	1 (low)	2	3	4	5 (high)
1	0.11	-0.05	0.00	-0.12	-0.28
	(0.89)	(-0.54)	(0.04)	(-0.40)	(-1.17)
10	0.13	-0.10	0.06	0.19	-0.44
	(0.55)	(-0.53)	(0.39)	(0.49)	(-1.44)
1-10	-0.02	0.04	-0.06	-0.31	0.16
	(-0.09)	(0.22)	(-0.32)	(-0.69)	(0.35)

Table 7 US Performance persistence: decile portfolios

The persistence result of decile-sorted portfolios is presented in the table below. Based on the t-statistics of alpha from the performance model estimated over the previous *f* (f =36 or 60) months, each fund is sorted into equal-weighted decile portfolios and then held for *h* (h = 1, 2, 3, 6, 12) months. The process is repeated on an h-month rolling basis, and a time series of holding period returns is generated for each decile. The table shows the alpha, t-statistic of alpha (Newey-West adjusted), and bootstrap p-value for each decile portfolio. The values in parentheses represent various formation and holding periods (f, h) over the sample period January 1990 – September 2021. There are 519 (501) funds with a minimum of 36 (60) observations in the analysis.

Panel A

Decile Portfolios	alpha (36,1)	t-alpha (36,1)	p-value (36,1)	alpha (36,2)	t-alpha (36,2)	p-value (36,2)	alpha (36,3)	t-alpha (36,3)	p-value (36,3)	alpha (36,6)	t-alpha (36,6)	p-value (36,6)	alpha (36,12)	t-alpha (36,12)	p-value (36,12)
1	0.018	0.449	0.572	0.004	0.094	0.760	0.003	0.073	0.676	-0.019	-0.417	0.832	-0.064	-1.198	0.944
2	-0.086	-2.017	1.000	-0.069	-1.681	0.980	-0.076	-1.846	0.988	-0.073	-1.754	0.984	-0.079	-1.626	0.980
3	-0.080	-1.794	0.984	-0.091	-1.998	0.984	-0.113	-2.422	0.996	-0.096	-2.054	0.992	-0.075	-2.138	1.000
4	-0.136	-3.153	1.000	-0.117	-2.744	1.000	-0.132	-3.057	1.000	-0.150	-3.284	1.000	-0.156	-3.919	1.000
5	-0.125	-3.420	1.000	-0.137	-3.652	1.000	-0.099	-2.828	1.000	-0.110	-3.310	1.000	-0.119	-3.273	1.000
6	-0.127	-3.378	1.000	-0.110	-2.936	1.000	-0.116	-3.335	1.000	-0.095	-2.708	1.000	-0.121	-3.609	1.000
7	-0.126	-4.459	1.000	-0.142	-4.767	1.000	-0.115	-3.778	1.000	-0.125	-3.921	1.000	-0.124	-3.474	1.000
8	-0.138	-4.385	1.000	-0.124	-4.344	1.000	-0.135	-4.159	1.000	-0.136	-4.252	1.000	-0.142	-4.163	1.000
9	-0.147	-4.588	1.000	-0.141	-4.337	1.000	-0.150	-4.820	1.000	-0.129	-4.518	1.000	-0.112	-3.951	1.000
10	-0.119	-3.639	1.000	-0.119	-3.584	1.000	-0.122	-3.792	1.000	-0.112	-3.182	1.000	-0.066	-1.831	0.988

Panel B

Decile Portfolios	alpha (60,1)	t-alpha (60,1)	p-value (60,1)	alpha (60,2)	t-alpha (60,2)	p-value (60,2)	alpha (60,3)	t-alpha (60,3)	p-value (60,3)	alpha (60,6)	t-alpha (60,6)	p-value (60,6)	alpha (60,12)	t-alpha (60,12)	p-value (60,12)
1	-0.008	-0.183	0.728	-0.009	-0.183	0.756	-0.036	-0.757	0.892	-0.049	-0.929	0.912	-0.038	-0.812	0.872
2	-0.073	-1.688	0.992	-0.078	-1.851	0.984	-0.055	-1.318	0.988	-0.062	-1.511	0.968	-0.107	-2.062	0.996
3	-0.107	-2.473	0.996	-0.101	-2.283	1.000	-0.114	-2.664	0.996	-0.106	-2.695	1.000	-0.107	-3.029	1.000
4	-0.155	-3.589	1.000	-0.147	-3.458	1.000	-0.137	-3.299	1.000	-0.129	-3.023	1.000	-0.117	-2.139	0.992
5	-0.137	-3.792	1.000	-0.139	-3.774	1.000	-0.145	-3.552	1.000	-0.127	-2.702	1.000	-0.118	-2.977	1.000
6	-0.115	-2.538	1.000	-0.113	-2.396	0.992	-0.108	-2.436	1.000	-0.125	-2.872	1.000	-0.119	-2.781	1.000
7	-0.159	-3.777	1.000	-0.141	-3.593	1.000	-0.134	-3.248	1.000	-0.127	-3.078	1.000	-0.116	-2.601	1.000
8	-0.146	-4.559	1.000	-0.165	-4.961	1.000	-0.156	-4.832	1.000	-0.162	-4.245	1.000	-0.165	-4.000	1.000
9	-0.137	-3.957	1.000	-0.125	-3.630	1.000	-0.140	-3.977	1.000	-0.149	-4.616	1.000	-0.160	-4.575	1.000
10	-0.143	-4.812	1.000	-0.151	-5.011	1.000	-0.139	-4.855	1.000	-0.128	-3.974	1.000	-0.135	-4.215	1.000

Table 8 US Performance persistence: small portfolios

The persistence result of small-size portfolios is presented in the table below. Based on the t-statistics of alpha from the performance model estimated over the previous *f* (f =36 or 60) months, each fund is sorted into equal-weighted portfolios of size 2, 3, 5, 7, 10, 20, 35, and 50 and then held for *h* (h = 1, 2, 3, 6, 12) months. The process is repeated on an h-month rolling basis, and a time series of holding period returns is generated. The table shows the alpha and t-statistic of alpha (Newey-West adjusted) and bootstrap p-value for each size portfolio. Cells shaded blue indicate positive statistical significance at the 10% level based on bootstrap p-values. The values in parentheses represent various formation and holding periods (f, h) over the sample period January 1990 – September 2021. There are 519 (501) funds with a minimum of 36 (60) observations in the analysis.

Panel A

Portfolio Size	(36,1) alpha	t-alpha	p-value	(36,2) alpha	t-alpha	p-value	(36,3) alpha	t-alpha	p-value	(36,6) alpha	t-alpha	p-value	(36,12) alpha	t-alpha	p-value
2	0.012	0.155	0.556	-0.034	-0.380	0.692	0.036	0.466	0.424	0.081	1.053	0.216	-0.012	-0.148	0.636
3	0.044	0.608	0.392	0.003	0.029	0.576	0.040	0.524	0.420	0.054	0.693	0.316	0.008	0.096	0.560
5	0.001	0.018	0.704	-0.030	-0.366	0.656	0.009	0.149	0.592	-0.009	-0.136	0.660	-0.047	-0.643	0.840
7	0.009	0.155	0.648	-0.007	-0.095	0.620	-0.010	-0.167	0.708	-0.022	-0.370	0.764	-0.058	-0.835	0.896
10	0.013	0.216	0.664	0.011	0.173	0.604	0.021	0.338	0.568	0.015	0.250	0.584	-0.020	-0.331	0.804
20	0.014	0.314	0.624	0.002	0.032	0.640	-0.001	-0.030	0.688	-0.032	-0.617	0.884	-0.053	-1.045	0.964
35	-0.011	-0.292	0.840	-0.014	-0.350	0.828	-0.021	-0.502	0.852	-0.046	-0.992	0.932	-0.067	-1.270	0.964
50	-0.032	-0.866	0.956	-0.034	-0.899	0.944	-0.050	-1.267	0.984	-0.057	-1.330	0.968	-0.075	-1.513	0.992

Panel B

Portfolio Size	(60,1) alpha	t-alpha	p-value	(60,2) alpha	t-alpha	p-value	(60,3) alpha	t-alpha	p-value	(60,6) alpha	t-alpha	p-value	(60,12) alpha	t-alpha	p-value
2	0.085	0.960	0.252	0.037	0.388	0.420	0.094	1.088	0.224	0.076	0.895	0.236	0.117	1.633	0.128
3	0.051	0.605	0.396	0.033	0.370	0.444	0.079	0.967	0.264	0.109	1.434	0.092	0.157	1.955	0.068
5	0.082	1.163	0.224	0.066	0.890	0.296	0.081	1.123	0.244	0.066	0.985	0.244	0.087	1.316	0.172
7	0.035	0.519	0.500	0.016	0.222	0.536	0.051	0.652	0.392	0.025	0.284	0.452	0.065	0.955	0.276
10	0.014	0.225	0.600	-0.007	-0.110	0.652	-0.009	-0.133	0.712	-0.016	-0.239	0.636	0.015	0.266	0.512
20	-0.015	-0.311	0.812	-0.016	-0.310	0.752	-0.028	-0.534	0.896	-0.033	-0.634	0.864	-0.053	-0.983	0.916
35	-0.036	-0.821	0.932	-0.040	-0.918	0.912	-0.054	-1.152	0.964	-0.070	-1.438	0.988	-0.070	-1.647	0.976
50	-0.050	-1.286	0.984	-0.051	-1.350	0.984	-0.059	-1.386	0.988	-0.066	-1.456	0.992	-0.069	-1.600	0.992

Table 9 UK model selection

The table shows results from estimating the various performance models using individual mutual funds. All betas shown are cross-sectional averages. T-statistics are reported in parentheses and are calculated as the cross-sectional averages of the absolute values of funds' t-statistics (Newey-West adjusted). The percentiles of adjusted R^2, Akaike information criterion (AIC), and Schwartz Information Criterion (SIC) are presented. The table shows statistics on the percentage of funds that reject the null hypothesis of no serial correlation in residuals at lag 1 to 6 (LM test) and reject normality in the residuals (Jarque-Bera test)-both at a 5% significance level. The table also shows alphas, adjusted R^2, AIC, SIC, Jarque-Beta test, and LM tests for equal-weighted portfolios of all mutual funds.

Model	1	2	3	4	5	6	7	8
Regression Coefficients								
Average Alpha	-0.042 (1.075)	-0.095 (1.243)	-0.084 (1.202)	-0.057 (1.135)	-0.053 (1.078)	-0.112 (1.298)	-0.104 (1.259)	-0.076 (1.185)
Stock Factor								
r_{sm}	0.550 (16.534)	0.498 (12.963)	0.499 (12.880)	0.488 (12.378)	0.550 (16.632)	0.497 (13.045)	0.498 (12.955)	0.488 (12.436)
SMB	0.095 (2.620)	0.062 (2.014)	0.063 (2.002)	0.056 (1.940)	0.104 (2.820)	0.071 (2.225)	0.072 (2.219)	0.063 (2.120)
HML	-0.010 (1.314)	-0.017 (1.333)	-0.017 (1.324)	-0.019 (1.282)	0.004 (1.224)	-0.001 (1.280)	-0.002 (1.258)	-0.007 (1.168)
MOM					0.019 (1.165)	0.022 (1.248)	0.023 (1.215)	0.018 (1.113)
Bond Factor								
r_{bm}	0.220 (3.836)	0.215 (1.704)	0.260 (2.942)		0.222 (3.856)	0.226 (1.765)	0.271 (3.028)	
DEF			0.116 (1.927)				0.121 (2.000)	
OPTION			-0.028 (0.761)				-0.045 (0.786)	
HY		0.127 (2.019)		0.061 (1.029)		0.131 (2.085)		0.071 (1.084)
MBS		-0.022 (0.750)		-0.050 (0.753)		-0.033 (0.774)		-0.059 (0.783)
GOV				-0.045 (1.215)				-0.018 (1.195)
CREDIT				0.338 (2.161)				0.315 (2.058)
Model Selection Criteria								
Adjusted R^2								
Min 1%	0.216	0.220	0.223	0.217	0.221	0.224	0.228	0.221
Min 5%	0.424	0.436	0.440	0.441	0.435	0.447	0.449	0.450
Min 10%	0.522	0.557	0.559	0.574	0.536	0.560	0.561	0.574
Min 25%	0.687	0.715	0.712	0.729	0.689	0.718	0.713	0.732
Median	0.806	0.819	0.819	0.826	0.805	0.823	0.822	0.827
Max 25%	0.865	0.871	0.870	0.876	0.866	0.873	0.873	0.876
Max 10%	0.902	0.907	0.905	0.909	0.903	0.908	0.908	0.910
Max 5%	0.919	0.922	0.922	0.927	0.922	0.925	0.924	0.927
Max 1%	0.951	0.961	0.962	0.961	0.950	0.962	0.962	0.961
Average	0.754	0.770	0.770	0.780	0.756	0.773	0.773	0.782

AIC								
Min 1%	91.59	77.57	75.48	69.19	92.06	77.85	77.27	67.05
Min 5%	118.92	112.65	112.70	109.67	119.47	111.45	113.77	110.46
Min 10%	136.93	131.40	131.75	130.13	137.36	132.75	133.15	131.63
Min 25%	212.85	208.79	208.76	204.36	214.78	204.34	204.45	203.69
Median	349.87	343.86	342.35	328.02	349.08	339.82	341.40	326.52
Max 25%	556.11	552.19	549.15	544.03	557.79	547.81	545.05	545.60
Max 10%	754.76	735.21	734.25	722.42	753.32	735.68	733.25	722.54
Max 5%	840.13	824.89	825.32	822.76	839.05	826.07	826.58	824.38
Max 1%	1160.07	1140.94	1139.68	1143.92	1154.16	1135.63	1134.03	1138.53
Average	405.85	399.58	399.26	393.48	405.352	398.62	398.41	393.16
SIC								
Min 1%	101.42	94.65	92.55	88.46	103.52	95.55	96.48	89.49
Min 5%	129.96	126.99	128.72	125.81	132.31	129.31	129.23	128.58
Min 10%	148.19	147.07	148.22	148.82	150.93	148.96	150.31	151.40
Min 25%	227.79	226.49	227.72	226.66	232.20	224.48	225.36	227.34
Median	366.90	365.54	363.80	354.93	369.60	365.35	366.18	355.35
Max 25%	576.69	579.79	575.50	573.99	581.00	577.99	574.18	576.78
Max 10%	774.02	761.88	759.93	753.75	775.79	764.57	762.03	757.34
Max 5%	859.74	852.73	853.16	854.09	862.30	857.39	857.90	859.19
Max 1%	1180.88	1168.68	1167.42	1175.13	1178.44	1166.84	1165.24	1173.21
Average	422.12	421.28	420.96	417.90	424.341	423.04	422.83	420.29
Normality and LM tests								
Rejection of Normality (% of funds)	56.2	54	54	49.6	54	51.1	51.4	49.3
LM(1) statistic (% of Funds)	37	39.1	37	41.3	38.4	42.8	41.7	43.5
LM(6) statistic (% of Funds)	29.3	30.8	31.5	39.5	30.8	33.3	35.1	40.6
Equal Weighted Portfolio								
Alpha	-0.037	-0.064	-0.057	-0.063	-0.044	-0.075	-0.067	-0.073
	(-0.764)	(-1.532)	(-1.213)	(-1.320)	(-0.863)	(-1.488)	(-1.346)	(-1.446)
Adjusted R^2	0.921	0.928	0.928	0.928	0.921	0.928	0.928	0.928
JB(p)	0.013	0.319	0.393	0.456	0.012	0.323	0.378	0.414
LM(1)	0.017	0.058	0.055	0.046	0.017	0.059	0.056	0.049
LM(6)	0.075	0.476	0.451	0.428	0.088	0.506	0.484	0.466
AIC	520.38	502.30	502.40	502.62	522.05	503.488	503.73	504.09
SIC	541.26	530.14	530.24	533.94	546.41	534.814	535.05	538.90

Table 10 UK allocation fund performance

This table shows results for selected points in the cross-sectional distribution of the full sample of asset allocation funds using the best-fit multifactor model. The first row reports the fund's alpha for each regression. r_{sm}, SMB and HML refer to the stock market, size, and value risk factors for the stock market, respectively. r_{bm}, DEF and Option refer to the bond market, default, and option risk factors for the bond market, respectively. Newey-West adjusted t-statistics are reported. The table shows the adjusted R-squared, number of observations, and p-values of the Jarque-Bera (JB) test statistic in the last three rows. Results relate to the sample period January 1998 – December 2017. Funds with a minimum of 36 observations are used, leaving 276 funds in the sample.

	Min	Min 5	Min 5%	Min 10%	Min 40%	Max 30%	Max 10%	Max 15	Max 12	Max 10	Max 7	Max 5	Max 3	Max 2	Max
alpha	-0.188	-0.298	-0.222	-0.345	-0.096	-0.015	0.241	0.080	0.187	0.198	0.188	0.400	0.218	0.235	0.854
t(alpha)	-3.919	-3.475	-3.039	-2.653	-1.005	-0.175	0.859	1.281	1.359	1.740	2.134	2.434	2.692	2.880	3.096
r_{sm}	0.541	0.598	0.199	0.306	0.518	0.267	0.522	0.636	0.601	0.273	0.075	0.436	0.084	0.473	0.344
t($r_s m$)	27.918	21.146	6.374	7.468	19.039	7.746	3.367	31.100	10.790	5.135	2.678	8.384	3.182	16.142	2.186
SMB	0.049	0.027	-0.003	0.064	0.104	-0.021	-0.176	0.080	0.243	0.015	0.048	0.195	0.054	0.109	-0.339
t(SMB)	2.751	0.839	-0.150	1.365	3.080	-0.488	-1.533	3.653	6.239	0.417	1.274	3.223	1.551	3.493	-2.781
HML	0.011	0.091	-0.007	-0.015	-0.024	-0.024	-0.008	0.034	-0.059	-0.171	0.076	-0.196	0.072	0.085	-0.155
t(HML)	0.437	3.994	-0.192	-0.267	-0.662	-0.577	-0.043	1.967	-1.086	-3.479	1.604	-2.608	1.567	2.650	-1.141
r_{bm}	0.448	0.291	0.380	0.506	0.189	0.244	0.301	0.343	0.099	0.074	0.443	0.057	0.451	0.329	0.123
t(r_{bm})	8.321	3.693	4.933	3.452	2.515	2.907	1.104	4.971	0.840	0.912	4.257	0.406	4.402	3.811	0.493
DEF	0.077	0.082	0.073	0.072	0.135	0.018	1.038	0.035	0.017	-0.081	0.327	0.016	0.327	0.076	0.162
t(DEF)	3.737	2.023	1.610	0.939	3.671	0.432	3.449	1.377	0.211	-1.837	8.211	0.249	8.120	2.197	0.511
Option	-0.069	0.115	-0.015	0.013	0.068	0.116	-0.944	0.103	-0.014	-0.020	-0.292	-0.012	-0.299	-0.056	-0.209
t(Option)	-0.863	1.244	-0.141	0.091	0.868	0.996	-1.868	1.310	-0.067	-0.160	-2.042	-0.056	-2.118	-0.472	-0.445
Adj R^2	0.945	0.895	0.678	0.860	0.866	0.753	0.583	0.897	0.690	0.259	0.717	0.431	0.727	0.781	0.321
JB(p)	0.008	0.303	0.001	0.856	0.000	0.523	0.034	0.000	0.000	0.000	0.007	0.000	0.004	0.240	0.073
Nobs	152	137	147	41	153	57	46	218	181	170	126	216	132	216	67

Table 11 UK market timing ability of asset allocation funds

This table presents UK market timing results using the TM and HM tests. Panel A shows results on stock market timing, while Panel B presents results on bond market timing. Columns headings All, CA, MA, AA, FA, and AM represent the full set of funds, Cautious Allocation, Moderate Allocation, Aggressive Allocation, Flexible Allocation, and Allocation Miscellaneous funds, respectively. Mean represents the cross-sectional average of timing coefficients, and Std represents the standard deviation. "% +" and "% -" represent the proportion of funds with positive or negative timing coefficients, respectively; "% sig +" and "% sig -" represent the proportion of funds that produce positive significant and negative significant timing coefficients at the 5% significance level, respectively.

	TM test						HM test					
Panel A: Stock Market Timing												
θ_1	All	CA	MA	AA	FA	AM	All	CA	MA	AA	FA	AM
Mean	-0.007	-0.007	-0.005	-0.009	-0.005	0.001	-0.135	-0.111	-0.112	0.171	-0.132	-0.006
Std	0.009	0.007	0.008	0.009	0.015	0.015	0.156	0.123	0.121	0.147	0.278	0.162
% +	14.86	16.39	10.60	13.56	28.57	20.00	14.49	22.95	10.60	8.47	28.57	30.00
% sig +	1.81	1.64	1.52	0.85	4.76	10.00	1.08	0.00	1.52	0.00	4.76	10.00
% -	85.14	83.60	89.40	86.44	71.43	80.00	85.51	77.05	49.40	91.53	71.43	70.00
% sig -	38.76	45.90	34.85	40.67	33.33	10.00	39.13	40.98	42.42	40.68	28.57	10.00
Panel B: Bond Market Timing												
θ_2	All	CA	MA	AA	FA	AM	All	CA	MA	AA	FA	AM
Mean	0.016	-0.001	0.017	0.023	0.023	0.020	0.150	0.011	0.162	0.204	0.222	0.182
Std	0.037	0.039	0.027	0.039	0.038	0.032	0.305	0.262	0.224	0.337	0.309	0.325
% +	70.65	36.07	74.24	71.18	76.19	70.00	71.74	63.93	77.27	73.72	66.67	70.00
% sig +	17.75	6.56	21.21	19.50	23.80	30.00	18.48	4.92	28.79	18.64	23.80	20.00
% -	29.34	63.93	25.76	28.82	23.81	30.00	28.26	36.07	22.72	26.27	33.33	30.00
% sig -	2.90	6.56	4.55	0.85	0.00	0.00	2.90	9.83	3.03	0.00	0.00	0.00
Nobs	276	61	66	118	21	10	276	61	66	118	21	10

Table 12 MDDs and UK allocation fund performance

We use a portfolio-sort approach to form decile portfolios based on funds' average past 6-month MDDs. At the beginning of month t, we rank funds according to the average MDDs across funds over the previous 36-month horizon and form equal-weighted decile portfolios based on rank. The Decile 1 (10) contains funds with the low (high) MDDs. The monthly excess returns of the portfolios over the next year are computed after which we roll the process by one year. We also calculate the return of the long-short portfolio, i.e., Decile 1 - 10. We then use the market condition variables to sort our sample month and create sub-samples of quintiles for each decile portfolio and long-short portfolio. These market conditions variables include: (i) stock market return, (ii) stock market volatility (iii) GDP growth rate and (iv) bond market return. After sorting each decile portfolio into quintile portfolios based on market conditions, we estimate the alphas of those quintile portfolios. The alphas of long-short quintile portfolios are also reported.

			Quintiles		
Panel A: stock market return					
Decile	1 (low)	2	3	4	5 (high)
1	0.15	-0.34	0.04	0.23	0.48
	(0.61)	(-1.67)	(0.31)	(0.74)	(1.63)
10	-0.14	-0.23	0.51	0.37	0.91
	(-0.51)	(-0.44)	(3.50)	(0.51)	(2.35)
1 -10	0.29	-0.11	-0.47	-0.15	-0.44
	(0.80)	(-0.30)	(-2.97)	(-0.21)	(-1.07)
Panel B: stock market volatility					
Decile	1 (low)	2	3	4	5 (high)
1	0.03	0.05	-0.01	-0.12	-0.49
	(0.47)	(0.63)	(-0.08)	(-1.64)	(-2.68)
10	0.46	0.04	0.11	-0.02	-0.37
	(4.58)	(0.19)	(0.67)	(-0.13)	(-1.43)
1 -10	-0.43	0.01	-0.12	-0.10	-0.12
	(-4.43)	(0.05)	(-1.11)	(-0.64)	(-0.51)
Panel C: GDP growth rate					
Decile	1 (low)	2	3	4	5 (high)
1	-0.26	-0.14	-0.05	-0.16	0.05
	(-2.36)	(-1.13)	(-0.56)	(-2.18)	(0.61)
10	-0.25	0.00	-0.19	0.16	-0.08
	(-1.26)	(-0.01)	(-1.32)	(1.35)	(-0.58)
1 -10	-0.01	-0.14	0.15	-0.31	0.13
	(-0.09)	(-0.99)	(0.99)	(-2.88)	(0.95)
Panel D: bond market return					
Decile	1 (low)	2	3	4	5 (high)
1	-0.76	-0.09	-0.19	-0.30	-0.03
	(-2.84)	(-0.52)	(-1.48)	(-0.89)	(-0.16)
10	-0.38	0.15	-0.42	0.29	-1.03
	(-1.24)	(0.42)	(-1.82)	(0.61)	(-2.47)
1 -10	-0.39	-0.24	0.23	-0.60	1.00
	(-1.51)	(-0.82)	(1.36)	(-1.23)	(3.09)

Table 13 UK Performance persistence: decile portfolios

The persistence result of decile-sorted portfolios is presented in the table below. Based on the t-statistics of alpha from the performance model estimated over the previous *f* (f =36 or 60) months, each fund is sorted into equal-weighted decile portfolios and then held for *h* (h = 1, 2, 3, 6, 12) months. The process is repeated on an h-month rolling basis, and a time series of holding period returns is generated for each decile. The table shows the alpha and t-statistic of alpha (Newey-West adjusted) and bootstrap p-value for each decile portfolio. Cells shaded blue indicate statistical significance at the 10% level, based on bootstrap p-values. The values in parentheses represent various formation and holding periods (f, h) over the sample period January 1998 – December 2017. There are 276 (235) funds with a minimum of 36 (60) observations in the analysis.

Panel A

Decile Portfolios	alpha	(36,1) t-alpha	p-value	alpha	(36,2) t-alpha	p-value	alpha	(36,3) t-alpha	p-value	alpha	(36,6) t-alpha	p-value	alpha	(36,12) t-alpha	p-value
1	0.061	1.226	0.204	0.067	1.268	0.196	0.082	1.651	0.112	0.084	1.684	0.080	0.013	0.232	0.524
2	-0.015	-0.305	0.664	0.000	0.001	0.596	-0.037	-0.796	0.824	-0.026	-0.491	0.768	-0.046	-0.758	0.860
3	-0.124	-1.932	0.960	-0.135	-2.001	0.976	-0.103	-1.618	0.944	-0.131	-2.014	0.972	-0.076	-1.230	0.888
4	-0.106	-1.840	0.972	-0.097	-1.780	0.968	-0.077	-1.444	0.936	-0.059	-1.105	0.872	-0.035	-0.599	0.780
5	-0.052	-1.066	0.868	-0.062	-1.222	0.904	-0.051	-0.872	0.820	-0.087	-1.587	0.944	-0.033	-0.670	0.744
6	-0.057	-0.992	0.856	-0.081	-1.517	0.936	-0.100	-1.696	0.952	-0.059	-1.137	0.908	-0.130	-2.408	0.988
7	0.097	0.722	0.296	0.081	0.593	0.368	0.061	0.445	0.436	0.048	0.346	0.472	0.073	0.538	0.400
8	-0.123	-1.869	0.972	-0.098	-1.579	0.940	-0.112	-1.786	0.956	-0.092	-1.489	0.920	-0.072	-1.455	0.904
9	-0.101	-1.785	0.960	-0.116	-2.060	0.968	-0.096	-1.539	0.944	-0.098	-1.589	0.908	-0.067	-1.317	0.896
10	-0.100	-1.745	0.872	-0.100	-1.783	0.896	-0.091	-1.733	0.888	-0.126	-2.391	0.948	-0.160	-2.305	0.936

Panel B

Decile Portfolios	alpha	(60,1) t-alpha	p-value	alpha	(60,2) t-alpha	p-value	alpha	(60,3) t-alpha	p-value	alpha	(60,6) t-alpha	p-value	alpha	(60,12) t-alpha	p-value
1	0.198	0.981	0.216	0.174	0.862	0.260	0.193	0.975	0.200	0.156	0.780	0.272	0.177	0.889	0.200
2	-0.047	-0.957	0.816	-0.008	-0.168	0.572	-0.036	-0.743	0.744	-0.026	-0.537	0.648	-0.129	-1.689	0.916
3	-0.077	-1.296	0.844	-0.067	-1.099	0.816	-0.095	-1.552	0.904	-0.073	-1.153	0.788	-0.079	-1.310	0.800
4	-0.013	-0.218	0.524	-0.002	-0.028	0.496	-0.026	-0.425	0.588	-0.020	-0.376	0.628	0.037	0.591	0.332
5	0.008	0.173	0.452	-0.013	-0.238	0.604	-0.002	-0.033	0.488	-0.040	-0.841	0.752	-0.045	-0.941	0.780
6	-0.028	-0.485	0.712	-0.029	-0.530	0.708	-0.064	-1.076	0.876	-0.036	-0.688	0.744	0.041	0.715	0.268
7	-0.025	-0.457	0.636	-0.035	-0.625	0.764	-0.002	-0.042	0.512	-0.052	-0.893	0.796	-0.108	-1.436	0.880
8	-0.111	-1.682	0.940	-0.066	-1.220	0.860	-0.082	-1.308	0.880	-0.056	-1.284	0.856	-0.100	-1.664	0.908
9	-0.133	-2.353	0.984	-0.147	-2.428	0.992	-0.169	-2.954	0.988	-0.144	-2.342	0.972	-0.115	-2.175	0.964
10	-0.099	-1.693	0.860	-0.111	-1.941	0.888	-0.079	-1.421	0.784	-0.076	-1.264	0.744	-0.040	-0.656	0.600

Table 14 UK Performance persistence: small portfolios

The persistence result of small-size portfolios is presented in the table below. Based on the t-statistics of alpha from the performance model estimated over the previous *f* (f =36 or 60) months, each fund is sorted into equal-weighted portfolios of size 2, 3, 5, 7, 10, 20, 30, and 40 and then held for *h* (h = 1, 2, 3, 6, 12) months. The process is repeated on an h-month rolling basis, and a time series of holding period returns is generated. The table shows the alpha and t-statistic of alpha (Newey-West adjusted) and bootstrap p-value for each size portfolio. Cells shaded green and blue indicate statistical significance at the 5% level and 10% level, respectively, based on bootstrap p-values. The values in parentheses represent various formation and holding periods (f, h) over the sample period January 1998 – December 2017. There are 276 (235) funds with a minimum of 36 (60) observations in the analysis.

Panel A

Portfolio Size	alpha	t-alpha	p-value	alpha	t-alpha	p-value	alpha	t-alpha	p-value	alpha	t-alpha	p-value	alpha	t-alpha	p-value
		(36,1)			(36,2)			(36,3)			(36,6)			(36,12)	
2	0.193	2.866	0.008	0.221	3.011	0.012	0.205	2.483	0.020	0.279	3.384	0.000	0.145	1.543	0.084
3	0.154	2.479	0.028	0.153	2.383	0.016	0.157	2.425	0.036	0.188	3.032	0.012	0.127	1.886	0.052
5	0.082	1.499	0.116	0.098	1.680	0.076	0.072	1.219	0.192	0.070	1.218	0.204	-0.003	-0.037	0.560
7	0.064	1.301	0.148	0.060	1.270	0.128	0.051	0.974	0.260	0.024	0.438	0.392	-0.031	-0.517	0.720
10	0.056	1.144	0.184	0.039	0.798	0.256	0.055	1.112	0.208	0.034	0.704	0.312	-0.014	-0.268	0.680
20	-0.006	-0.129	0.632	0.000	0.005	0.596	0.000	0.001	0.632	-0.001	-0.024	0.612	-0.048	-0.896	0.876
30	-0.027	-0.617	0.820	-0.027	-0.621	0.844	-0.025	-0.589	0.816	-0.019	-0.415	0.784	-0.043	-0.919	0.912
40	-0.049	-1.122	0.920	-0.036	-0.827	0.864	-0.040	-0.934	0.884	-0.027	-0.607	0.840	-0.031	-0.689	0.848

Panel B

Portfolio Size	alpha	t-alpha	p-value	alpha	t-alpha	p-value	alpha	t-alpha	p-value	alpha	t-alpha	p-value	alpha	t-alpha	p-value
		(60,1)			(60,2)			(60,3)			(60,6)			(60,12)	
2	0.735	1.257	0.148	0.776	1.321	0.112	0.655	1.123	0.188	0.647	1.115	0.192	0.691	1.186	0.144
3	0.429	1.096	0.180	0.456	1.157	0.168	0.398	1.016	0.248	0.393	1.003	0.216	0.386	0.988	0.208
5	0.253	1.054	0.208	0.249	1.034	0.196	0.215	0.901	0.264	0.184	0.772	0.268	0.221	0.938	0.236
7	0.169	0.961	0.188	0.160	0.903	0.236	0.152	0.860	0.228	0.109	0.613	0.312	0.149	0.852	0.240
10	0.112	0.863	0.212	0.058	0.430	0.356	0.099	0.761	0.228	0.063	0.472	0.340	0.050	0.365	0.400
20	0.026	0.342	0.340	0.020	0.259	0.404	0.033	0.437	0.328	0.014	0.181	0.428	-0.023	-0.256	0.496
30	-0.005	-0.075	0.524	-0.003	-0.044	0.528	0.002	0.039	0.460	-0.010	-0.149	0.528	-0.019	-0.283	0.544
40	-0.009	-0.168	0.552	0.004	0.067	0.484	-0.006	-0.102	0.516	-0.010	-0.172	0.584	-0.011	-0.193	0.536

Table 15 Asset allocation and market returns

We regress the following equation to test our hypotheses:

$$\Delta\beta = \beta_0 + \lambda_1 stock_{t-1} + \lambda_2 bond_{t-1} + \varepsilon_{i,t}$$

Where $\Delta\beta$ is the beta difference between month t and $t-1$, $stock_{t-1}$ and $bond_{t-1}$ are the stock and bond market returns at time $t-1$, respectively. Columns headings All, CA, MA, AA, FA, and AM represent the full set of funds, Cautious Allocation, Moderate Allocation, Aggressive Allocation, Flexible Allocation, and Allocation Miscellaneous funds, respectively.

	US funds						UK funds					
	All	CA	MA	AA	FA	AM	All	CA	MA	AA	FA	AM
β_0	0.36	0.29	0.38	0.40	0.30	0.23	0.17	0.13	0.15	0.22	0.19	0.37
	(2.55)	(2.84)	(2.63)	(2.22)	(2.19)	(1.47)	(1.07)	(1.20)	(0.97)	(1.12)	(1.01)	(2.08)
λ_1	0.04	0.03	0.04	0.07	0.05	0.04	0.09	0.10	0.08	0.10	0.09	-0.01
	(1.29)	(1.16)	(1.19)	(1.70)	(1.74)	(1.24)	(2.30)	(3.61)	(2.19)	(2.03)	(1.90)	(-0.25)
λ_2	0.20	0.19	0.19	0.25	0.22	0.12	0.20	0.11	0.20	0.24	0.17	0.35
	(1.51)	(2.04)	(1.43)	(1.45)	(1.69)	(0.82)	(1.88)	(1.57)	(1.99)	(1.98)	(1.41)	(3.18)
Nobs	519	126	251	114	19	9	276	61	66	118	21	10