CFR Working Paper No. 20-06

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This Version: August 2020

Abstract

We investigate the relationship between a mutual fund's variation in factor exposures and its future performance. Using a dynamic state space version of Carhart (1997)'s four factor model to capture factor variation, we find that funds with volatile factor exposures underperform funds with stable factor exposures by 147 basis points p.a. This underperformance is neither explained by volatile factor loadings of a fund's equity holdings nor driven by a fund's forced trading through investor flows. We conclude that fund managers voluntarily attempt to time factors, but they are unsuccessful at doing so.

JEL Classification: G11, G14, G20, G23

Keywords: Mutual Fund, Market Timing, Factor Timing, Factor Exposure, Kalman Filter, Underperformance

We thank Yakov Amihud, Lars Kaiser, Stefan Ruenzi, Sebastian Stöckl, Erik Theissen, Marco Wilkens, the participants of the Annual Meeting of the German Finance Association 2017, the Cologne Colloquium on Financial Markets 2018, the Lancaster Frontiers of Factor Investing Conference 2018, the participants at the research seminars of the University of Liechtenstein, the Universities of Constance and the University of St. Gallen for their helpful comments. Florian Weigert would like to thank the Centre for Financial Research (CFR) Cologne for their support.

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To achieve the goal of future benchmark-adjusted outperformance, a fund manager can generally pursue two different investment approaches. First, she can deviate from the benchmark portfolio and engage in stock picking, i.e., tilt her portfolio towards stocks that are likely to outperform in the future (see Wermers, 2000, and Cremers and Petajisto, 2009). Second, the fund manager can vary her exposure to asset pricing factors, i.e., increase (decrease) her exposure to a factor when it is likely to pay a high (low) premium in the future. Our paper is concerned with the latter investment approach and provides a new framework to study a fund manager's factor exposure variation in a comprehensive way.

We proceed as follows: Fist, for each week, we estimate a fund's *dynamic* exposures to the factors of the Carhart (1997) model, i.e., to the market (MKT), size (SMB), book-to-market (HML), and momentum (UMD) factor over a rolling horizon of 156 weeks by applying the Kalman filter and Kalman smoother techniques (see Kalman, 1960). Second, we measure a fund's factor exposure variation by the volatility of the factor loadings during the estimation period to the MKT, SMB, HML, and the UMD factor. To express a fund's overall level of factor exposure variation we compute an aggregated, overall *Factor Exposure Variation (FEV) Indicator* by standardizing and averaging the individual market, size, value, and momentum factor exposure measures.[1] To the best of our knowledge, this comprehensive approach has never been studied in the literature before and is conceptually very different to the state-dependent market timing measures of Treynor and Mazuy (1966, TM) and Henriksson and Merton (1981, HM).

We investigate whether there exist performance differences between funds with high *FEV* and funds with low *FEV* in a large sample of US equity mutual funds in the time period from the late 2000 to 2016. We find that funds' *FEV* is associated with future fund underperformance: A portfolio of the 20% funds with the highest *FEV Indicator* underperforms the 20% funds with the

[1] Our results do not necessarily depend on the Kalman filter and Kalman smoother techniques. The negative relation between factor exposure variation and fund performance remains robust when we compute *FEV* coefficients based on the volatility of time-varying betas from rolling OLS regressions. We report these robustness checks in Appendix A.2.

lowest *FEV Indicator* by 147 basis points p.a. at 1% statistical significance when we benchmark the returns against the Carhart (1997) four-factor model. Similarly, sorting funds on individual MKT, HML, or UMD factor exposure variation, results in underperformance of the most volatile funds by 102, 82, and 120 basis points p.a., respectively, with statistical significance at least at the 5% level.[2] The performance differences between high *FEV* and low *FEV* funds remain statistically and economically significant when we apply the Fama and French (2015) five-factor model plus the momentum factor for the computation of *FEV*, use different asset pricing models for the risk adjustment and control for the impact of fund characteristics.

Why do funds with high factor exposure variation earn low risk-adjusted returns in the future? We take a closer look at two channels which are intuitively related to the underperformance of high *FEV* funds. First, we investigate whether underperformance is explained by the factor exposure variation of the funds' disclosed long equity portfolio holdings (as indicated by Armstrong et al., 2013).[3] Second, we analyze whether the underperformance of high *FEV* funds is related to forced trading of funds due to substantial investor inflows / outflows. Our empirical results indicate that the negative relationship between *FEV* and future performance is neither explained by *FEV* of the disclosed equity portfolio holdings nor by trading triggered by new investor deposits / redemptions. Given that both explanations fail, our conjecture is that fund managers voluntarily alter the exposure to factors to earn the associated premia in the future, i.e., the manager engages in (unsuccessful) factor timing.[4]

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[2] Funds with high SMB factor exposure variation activity underperform funds with low SMB factor exposure variation by 61 basis points p.a. The performance spread between high and low SMB factor exposure variation funds is statistically indifferent from zero.

[3] Armstrong et al. (2013) observe that stocks with high factor loading uncertainty earn low future returns; hence, the underperformance of high *FEV* funds could be driven by the low returns of stocks with high factor loading uncertainty in their portfolios.

[4] Note that this definition of factor timing does not distinguish between explicit intended timing attempts (based on a fund's explicit factor timing strategy) and tolerated portfolio shifts (which nevertheless induce factor exposure variation in systematic factors). We do not differentiate between these approaches since managers usually do not have to report their investment strategy in a detailed way and even when they do, this strategy description is potentially misleading (see Sensoy, 2009, for the case of deceptive self-designed benchmark indices in the mutual fund industry). In an unreported test, we investigate funds for which their detailed investment strategy is provided in Morningstar. We search for phrases that indicate a fund's intention to time factors and find 18 funds (with 1,259 fund-month

To check which fund manager characteristics are associated with unstable factor exposures, we regress a fund's *FEV* in month *t+1* on different observable variables in month *t*. We find that factor timing is particularly prevalent among funds with long management tenure, high turnover, and high total expense ratios. These results are in line with previous results from the literature and support the notion that (i) fund manager behavior being influenced by career concerns from young managers to risk their reputation by exposing their portfolios to unsystematic risk (Chevalier and Ellison, 1999) and (ii) factor timing being an actively enforced and expensive investment strategy. The question whether mutual funds can successfully alter factor exposures has so far mainly been studied in the context of market timing and produced conflicting results. Whereas the majority of earlier studies, such as TM (1966), HM (1981), Ferson and Schadt (1996) and Kacperczyk and Seru (2007), do not find evidence that fund managers can time the market, more recent studies, such as Mamaysky et al. (2008), Jiang et al. (2007), Bollen and Busse (2001), Elton et al. (2012), and Kacperczyk et al. (2014), provide at least some evidence for successful attempts when applying daily mutual fund data or concentrating on special market situations. Chen and Liang (2007) find that hedge funds, which explicitly claim to time the market, have more favorable risk-return profiles due to successful return and volatility timing. The literature on timing ability beyond the market factor is rather scarce. Kryzanowski et al. (1997) find that only a low proportion of funds attempts to time macroeconomic factors. Investigating changes in fund holdings, Daniel et al. (1997) observe that mutual fund managers do not possess timing abilities with respect to stock characteristics. Bazgour et al. (2017) and Benos et al. (2010), who extend the analysis of Bollen and Busse (2001) to a Carhart (1997) model, do not detect factor timing abilities either.[5] Busse (1999), Giambona and Golec (2009), and Kim and In (2012) examine volatility timing of mutual funds, while Bodnaruk et al. (2018) document downside risk timing ability of some fund managers.

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observations) that explicitly state to conduct an investment strategy that involves factor timing. In line with our results of the full sample, these funds generally show an abnormally high *FEV indicator* and low performance.

[5] In contrast, Swinkels and Tjong-a-Tjoe (2007) detect positive factor timing skills within a very small US fund sample when applying the TM and HM measures to a four-factor model.

Finally, Huang et al. (2011) document that funds that intensively shift their total risk exposure over time underperform funds with a stable risk level.

Our paper contributes to the scientific literature in several dimensions; moreover, we also provide new insights relevant for the financial practitioner. First, by using our proposed *FEV Indicator*, one can directly assess a fund's factor exposure variation whereas most earlier models, e.g., the measures of TM and HM, only observe performance effects of these factor exposure changes. Moreover, and in contrast to the measure proposed by Jiang et al. (2007), the interested investor does not need to retrieve portfolio holding data to assess factor exposure variation which is frequently costly and only available on a low (quarterly) frequency. Second, our model allows us to estimate a fund's *FEV* simultaneously with respect to different factors. The vast majority of prior research on timing ability of mutual funds focuses on market risk only. We add a new perspective in evaluating exposure variation to alternative risk and behavioral factors (which are potentially not restricted to MKT, SMB, HML, and UMD) in a comprehensive model. Finally, we contribute to the ongoing debate among academics and investment management practitioners, whether (and how) asset pricing factors can be timed. Numerous papers, such as Barroso and Santa-Cara (2015) and Moreira and Muir (2017), show that a variation-adjusted trading strategy improves the profitability of momentum and other alternative premiums. Yet, the question whether these results can be exploited out-of-sample including trading costs, remains unsolved. Asness (2016) articulates doubts about the performance of factor timing. We contribute to this discussion by documenting that professional and sophisticated investors, such as mutual fund managers, are apparently unsuccessful in timing factors.

1. Data and the *Factor Exposure Variation Indicator*

In this section we describe the data used in this study and discuss the methodology of the empirical analysis.

1.1. Data selection

We investigate the relationship between a fund's *FEV* and its future performance using a sample of actively managed US equity mutual funds. We select our fund universe from the CRSP survivorship-bias free mutual fund database and use daily net returns as well as quarterly updated fund characteristics in the empirical analysis. We start our data selection process with all mutual funds included in the CRSP survivorship-bias free mutual fund database during the 1998 - 2016 time period. This time window is determined by the availability of daily fund returns. We use Objective Codes from CRSP and Lipper as well as the Strategic Insights Objective Code to determine fund styles and assign each fund to either "Growth and Income", "Growth", "Income", "Hedged", "Mid Cap", "Small Cap" or "Micro Cap".[6] The assigned style "Other" summarizes very few funds that have been included in our sample but whose assigned styles change during the sample period. Funds that cannot be matched to one of these categories as well as funds with missing fund names are dropped from our sample. We exclude index funds, balanced funds, international funds, and sector funds according to the CRSP Index Fund Flag, CRSP Objective Code and by screening fund names for key terms such as "Balanced" or "Index". We additionally exclude funds with less than 70% of equity holdings and funds with total net assets of less than 15 million USD. This leaves us with a total number of 3,816 funds in the sample.

We obtain quarterly data on fund age, management tenure, turnover ratio, total expense ratio and total assets under management as well as daily net returns for our sample funds and aggregate those data across all share classes of each fund. Fund age is the age of the oldest share class, total net assets are the sum of the total net assets of all share classes and turnover ratio, total expense

[6] We find that actively managed funds that mainly invest into large caps or whose name contains strings that indicate a large cap investment strategy are mostly classified as "Growth" or "Growth and Income".

ratio and daily returns are the weighted means of single share classes' data, weighted by the share classes' total net assets. We additionally calculate 12-months fund flows for each fund by $flow_t = (tna_t - tna_{t-1year})/(tna_{t-1year} * (1 + ret_{(t-1year,t)}))$, where tna_t are the total net assets at time t and $ret_{(t-1year,t)}$ is the 1-year return (net of fees) during the past 12 months. We winsorize the data on age, tenure, turnover, expense ratio, flows, and total net assets at the 1%-level. In Section 3.1 of the paper, we also use equity portfolio holding implied returns. To calculate these returns, we obtain quarterly holding data from CRSP and use the securities' historical CUSIP number to link it to daily stock returns from CRSP.

For our empirical analysis, we aggregate daily returns into weekly as well as monthly data. Following Bollen and Busse (2001), we measure a fund's *FEV* based on weekly returns. Our performance analysis based on portfolio sorts and multivariate regressions is then based on monthly returns.[7] For fund characteristics which are not available on a monthly basis (such as a fund's expense ratio), we assign the last available data point to each fund if it is not older than 12 months. We calculate weekly and monthly Fama and French (1993) as well as momentum factors from daily data, which we obtain from Kenneth R. French's website. We also collect monthly data for the short and long-term reversal factor from Kenneth R. French's website. In addition, we gather data on the Frazzini and Pedersen (2014) betting against beta factor from AQR, data for the Baker and Wurgler (2006) sentiment factor from Jeffrey Wurgler's website and data for the Pástor and Stambaugh (2003) liquidity factor from WRDS.

1.2. Factor exposure variation in a dynamic factor model

Traditional asset pricing factor models such as the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model assume a linear relationship between an asset's excess return and

[7] Our results are stable when we estimate *FEV* using daily (instead of weekly) returns and applying weekly returns (instead of monthly returns) in the performance analysis.

the respective factor premia. The size of this relationship, represented by β, is traditionally assumed to be constant over time, which allows estimating values of β using an OLS regression framework. Even if this assumption of constant βs holds for single securities it might not be valid for managed portfolios such as mutual funds, as pointed out by Mamaysky et al. (2008), because any varying exposure due to a fund's tactical asset allocation would not be reflected correctly. We model such time-varying exposures by applying the Carhart (1997) four-factor model with dynamic factor loadings β_t, which is represented by the following state space model:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{RMRF,i,t} * (r_{m,t} - r_{f,t}) + \beta_{SMB,i,t} * SMB_t + \beta_{HML,i,t} * HML_t + \beta_{UMD,i,t} * UMD_t + \varepsilon_{i,t},$$

$$\beta_{j,i,t} = \beta_{j,i,t-1} + \theta_{j,i}(\mu_{j,i} - \beta_{j,i,t-1}) + \eta_{j,i,t} \quad \text{for} \quad j \in \{RMRF, SMB, HML, UMD\},$$

where $r_{m,t}$ is the market return, $r_{f,t}$ the risk-free rate, and SMB_t, HML_t, and UMD_t denote the Fama and French (1993) and Carhart (1997) factors at time t. The model differs from a classical Carhart (1997) model as it allows the factor loadings to change over time. In our main empirical specification, we assume the factor loadings to follow a mean-reverting process with four time-invariant mean factors μ (one with respect to each factor).[8] The four time-invariant values of θ indicate the pace at which the loadings revert to its mean. Those values are unknown and estimated empirically together with the values of β_t. The disturbance terms $\varepsilon_{i,t}$ and $\eta_{j,i,t}$ are assumed to be normally distributed with zero mean and unknown standard deviations.

For each month t, we calculate a fund's *FEV*. To do so, we apply the model to the past three years of weekly fund return data and use the Kalman filter and Kalman smoother techniques to estimate the dynamics of all unknown parameters.[9] This yields a time series of 156 weekly values of β_{RMRF},

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[8] Previous literature in asset pricing assumes either a mean-reverting process or a random walk to model factor loadings with the Kalman filter and smoother. We decide in favor of a mean-reverting process based on two reasons: First, mean reversion of factor loadings is documented in Blake et al. (1999) for funds' portfolio weights within a sample of UK pension funds. Second, the mean-reverting process nests a random walk for the factor loadings in the case of $\theta = 0$. In Appendix A.2 we show that both alternatives produce very similar results when evaluating the relationship between factor exposure variation and future fund performance.

[9] We shortly describe the Kalman filter and the Kalman smoother techniques in Appendix A.1. Within each three-year window we require funds to have at least 104 weekly return observations.

β_{SMB}, β_{HML} and β_{UMD} per fund in the three-year period. For each of the four βs, we compute the standard deviation across time, i.e. $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$. These standard deviations express the variation of the fund's exposure to the respective factors during the three-year period: Generally, a higher $\sigma(\beta)$ indicates a less stable exposure with regard to a certain factor.[10] To express a fund's overall level of exposure variation with respect to all factors we aggregate the four measures to one overall *Factor Exposure Variation (FEV) Indicator*. We determine this *FEV Indicator* as follows: At each point in time, we calculate the cross-sectional mean and standard deviation for each *FEV* measure $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ and standardize all estimated values of $\sigma(\beta)$ by demeaning (using the cross-sectional mean) the estimates and dividing them by the respective cross-sectional standard deviation. Our *FEV Indicator* is then defined as the average of the four standardized values, i.e.,

$$FEV\ Indicator = \frac{1}{4}\left(\frac{\sigma(\beta_{RMRF})-\overline{\sigma(\beta_{RMRF})}}{SD(\sigma(\beta_{RMRF}))} + \frac{\sigma(\beta_{SMB})-\overline{\sigma(\beta_{SMB})}}{SD(\sigma(\beta_{SMB}))} + \frac{\sigma(\beta_{HML})-\overline{\sigma(\beta_{HML})}}{SD(\sigma(\beta_{HML}))} + \frac{\sigma(\beta_{UMD})-\overline{\sigma(\beta_{UMD})}}{SD(\sigma(\beta_{UMD}))}\right),$$

where $\overline{\sigma(\beta)}$ is the cross-sectional mean and $SD(\sigma(\beta))$ the cross-sectional standard deviation of $\sigma(\beta)$.[11] We will refer to a fund's factor exposure variation measured over the past three years ending at time *t* as the fund's exposure variation (*FEV)* at time *t*. The relationship between future fund performance in month *t+1* and a fund's *FEV* in month *t* is investigated in Section 2.

1.3. Summary statistics

Daily fund returns – and hence, calculated weekly returns for our empirical tests – are available from CRSP by the end of 1998. We calculate our *FEV* measures from past three years' net returns.

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[10] To prevent outliers influencing our empirical tests, we censor observations for which the estimated values of $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ or $\sigma(\beta_{UMD})$ are among the highest 1% of all observations.

[11] Equal-weighting of the four standardized measures is an ad-hoc and simple way to obtain an overall *FEV Indicator* that does not overweight an individual factor exposure variation. In unreported tests, we also construct two alternative *FEV Indicators* by (i) equal-weighting the unstandardized *FEV*s and (ii) value-weighting the standardized *FEV*s by their *t*-statistic of the high minus low portfolio strategy to predict future abnormal returns as shown in Table 2, specifications (1) to (4). The resulting alternative *FEV Indicators* have a correlation of 0.93 and 0.99 with the baseline *FEV Indicator* and the results in the performance analysis are almost identical. Detailed results are available upon request.

If more than two but less than three years of data are available, we calculate the *FEV* measures using the available data. Therefore, our final dataset reaches from the end of 2000 to 2016. It contains 300,519 observations and 3,816 distinct funds. Table 1 provides summary statistics for the main variables of the empirical analysis.

[Insert Table 1 around here]

Average and median fund sizes are 1,329 and 324 million USD, which indicate a skewed distribution of size across funds. On average, the age of a fund is 15.7 years and management has been in office for 7.5 years. The average turnover ratio is 75% per year, but there is a wide variance ranging from 3% to 342%. Total expenses range from 0.14% p.a. to 2.23% p.a. with a mean of 1.15%. The average yearly flow is positive (2.0% of past TNA) but its median is at -6.0% suggesting that there are high net inflows into few funds but smaller net outflows from the majority of funds. All four estimated parameters of $\sigma(\beta)$ show a pronounced heterogeneity in factor exposure variation ranging from a very stable $\sigma(\beta) < 0.0001$ to values as large as 4.2 times the average $\sigma(\beta)$. Mean $\sigma(\beta)$ is highest for the HML factor, followed by the SMB, the UMD, and the market *FEV* measure, which is in line with results of Engle (2016) who finds betas of industry portfolios to vary over time with the HML being the most volatile. As expected and by construction, the average *FEV Indicator* is close to zero, but there are some funds with very volatile factor loadings (maximum *FEV Indicator* = 4.57) and some funds with very stable factor loadings (minimum *FEV Indicator* = -1.80). Panel B reports the estimates of *FEV* by fund style and shows that "Mid Cap", "Small Cap", and "Micro Cap" funds tend to have less stable factor exposures than "Growth", "Growth and Income", and "Income" funds. We report the average cross-sectional correlations between the four measures of exposure variation in Panel C. The correlation between the individual *FEV*s ranges from 0.20 to 0.33, thus indicating that factor exposure variation to a single factor does not strongly imply exposure variation with respect to other factors.

Figure 1 plots the time-series of equal-weighted average measures of *FEV* over all funds in our sample.

[Insert Figure 1 around here]

Measures of *FEV* with respect to the market, SMB and UMD factors appear to be relatively stable over time whereas HML exposure variation slightly peeks during the pre-crisis years and after 2013. Overall, *FEV* seems to be prevalent in different market situations and periods of economic booms and recessions.

2. Factor exposure variation and mutual fund performance

This section investigates the relationship between *FEV* and future fund performance of mutual funds. We examine univariate portfolio sorts in Section 2.1 and multivariate regressions in Section 2.2. Additional robustness checks that document the stability of our main results are reported in Section 2.3.

2.1. Univariate portfolio sorts

We are interested in the relationship between the variation of factor exposures, measured by $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ as well as the overall *FEV Indicator*, and the future performance of mutual funds. We start by applying univariate portfolio sorts to investigate this relationship. Each month *t*, we sort all funds in our sample by the variation of either a specific factor exposure (i.e., by either $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$, $\sigma(\beta_{UMD})$) or by the *FEV Indicator* and assign them into five quintile portfolios, each portfolio holding one fifth of all funds. As *FEV* differs significantly between fund styles, we sort the funds within the same style, thus ensuring that the number of funds of a certain fund style is (almost) the same for all five quintile portfolios. We keep these portfolios unchanged for one month and calculate the quintile portfolio returns – completely out-of-sample – in month *t+1* as the equal-weighted mean of the funds' returns within this portfolio. We resort the portfolios every month by the most recent *FEV* and therefore obtain a monthly return time series for each quintile portfolio.

[Insert Table 2 around here]

Panel A of Table 2 reports the average abnormal, risk-adjusted returns of these portfolios with each column referring to a specific sorting criterion. As our asset pricing model for the risk-adjustment, we use the Carhart (1997) four-factor model. We specifically examine the differences in abnormal returns between funds with high and low *FEV*, i.e., funds that are sorted in portfolio five and portfolio one according to each measure.

Our results reveal that the risk-adjusted spread between funds with high and low *FEV* is negative and statistically significant (at least at the 5% significance level) for the individual market, value, and momentum factors as well as for the overall *FEV Indicator*. Funds in the fifth portfolio, i.e. funds with a high *FEV*, underperform the funds in the first portfolio, i.e., funds with a low *FEV*, in terms of abnormal returns by 102 (market factor), 82 (value factor), 120 (momentum factor) and 147 (overall *FEV Indicator*) basis points p.a., respectively. Furthermore, the abnormal returns monotonically decrease in market, value, and momentum exposure variation as well as in the overall *FEV Indicator*.[12]

The *FEV Indicator* is defined conditional on taking a stance on the appropriate asset pricing model.[13] As there is no consensus in the academic literature about the nature of the "correct" asset pricing model, we want to check the stability of our finding and compute a second *FEV Indicator* based on the Fama and French (2015) five-factor model plus the momentum factor as the state space model, i.e., we use:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{RMRF,i,t} * (r_{m,t} - r_{f,t}) + \beta_{SMB,i,t} * SMB_t + \beta_{HML,i,t} * HML_t + \beta_{CMA,i,t} * CMA_t + \beta_{RMW,i,t} * RMW_t + \beta_{UMD,i,t} * UMD_t + \varepsilon_{i,t},$$

$$\beta_{j,i,t} = \beta_{j,i,t-1} + \theta_{j,i}(\mu_{j,i} - \beta_{j,i,t-1}) + \eta_{j,i,t} \quad \text{for} \quad j \in \{RMRF, SMB, HML, CMA, RMW, UMD\},$$

[12] We also examine the relationship between the overall *FEV* indicator and future fund performance separately for different fund styles. Our results reveal a significant negative effect for five out of the seven styles (i.e., for Growth", "Hedged", "Micro-Cap", "Mid-Cap", and "Small" funds).

[13] Note that the necessity of an appropriate asset pricing model is unavoidable when defining the *FEV Indicator*.

where $r_{m,t}$ is the market return, $r_{f,t}$ is the risk-free rate, SMB_t, HML_t, and UMD_t denote the Fama and French (1993) and Carhart (1997) factors, and CMA_t and RMW_t denote the investment and profitability factors of the Fama and French (2015) model at time *t*. The corresponding *FEV 6-Factor Indicator* is defined as the average of the six standardized *FEV*s. Panel B of Table 2 reports the average abnormal, risk-adjusted returns of these portfolios with each column referring to a specific sorting criterion. Correspondingly to the construction of the *FEV 6-Factor Indicator,* we use the factors of the Fama and French (2015) model and momentum for the risk-adjustment. In line with the results in Panel A, our results reveal that funds with high *FEV* underperform funds with low *FEV*. The spread between funds with the highest *FEV 6-Factor Indicator* and the lowest *FEV 6-Factor Indicator* amounts to 94 basis points p.a. and is statistically significant at the 5% level.[14]

To rule out that the results of higher future returns of low *FEV* funds are driven by other risk and behavioral factors and/or the choice of the factor model, we repeat the portfolio sorts for the *FEV Indicator* and calculate each quintile's abnormal return for different alternative asset pricing models in Table 3. Again, we focus on interpreting the results of the (5) – (1) difference portfolio between funds with high and low *FEV*.

[Insert Table 3 around here]

To control for additional asset pricing factors, we use the one-factor CAPM model, the Fama and French (1993) three-factor model, and the Fama and French (1993) model plus a short and a long-term reversal factor provided by Kenneth French's homepage. We also apply the Carhart (1997) model including, either, the Frazzini and Pedersen (2014) betting against beta factor, the Baker and Wurgler (2006) sentiment factor or the Pástor and Stambaugh (2003) liquidity factor in alternative specifications. We find that our results remain qualitatively unchanged and statistically

[14] In order to keep the content of the paper concise, we focus to present the results of the *FEV Indicator* based on the Carhart (1997) model in the following tables. All results are stable when we compute the *FEV* Indicator based on the five-factor Fama and French (2015) model extended by the momentum factor.

significant for all alternative factor models (while getting even more significant for some of the additional models). We conclude that the underperformance of mutual funds with high *FEV* is not explained by alternative asset pricing factors.

2.2. Fama-MacBeth regressions

To check whether there is a negative impact of factor exposure variation on performance when controlling for different fund characteristics at the same time, we proceed to investigate the relationship between *FEV* and future fund returns using Fama-MacBeth regressions. We calculate a fund's abnormal return at month t, α_t, as the difference between the actual fund performance during this month and the expected fund performance calculated from a Carhart (1997) model, that is $\alpha_t = r_{i,t} - E[r_{i,t}]$, where

$$E[r_{i,t}] = r_f + \beta_{mkt,i,t} * (r_{m,t} - r_{f,t}) + \beta_{smb,i,t} * SMB_t + \beta_{hml,i,t} * HML_t + \beta_{mom,i,t} * UMD_t,$$

and β_t are estimated by an OLS regression over the previous three years of weekly return data. We conduct Fama-MacBeth regressions with annualized abnormal returns during the next month t+1 (or cumulated over the next six and twelve months) as the dependent variable and measures of *FEV* as well as different fund characteristics measured in month t as independent variables. As independent variables, we use a fund's *ln*(TNA), *ln*(fund age), *ln*(manager tenure), expenses, turnover, lagged alpha and past fund flows. Table 4 reports our results using Newey-West standard errors with a lag of 1 month and style dummies.

[Insert Table 4 around here]

Specification (1) reports that variable market, size, value, and momentum exposures have, on average, a negative effect on abnormal returns. This effect is statistically significant for *FEV* of the market and size factor. In specification (2), we pool the individual measures to the *FEV Indicator*. The average effect of the *FEV Indicator* on future abnormal returns is negative and statistically significant at the 1% level. We also show that this result holds for the six-month and twelve-month abnormal returns in specifications (3) and (4) where the respective *t*-statistics of the *FEV Indicator* coefficient estimates negatively exceed the Harvey (2017) *t*-value threshold of minus three.

We also analyze the economic impact of our results. The average cross-sectional standard deviation our measures of market, size, value and momentum exposure variation are 0.06, 0.12, 0.14, and 0.09. Thus, a one standard deviation increase of market, size, value, and momentum exposure variation leads to a decrease of annualized abnormal returns by 35, 38, 15, and 22 basis points p.a. The economic impact of the overall *FEV Indicator* is the most substantial: Specification (2) reports that a one standard deviation increase in factor exposure variation reduces abnormal future returns by 71 basis points p.a.[15]

2.3. Robustness tests

We conduct a series of robustness tests to check that the negative relationship between *FEV* and mutual fund performance remains strong when applying value-weighting (instead of equal-weighting), using alternative performance measures, varying the frequency of returns in the analysis, altering the estimation procedure for the *FEV Indicator*, and varying the dynamics of our state space model. Results of these tests are discussed in Appendix A.2 and confirm that our main results are not sensitive to several choices we make in our empirical analysis.

3. Potential drivers of factor exposure variation

Our empirical results indicate a strongly negative relationship between a fund's *FEV* and future performance. In this section, we analyze potential drivers of mutual funds' factor exposure variation. In particular, we consider equity-induced factor loading variation in Section 3.1. and examine forced trading due to fund flows in Section 3.2. Section 3.3 investigates fund characteristics that are correlated with *FEV*.

[15] Note that the result of a significant negative impact of the *FEV Indicator* on future fund performance remains when we explicitly control for the effect of the expense ratio and turnover in bivariate portfolio sorts.

3.1. Factor exposure variation induced by unstable factor loadings of equity holdings

There are generally two potential sources, not related to active decisions, that can lead to variation in factor exposures. On the one hand, a fund's trading activity might be forced by strong inflows and outflows of investor money. On the other hand, even a buy-and-hold strategy might have volatile factor exposures if the holdings' factor exposures vary over time. Prior research finds evidence consistent with the latter explanation: Armstrong et al. (2013) show that stocks with high factor loading uncertainty with respect to the MKT factor, the SMB factor, the HML factor, and the UMD factor earn low future returns. This pattern might be also potentially present on the fund level.

We aim to disentangle variation in factor loadings induced by changes in a fund's asset allocation (i.e., actual fund *FEV*) from factor exposure variation caused by the variation of the holdings' factor loadings. Therefore, we calculate an additional set of *FEV* measures directly imputed from mutual fund equity portfolio holdings. Most funds report holdings at the end of each quarter and we then calculate weekly returns during a quarter q as the weighted average stock returns during this week, weighted by the fund's portfolio weights as of the end of quarter q-1.[16] This procedure yields a return series for each fund, where short-term investment decisions and the timing of trades of the fund manager remain unconsidered. As in Section 1.2, we apply the Kalman filter and smoother to estimate our dynamic version of the Carhart model for this holding-based return series instead of actual fund returns. As before, we compute the *FEV* measures to MKT, SMB, HML, and UMD factor over a period of 156 weeks and form a *FEV Indicator* by averaging the standardized values of these individual variation measures. We then investigate whether this overall *FEV Indicator* calculated from fund holdings is also related to future abnormal returns of the fund using Fama-MacBeth regressions in Table 5.

[Insert Table 5 around here]

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[16] We do not consider a fund whenever the most recent holdings were reported more than one year ago and are missing in the upcoming quarters.

Specification (1) repeats the baseline regression setup of specification (2) in Table 4 for a comparison of coefficients. In specification (2), we report the results of the relationship between *FEV* measures based on equity holdings data and fund performance. In line with the results of Armstrong et al. (2013), we find that the association between the holdings-based *FEV Indicator* and future abnormal returns is significantly negative. However, we also observe that the coefficient estimate of the *FEV Indicator* decreases by more than 30% in magnitude in comparison to the *FEV Indicator* based on actual net returns. If we use both indicators as explanatory variables in regression (3), we document that only the coefficient of the *FEV Indicator* calculated from actual net returns remains statistically significant at the 5% level and is 3.4 times as large as the coefficient on the holdings-based *FEV Indicator*.

Altogether, these results indicate that the holdings-based *FEV Indicator* relates negatively to future abnormal returns; however, it cannot explain the negative association between the *FEV Indicator* calculated from actual net returns and future performance. Hence, we conclude that *FEV* induced by fund managers' active trading decisions (as opposed to the variation of fund holdings' factor exposures) is the main driver of a fund's underperformance.

3.2. Forced versus unsolicited trading

Section 3.1 shows that the negative relationship between *FEV* and future fund performance is not explained by the underlying portfolio holdings' exposure variation and hence must be due to *FEV* induced by fund managers' trading. This section aims to distinguish between unsolicited trading and forced trading, i.e., trading that is driven by a fund's investor flows. If investors withdraw large amounts from a fund (or invest new money into the fund), the fund management will be forced to sell (or buy) assets and factor exposure might vary as a result of this forced trading.[17] If the negative relationship between the variation of factor exposures and fund performance is

[17] Coval and Stafford (2007) discuss the phenomena of asset fire sales and purchases for mutual funds. They show that, among others, funds experiencing large outflows tend to decrease existing positions, which creates price pressure in the underlying securities held by the fund.

stronger and only present among funds that experience large inflows or outflows, forced trading could explain this empirical finding.

We measure *FEV* over a three-year period and investigate the impact of contemporaneous flows, observed over the identical period. Hence, we compute a fund's three-year flow as the sum of yearly flows as described in Section 1.1. To detect the impact of fund inflows and outflows on the *FEV* – performance relationship we construct three subsamples. One subsample consists of all fund-month observations for which the three-year flow lies below the 30% quantile of all three-year flows during the same time period. A second subsample consists of all observations with a three-year flow above the 70% quantile. All remainder funds, i.e., those with a medium three-year flow between the 30% and 70% quantile, constitute a third subsample. Within each subsample we repeat the Fama-MacBeth regression procedure as before and specifications (1) – (3) of Table 6 report the results. If forced trading is driving our results, we would expect the relationship between *FEV* and future fund performance to be particularly pronounced for funds with negative or high three-year-flows.

[Insert Table 6 around here]

Our empirical results do not support this idea. In fact, the coefficient for *FEV* in the regressions is lowest for funds in the medium-flow sample, that is, for funds with moderate flows.

Summing up flows over the previous three years might disguise cases where funds had to react to large inflows in one year and to large outflows during another year, i.e., these flows could level out each other. We therefore calculate an absolute flow measure as the sum of the absolute flow values during the three years.[18] We repeat the subsample analysis using this absolute flow measure. We consider subsamples with the 30% highest, 30% lowest and 40% median absolute flows. If large inflows or outflows are driving our results, we would expect the *FEV* – performance relationship to be stronger for funds with a higher absolute flow measure. However, the results in

[18] As an example, a fund with yearly flows of +50%, -50% and +20% would have an absolute flow measure of 120%.

specifications (4) – (6) of Table 6 do not support this expectation and the most negative coefficient estimate of the *FEV* can be seen for funds with median absolute flows. We thus conclude that the negative relationship between *FEV* and future fund performance cannot be explained by fire sales (or purchases) of funds and is mainly due to voluntary trading decisions of fund managers.

3.3. Fund determinants

To understand which funds are pursuing high *FEV*, we study the relationship between fund characteristics and the individual measures of factor exposure variation to the MKT, SMB, HML, and UMD factors as well as the overall *FEV Indicator*. From a theoretical view and results of the previous literature, we expect that funds with long manager tenure as well as high turnover and total expense ratios show high *FEV*. First, Chevalier and Ellison (1999) document that young managers do not have the incentive to expose their portfolios to unsystematic risk and risky bets in order not to hurt their future career prospects. Hence, funds with short manager tenure should avoid unsolicited trading and show low *FEV*. Second, Huang et al. (2011) and Amihud and Goyenko (2013) reveal that high turnover and total fund expenses go together with an active fund management style and a substantial deviation from the benchmark. Consequently, these active funds are likely to also show high *FEV*.

Since measures of *FEV* are estimated using 3-year time windows during our 09/1998-12/2016 sample period, we split our sample into six non-overlapping sub-periods, namely 1999-2001, 2002-2004, 2005-2007, 2008-2010, 2011-2013, and 2014-2016. We regress the measures of factor exposure variation during those periods on the fund characteristics at the beginning of these periods to observe the relationship between ex-ante fund characteristics and *FEV*. Table 7 reports the results of the multivariate regressions.

[Insert Table 7 around here]

Specifications (1) – (4) show the results with the individual *FEV* measures as dependent variables, while specification (5) adapts the overall *FEV Indicator* as the dependent variable. We focus on interpreting results for variables with significant coefficient estimates in all specifications. In column (6) we report the economic effect of a one standard deviation increase in the respective fund characteristic on the overall *FEV Indicator*.

First, and in line with the results of Chevalier and Ellison (1999), we find that managers with long management tenure show higher *FEV* than managers with short management tenure, probably due to concerns of young managers of underperforming due to risky bets in the first years of their career. A standard deviation increase in the natural logarithm of manager tenure is associated with a 0.05 increase in the *FEV Indicator*. Second, *FEV* is indeed positively related to fund expenses and portfolio turnover. A positive standard deviation change in each of these variables elevates the *FEV Indicator* by 0.20 and 0.08, respectively. Given an unconditional standard deviation of 0.68 for the *FEV Indicator* in our sample, these numbers describe economically significant associations. These findings complement the results from Sections 3.1 and 3.2 in pointing out that *FEV* captures an actively pursued investment strategy by fund managers.

4. Conclusion

Mutual fund managers vary their exposure to different behavioral and risk factors over time. To measure this investment pattern, we propose a new measure of factor exposure variation (*FEV*) which is based on a dynamic version of the Carhart (1997) four-factor model. Using this measure, we investigate whether variation in factor exposure is linked to future fund performance within a sample of US mutual funds during the time period from the late 2000 up to 2016.

We find that variation of factor exposures is associated with future underperformance: A portfolio of the 20% funds with the highest *FEV Indicator* underperforms the 20% funds with the lowest *FEV Indicator* by risk-adjusted 147 basis points p.a. with statistical significance at the 1% level. Similarly, sorting funds on the variation of individual MKT-, HML-, or UMD exposures, results in underperformance of the funds with the most unstable factor loadings by 102, 82, and 120 basis points p.a., respectively, with statistical significance at least at the 5% level. Our results indicate that the underperformance is neither explained by volatile factor loadings of a fund's equity holdings nor driven by a fund's forced trading through investor flows. We thus conclude that fund managers voluntarily attempt to time factors, but they are unsuccessful at doing so.

From a practitioner's perspective, our results are important for both investors and fund managers. Using our methodology, investors can directly assess a fund's *FEV* to different factors without relying on costly and low-frequent portfolio holdings data. Subsequently, they can use the *FEV Indicator* for manager selection. Our findings do not support the hypothesis that deviations in factor exposures are a signal of skill and we recommend that investors should carefully take our results into account before investing in funds with high *FEV*.

In the same way as for investors, fund managers can apply the *FEV Indicator* to evaluate their own intended or unintended trading activity to different risk and behavioral factors. Although recent academic literature has proposed different approaches to time factor premiums, it is unclear whether these strategy refinements can be exploited out-of-sample, especially when taking account of trading costs and other limits of arbitrage. We contribute in showing that the *average* US equity fund manager is apparently unsuccessful at timing the MKT, SMB, HML, and UMD factors which gives rise to the notion that timing factors is difficult in practice. Our study does not answer the questions whether the relationship between *FEV* and future performance is similar for other investment classes (such as for bonds or commodities) or different geographical regions (such as for European or Emerging Markets stocks). We leave these questions open for future research on the topic.

Appendix A.1: Kalman Filter

Kalman filtering was introduced to engineering in 1960. The algorithm derives estimates of unobservable state variables from a time-series of observable variables that contains statistical noise. In our case, the unobservable state variables are the factor loadings, which are estimated from a return time series. The Kalman filter requires a mathematical model that describes the dynamics of the unobservable state variables. In our main specification, we assume the factor loadings to follow a mean-reverting process.

The optimization follows a recursive two-step process. At each time *t*, the Kalman filter uses information up to time *t* to estimate the current state variables (i.e., factor loadings) as well as their uncertainties. It then uses the observed noisy measurement (i.e., the fund return) to update the estimate using a weighted average forecast. The algorithm gives more weight to estimates with lower uncertainty. In addition to the Kalman *filter* technique, we also apply a Kalman *smoother* in our estimations. The Kalman smoother additionally contains a backward procedure that utilizes observations that occur after time *t* to estimate state variables at time *t*. The advantage of the Kalman filter and Kalman smoother techniques compared to a rolling regression framework lies in the efficient use of information and the quick detection of factor loading variations. In our empirical analysis we apply the Kalman *filter and* Kalman *smoother* techniques to calculate a fund's factor exposure variation based on a rolling window of three years of weekly fund return data to relate the estimates – out-of-sample – to measures of future fund performance.

Rachev et al. (2015) provide an introduction into the Kalman filter and its application in finance. Black, Fraser, and Power (1992) have been the first to measure time-varying factor exposures via the Kalman filter and similar approaches have later been used e.g. by Wells (1994), Brunnermeier and Nagel (2004), Jostova and Philipov (2005), Swinkels and van der Sluis (2006), Mamaysky, et al. (2007) and Mamaysky, et al. (2008). Hollstein and Prokopczuk (2016) find that a Kalman Filter model outperforms other methods in estimating market betas of single stocks. An important difference among earlier studies and our paper is the assumed process of factor loadings. Whereas some papers assume a random walk, we follow Wells (1994), Jostova and Philipov (2005) who assume a mean-reverting process. This is also in line with the findings of Blake et al. (1999) who document a mean reversion in funds' portfolio weights within a sample of U.K. pension funds. We execute the Kalman filter using adapted functions from the Jouni Helske's KFAS package (Helske, 2016) in the software environment R.

Appendix A.2: Robustness Checks

Table A.1 of the Appendix reports results of several robustness checks to confirm that the significantly negative relationship between *FEV* and mutual fund performance is stable when we alter different specifications in the empirical analysis. We report the risk-adjusted returns for the High-Low portfolios based on *FEV* (or related robustness measure) as in Table 2. In addition, we adapt the Fama-MacBeth regression framework presented in specification (2) of Table 4 and display the results of the stability checks in Table A.1. We only show the coefficient estimate of the *FEV Indicator* and suppress the coefficient estimates of the control variables for better illustration purposes.

In specification (1), we value-weight the funds in portfolio sorts and during the first stage regressions of the Fama-MacBeth procedure. In specification (2), we use the skill measure of Berk and van Binsbergen (2015), which measures the dollar value a fund manager generates, either presenting itself as a management fee or as over- or underperformance to the investor, as the dependent variable. In specifications (3) – (5), we apply a fund's Sharpe ratio and the manipulation-proof performance measure of Goetzmann et al. (2007) as the dependent variable, respectively. For the latter, we set $\rho=2$ and $\rho=3$ to alternate the level of risk penalty. We find that – in all specifications – the High-Low portfolio return is negative and the coefficient estimate for the *FEV Indicator* remains negative and statistically significant at the 5% level.

In our baseline specification, we estimate *FEW* with weekly return data and perform portfolio sorts and Fama-MacBeth regressions with monthly returns. An interesting robustness test is to check whether our results prevail when we alter the frequency of returns (i) from weekly to daily when estimating *FEW* and (ii) from monthly to weekly in the performance analysis. Results are reported in specifications (6) and (7) and show that our results do not depend on a specific return frequency and are robust.

Our dynamic factor model relies on an assumption about the underlying process of factor loadings and we assume a mean reverting process that is for each fund *i* at time *t*:

$$\beta_{j,i,t} = \beta_{j,i,t-1} + \theta_{j,i}\left(\mu_{j,i} - \beta_{j,i,t-1}\right) + \eta_{j,i,t} \quad \text{for } j \in \{RMRF, SMB, HML, UMD\}.$$

As an additional robustness test, in specification (8), we restrict this process to a random walk by setting $\theta_{j,i} = 0$. Hence, we have:

$$\beta_{j,i,t} = \beta_{j,i,t-1} + \eta_{j,i,t} \quad \text{for } j \in \{RMRF, SMB, HML, UMD\}.$$

We estimate the dynamics assuming this random walk, measure the variation of βs and calculate a corresponding version of the *FEV Indicator* as described in Section 1.2. The relationship between the *FEV Indicator* and future fund performance remains negative and statistically significant at the 5%-level in portfolio sorts and multivariate regression analysis.

Another methodological alternative considers the measurement of *FEV*. Instead of measuring the variation of βs over time we use the standard deviation of ηs as a measure of factor exposure volatility. For each of the four factors, the error term η is normally distributed and we use the standard deviation of these distributions to the four factors as the measures of interest. As before, we calculate the *FEV Indicator* as the average of the cross-sectional standardized measures. Specification (9) shows that the relationship between the *FEV Indicator* and fund performance is negative and statistically significant at the 5%-level.

Our baseline specification applies the factors of the Carhart (1997) model, i.e., MKT, SMB, HML, and UMD to compute the *FEV Indicator*. We investigate the robustness of our results when we use the three factors of the Fama and French (1993) model to compute the *FEV Indicator.* Specification (10) reports that the negative relationship between *FEV* and future fund performance remains unaffected.

A potential concern of our empirical analysis is the use of the Kalman filter and smoother techniques to compute a fund's *FEV Indicator*. In specification (11) we compute the *FEV Indicator* based on the volatility of time-varying betas obtained from rolling OLS regressions of 36 months (i.e., the Kalman filter and smoother are not applied here). Our results that the negative and statistically significant association between *FEV* and future fund performance is not dependent on the use of the Kalman filter and smoother technique.

Finally, we perform a placebo test to examine the relationship between *FEV* and fund performance for a sample of index funds. For these funds, any variation of factor exposure should be coincidental and not influenced by fund managers' trading decisions. If the relationship between *FEV* (which, in the case of index funds, is not an intended timing) and fund returns was due to fund managers' actions, we should not expect this relationship for index funds. We exactly follow the data selection procedure from Section 1.1 but instead of dropping index funds, we solely keep index funds in our sample. We identify those funds by the index fund flag from CRSP and additionally hand-pick funds whose names include one of the terms "Index", "S&P", "Wilshire", "Dow" or "Russell". This leaves us with 631 index funds and 33,515 fund-month observations. Specification (12) reports the results of the portfolio sorts and Fama-MacBeth regressions on this index fund sample. As expected, the relationship between the *FEV Indicator* and future abnormal fund performance is close to zero. This result provides evidence that our main result of a negative relation between *FEV* and future fund performance stems from fund managers' trading decisions.

Table A.1: Robustness checks

Specification		High-Low Return	*FEV Indicator*	Control Variables
(1)	Size-weighted	-1.47%**	-1.029*	Yes
(2)	Skill measure	-470,000**	-977.48*	Yes
(3)	Sharpe ratio	-0.097*	-0.031**	Yes
(4)	MPPM (ρ=2)	-1.16%*	-0.828*	Yes
(5)	MPPM (ρ=3)	-1.22%**	-1.103**	Yes
(6)	Daily Returns in Estimation	-1.39%**	-1.011**	Yes
(7)	Weekly Returns in Performance Analysis	-1.54%**	-0.312**	Yes
(8)	Random Walk	-1.49%**	-0.974*	Yes
(9)	Variation in η	-1.40%*	-0.842*	Yes
(10)	FF 3-factors	-1.11%*	-0.971*	Yes
(11)	OLS betas	-0.74%*	-0.743*	Yes
(12)	Placebo Test	-0.28%	-0.045	Yes

This table reports the results of different robustness checks. We report the risk-adjusted returns for the High-Low portfolios based on *FEV* (or a related robustness measure) as in Table 2. In addition, we adapt the Fama-MacBeth regression framework presented in specification (2) of Table 4 of alternative dependent variables on the *FEV Indicator* and control variables. The detailed performed robustness checks are explained in the Appendix. We only show the coefficient estimate of the *FEV* Indicator and suppress the coefficient estimates of the control variables for better illustration purposes. We use Newey-West standard errors (lag=1 month) for the regressions with abnormal returns as the dependent variable. Statistical significance at the 5% and 1% level is denoted by * and **.

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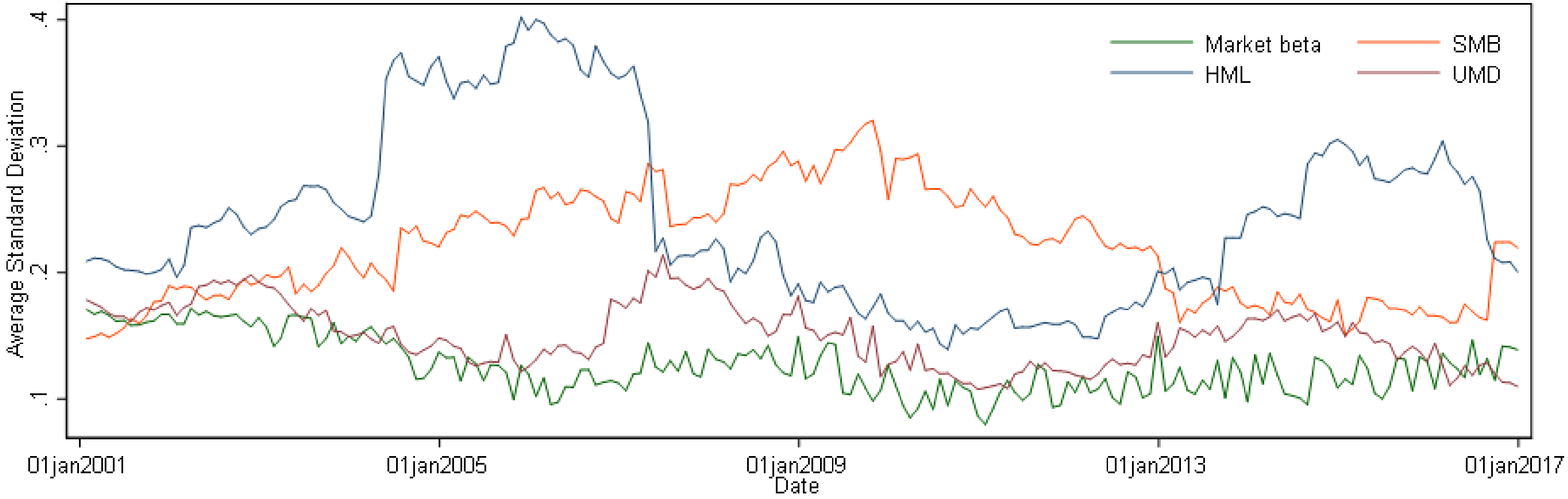
Figures and Tables

Figure 1: *FEV* over time



This figure shows the evolution of the *FEV* measures $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ over time. The *FEV* measures are the standard deviation of factor loadings during the past three years and factor loadings are estimated from a dynamic version of Carhart's (1997) four-factor model as introduced in Section 1.2. We assume factor exposures to follow a mean-reverting process.

Table 1: Descriptive statistics, *FEV* by fund style, and correlations

Panel A: Fund characteristics

	# Obs.	Mean	1%	25%	50%	75%	99%
Number of funds	3,816						
Fund-Week-obser-vations	300,519						
Total assets (in million USD)	300,519	1,329	19	107	324	1,049	21,268
Fund age (years)	300,361	15.73	2.57	7.65	12.68	19.04	72.42
Manager tenure (years)	241,442	7.51	0.42	3.66	6.33	10.09	25.76
Turnover ratio	265,402	0.75	0.03	0.30	0.58	0.99	3.42
Total expense ratio (in %)	266,142	1.15	0.14	0.92	1.14	1.37	2.23
Relative fund flow	300,311	0.02	-0.59	-0.15	-0.06	0.08	1.90
$\sigma(\beta_{RMRF})$	300,519	0.1220	0.0260	0.0828	0.1105	0.1495	0.3343
$\sigma(\beta_{SMB})$	300,519	0.2179	0.0250	0.1242	0.1936	0.2847	0.6311
$\sigma(\beta_{HML})$	300,519	0.2401	0.0200	0.1295	0.2035	0.3099	0.7831
$\sigma(\beta_{UMD})$	300,519	0.1465	0.0138	0.0814	0.1278	0.1925	0.4273
FEV Indicator	301,908	0.0065	-1.1529	-0.4874	-0.0937	0.3895	2.0284

Panel B: Mean values of *FEV* by fund style

Fund Style	# Funds / # Obs.	$\sigma(\beta_{RMRF})$	$\sigma(\beta_{SMB})$	$\sigma(\beta_{HML})$	$\sigma(\beta_{UMD})$	*FEV Indicator*
Growth and Income	773 / 57,877	0.105	0.173	0.194	0.118	-0.343
Growth	1,636 / 127,455	0.120	0.212	0.235	0.144	-0.029
Hedged	49 / 2,369	0.132	0.223	0.236	0.127	0.071
Income	202 / 14,016	0.108	0.175	0.209	0.130	-0.247
Mid Cap	430 / 36,644	0.141	0.263	0.275	0.184	0.365
Small Cap	675 / 58,711	0.133	0.249	0.277	0.159	0.217
Micro Cap	45 / 4,275	0.155	0.315	0.321	.0190	0.629
Other	6 / 172	0.105	0.173	0.194	0.118	-0.177

Table 1: Continued

Panel C: Average cross-sectional correlations between *FEV* measures					
	$\sigma(\beta_{RMRF})$	$\sigma(\beta_{SMB})$	$\sigma(\beta_{HML})$	$\sigma(\beta_{UMD})$	*FEV Indicator*
$\sigma(\beta_{RMRF})$	1.00				
$\sigma(\beta_{SMB})$	0.26	1.00			
$\sigma(\beta_{HML})$	0.28	0.20	1.00		
$\sigma(\beta_{UMD})$	0.33	0.31	0.29	1.00	
FEV Indicator	0.69	0.65	0.65	0.71	1.00

Panel A of this table reports a descriptive overview over the sample size and fund characteristics. Size, age, management tenure, turnover ratio and total expense ratio are obtained from the CRSP survivorship bias free database and relative fund flows are calculated over the past year using $flow_t = (tna_t - tna_{t-1year})/(tna_{t-1year} * (1 + ret_{(t-1year,t)}))$. Fund styles are mainly determined by a fund's CRSP objective code. Funds are aggregated on a portfolio level and size is the sum of all share classes' total assets, fund age is the age of the oldest share class and all other characteristics as well as returns are calculated as the size-weighted mean of all share classes. The *FEV* measures $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ are the standard deviation of a fund's weekly factor loading during the past three years. The factor loadings are estimated from a dynamic version of Carhart's (1997) four-factor model as introduced in Section 1.2. We assume factor exposures to follow a mean-reverting process. The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of factor exposure variation. Data on age, tenure, turnover, expense ratio, flows, and total net assets are winsorized at the 1%-level and observations for which the estimated values of $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ are amongst the highest 1% are dropped from the sample. Panel B of this table reports the average *FEV* measures and the *FEV Indicator* by fund style. Panel C of this table reports the average cross-sectional correlations between the measures of factor exposure variation $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ and the *FEV Indicator*.

Table 2: Abnormal returns of quintile portfolios sorted by the *FEV Indicator*

Panel A: *FEV Indicator* based on the Carhart (1997) four-factor model

	(1) $\sigma(\beta_{RMRF})$	(2) $\sigma(\beta_{SMB})$	(3) $\sigma(\beta_{HML})$	(4) $\sigma(\beta_{UMD})$	(5) *FEV Indicator*
Low *FEV*	-0.96%**	-1.17%**	-1.01%*	-0.91%**	-0.80%*
(2)	-1.28%**	-1.39%**	-1.10%**	-1.12%**	-0.97%**
(3)	-1.33%**	-1.25%**	-1.43%**	-1.19%**	-1.34%**
(4)	-1.44%**	-1.40%**	-1.59%**	-1.62%**	-1.58%**
High *FEV*	-1.98%**	-1.78%**	-1.82%**	-2.11%**	-2.27%**
High-Low	-1.02%* (-2.24)	-0.61% (-1.33)	-0.82%* (-2.43)	-1.20%** (-2.68)	-1.47%** (-2.76)

Table 2: Continued

Panel B: *FEV 6-Factor Indicator* based on the Fama and French (2015) + momentum factor model

	(1) $\sigma(\beta_{RMRF})$	(2) $\sigma(\beta_{SMB})$	(3) $\sigma(\beta_{HML})$	(4) $\sigma(\beta_{CMA})$	(5) $\sigma(\beta_{RMW})$	(6) $\sigma(\beta_{UMD})$	(7) *FEV 6-Factor Indicator*
Low *FEV*	-1.10%**	-1.18%**	-1.15%**	-1.25%**	-1.09%**	-1.17%**	-1.07%**
(2)	-1.34%**	-1.35%**	-1.25%*	-1.34%*	-1.34%*	-1.03%**	-1.25%**
(3)	-1.35%**	-1.44%**	-1.40%**	-1.33%**	-1.53%**	-1.37%**	-1.33%**
(4)	-1.79%**	-1.60%**	-1.56%**	-1.62%**	-1.55%**	-1.81%**	-1.74%**
High *FEV*	-1.80%**	-1.83%**	-2.03%**	-1.85%**	-1.88%**	-2.00%**	-2.01%**
High-Low	-0.69%	-0.65%	-0.88%*	-0.61%	-0.80%*	-0.83%*	-0.94%*
	(-1.72)	(-1.63)	(-2.30)	(-1.37)	(-2.01)	(-2.07)	(-2.05)

This table reports the abnormal returns of fund portfolios sorted on measures of *FEV*. In Panel A, each month we sort funds into five quintiles by either a single *FEV* $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ or by the *FEV Indicator*. Measures of *FEV* are the weekly standard deviation of a fund's factor loadings obtained from a dynamic version of Carhart's (1997) four-factor model over the previous three years as introduced in Section 1.2. We assume factor exposures to follow a mean-reverting process. The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of *FEV*. In Panel B, each month we sort funds into five quintiles by either a single *FEV* $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$, $\sigma(\beta_{CMA})$, $\sigma(\beta_{RMW})$, and $\sigma(\beta_{UMD})$ or by the *FEV 6-Factor Indicator*. Measures of *FEV* are the weekly standard deviation of a fund's factor loadings obtained from a dynamic version of the by the momentum factor extended Fama and French (2015) five-factor model over the previous three years. We assume factor exposures to follow a mean-reverting process. The *FEV 6-Factor Indicator* is the mean of the six cross-sectionally standardized measures of *FEV*. The sorting is done within each style category, where fund styles are mainly determined by a fund's CRSP objective code. We keep the portfolios constant for one month and calculate the equal weighted portfolio return from funds' net return. Each column represents the sorting by the *FEV* with respect to a distinct factor. We report annualized Carhart (1997) alphas for each quintile portfolio (Rows 1-5) as well as the difference between the portfolios with highest and lowest *FEV* (High-Low) in Panel A. We report annualized Fama and French (2015) + momentum alphas for each quintile portfolio (Rows 1-5) as well as the difference between the portfolios with highest and lowest *FEV* (High-Low) in Panel B. T-statistics are reported in parentheses. We use Newey-West standard errors (lag = 1 month) for the portfolio sorts. Statistical significance at the 5% and 1% level is denoted by * and **.

Table 3: Abnormal returns of quintile portfolios sorted by the *FEV Indicator* under different factor models

	(1) Carhart (1997)	(2) 1-Factor	(3) Fama/French 3 Factors (1993)	(4) FF3 + Reversal	(5) Carhart + BaB	(6) Carhart + Sentiment	(7) Pástor-Stambaugh
Low *FEV*	-0.80%*	-0.14%	-0.76%*	-0.81%*	-1.20%**	-0.62%	-0.94%**
(2)	-0.97%**	-0.37%	-0.94%**	-0.98%**	-1.34%**	-0.84%*	-1.20%**
(3)	-1.34%**	-0.76%	-1.30%**	-1.34%**	-1.70%**	-1.21%**	-1.57%**
(4)	-1.58%**	-0.96%	-1.52%*	-1.53%**	-1.98%**	-1.41%**	-1.83%**
High *FEV*	-2.27%**	-1.61%	-2.20%**	-2.20%**	-2.82%**	-2.12%**	-2.50%**
High-Low	-1.47%** (-2.76)	-1.47%* (-2.08)	-1.43%** (-2.65)	-1.39%** (-2.67)	-1.61%** (-2.93)	-1.50%** (-2.78)	-1.56%** (-2.77)

This table reports the abnormal returns of fund portfolios sorted by the *FEV Indicator*. The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of *FEV*, which are defined as the standard deviation of a fund's weekly factor exposures during the past three years. The factor loadings are estimated from a dynamic version of Carhart's (1997) four-factor model as introduced in section 1.2. We assume factor exposures to follow a mean-reverting process. The sorting is done within each style category, where fund styles are mainly determined by a fund's CRSP objective code. We keep the portfolios constant for one month and calculate the equal weighted portfolio return from funds' net return. We regress each quintile portfolio's return time series on different factor models. Each column refers to one factor model, namely the one-factor model including only the market factor, the Fama/French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama/French (1993) three-factor model extended by a short and long term reversal factor as well as the Carhart (1997) model extended by the Frazzini/Pedersen (2014) betting against beta factor, the Baker/Wurgler (2006) sentiment factor and the Pástor/Stambaugh (2003) liquidity factor. We report annualized alphas for each quintile portfolio (Rows 1-5) as well as the difference between the portfolios with highest and lowest *FEV* (High-Low). T-statistics are reported in parentheses. We use Newey-West standard errors (lag = 1 month) for the portfolio sorts. Statistical significance at the 5% and 1% level is denoted by * and **.

Table 4: Fama-MacBeth regressions: Effect of *FEV* on future returns and alphas

Explanatory variables	(1) annualized $alpha_{j,t}$	(2) annualized $alpha_{j,t}$	(3) 6-months CAR	(4) 12-months CAR
$\sigma(\beta_{RMRF})$	-0.060**			
	(-3.33)			
$\sigma(\beta_{SMB})$	-0.032*			
	(-2.15)			
$\sigma(\beta_{HML})$	-0.011			
	(-1.15)			
$\sigma(\beta_{UMD})$	-0.025			
	(-1.78)			
FEV Indicator		-1.036**	-0.763**	-0.616**
		(-2.78)	(-3.99)	(-5.21)
ln(tna)	-0.158*	-0.160*	-0.157**	-0.135**
	(-2.02)	(-2.03)	(-3.50)	(-4.96)
ln(fund age)	0.144	0.163	0.150*	0.090
	(1.03)	(1.18)	(2.46)	(1.77)
ln(manager tenure)	0.013	0.006	-0.024	-0.017
	(0.17)	(0.08)	(-0.50)	(-0.56)
Expenses	-0.777**	-0.783**	-0.743**	-0.731**
	(-5.72)	(-5.58)	(-12.63)	(-18.50)
Turnover	-0.207	-0.211	-0.349*	-0.348**
	(-0.96)	(-0.96)	(-2.56)	(-3.16)
Lagged Alpha	0.262**	0.259**	0.189**	0.160**
	(5.86)	(5.70)	(8.11)	(8.70)
Fund Flows	0.181	0.201	0.105	-0.101
	(0.68)	(0.75)	(0.84)	(-1.12)
Style Dummies	YES	YES	YES	YES
Average R^2	0.14	0.13	0.14	0.15

This table reports the results of Fama-MacBeth regressions of future one-month annualized abnormal fund returns on measures of *FEV* and controls. Each month expected returns are calculated from a Carhart (1997) model where the factor loadings are estimated over the past three years of weekly return data from an OLS regression. Abnormal returns are the differences between actual monthly returns and the expected returns. Fama-MacBeth regressions are applied to the panel data of monthly abnormal returns. The first two columns report results where the dependent variable is the next month's abnormal return, the last two columns report results where the cumulated abnormal return over the next six or 12 months is regressed on fund characteristics. Funds are aggregated on a portfolio level and fund characteristics are calculated as described in Section 1.1. Measures of *FEV* ($\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$) are the weekly standard deviations of a fund's factor loadings obtained from a dynamic version of Carhart's (1997) four-factor model over the previous three years as introduced in Section 1.2. We assume factor exposures to follow a mean-reverting process. The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of *FEV*. Data on age, tenure, turnover, expense ratio, flows, and total net assets are winsorized at the 1%-level and observations for which the estimated values of $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ are amongst the highest 1% are dropped from the sample. T-statistics are reported in parentheses. We use Newey-West standard errors (lag = 1 month) for the regressions with abnormal returns as the dependent variable. Statistical significance at the 5% and 1% level is denoted by * and **.

Table 5: Fama-MacBeth regressions: Effect of *FEV* based on equity portfolio holdings on future returns and alphas

Explanatory variables	(1)	(2)	(3)
FEV Indicator (based on returns)	-1.036** (-2.78)		-0.643* (-1.98)
FEV Indicator (based on holdings)		-0.725* (-2.11)	-0.188 (-0.94)
ln(tna)	-0.160* (-2.03)	-0.075 (-0.97)	-0.078 (-0.91)
ln(fund age)	0.163 (1.18)	0.110 (0.92)	0.111 (0.80)
ln(manager tenure)	0.006 (0.08)	-0.018 (-0.28)	-0.019 (-0.22)
Expenses	-0.783** (-5.58)	-0.900** (-4.25)	-0.861** (-4.03)
Turnover	-0.211 (-0.96)	-0.180 (-0.66)	-0.161 (-0.60)
Lagged Alpha	0.259** (5.70)	0.271** (5.07)	0.279** (5.10)
Fund Flows	0.201 (0.75)	0.093 (0.41)	0.096 (0.41)
Style Dummies	YES	YES	YES
Average R^2	0.13	0.12	0.13

This table reports the results of Fama-MacBeth regressions of future one-month annualized fund returns on measures of *FEV* and controls. Each month expected returns are calculated from a Carhart (1997) model where the factor loadings are estimated over the past three years of weekly return data from an OLS regression. Abnormal returns are the differences between actual monthly returns and the expected returns. Abnormal returns are the differences between actual monthly returns and the expected returns. Fama-MacBeth regressions are applied to the panel data of monthly abnormal returns. Funds are aggregated on a portfolio level and fund characteristics are calculated as described in Section 1.1. Measures of *FEV* ($\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$) are the weekly standard deviations of a fund's factor loadings obtained from a dynamic version of Carhart's (1997) four-factor model over the previous three years as introduced in Section 1.2. We assume factor exposures to follow a mean-reverting process. The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of *FEV*. Besides the *FEV Indicator* calculated from funds' net returns, we calculate a second *FEV Indicator* from funds' equity portfolio holdings. Portfolio holdings are reported on a quarterly basis and we assume that between those reporting dates a fund held constant portfolio weights. Data on age, tenure, turnover, expense ratio, flows, and total net assets are winsorized at the 1%-level and observations for which the estimated values of $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ are amongst the highest 1% are dropped from the sample. T-statistics are reported in parentheses. We use Newey-West standard errors (lag = 1 month) for the regressions with abnormal returns as the dependent variable. Statistical significance at the 5% and 1% level is denoted by * and **.

Table 6: Fama-MacBeth regressions: Effect of *FEV* on future returns and alphas when trading is forced

	(1)	(2)	(3)	(4)	(5)	(6)
	30% lowest flows	Medium flows	30% highest flows	30% lowest absolute flows	Medium absolute flows	30% highest absolute flows
FEV Indicator	-0.668*	-1.117**	-0.967***	-0.984**	-1.036**	-0.943***
	(-1.89)	(-2.55)	(-2.62)	(-2.32)	(-2.44)	(-2.69)
ln(tna)	-0.069	-0.134*	-0.191*	-0.140	-0.181*	-0.218**
	(-0.72)	(-1.79)	(-1.77)	(-1.50)	(-1.91)	(-1.98)
ln(fund age)	-0.266	0.139	-0.077	0.028	0.206	0.034
	(-1.22)	(1.00)	(-0.41)	(0.14)	(1.05)	(0.17)
ln(manager tenure)	0.106	-0.136	-0.135	0.159**	-0.099	-0.169
	(1.01)	(-0.89)	(-0.61)	(1.97)	(-0.74)	(-0.77)
Expenses	-0.929**	-0.960***	-0.524**	-0.980***	-0.642***	-0.969***
	(-2.40)	(-4.35)	(-2.03)	(-2.99)	(-2.83)	(-3.47)
Turnover	-0.529	-0.255	-0.115	-0.512	-0.253	-0.052
	(-1.43)	(-1.00)	(-0.52)	(-1.44)	(-0.97)	(-0.24)
Lagged Alpha	0.250***	0.312***	0.239***	0.317***	0.244***	0.248***
	(4.72)	(5.78)	(3.93)	(5.14)	(4.73)	(4.59)
Fund Flows	1.809	0.405	0.356	-0.351	0.512	0.223
	(1.82)	(0.70)	(1.43)	(-0.35)	(0.96)	(0.85)
Style Dummies	YES	YES	YES	YES	YES	YES
Average R^2	0.16	0.17	0.17	0.17	0.16	0.16

This table reports the results of Fama-MacBeth regressions of future one-month annualized fund returns on measures of *FEV* and controls fund subsamples. Funds are sorted into subsamples by either the past 3-year flow (columns 1-3) or the past 3-year absolute flow (columns 4-6). Yearly flows are calculated as $flow_t = (tna_t - tna_{t-1year})/(tna_{t-1year} * (1 + ret_{(t-1year,t)}))$. The 3-year flow is the sum of the year flows during the most recent three years. The 3-year absolute flow is calculated as the sum of the absolute values of yearly flows during the previous three years. In all regressions, we apply specification (2) of Table 4. . The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of *FEV*. Data on age, tenure, turnover, expense ratio, flows, and total net assets are winsorized at the 1%-level and observations for which the estimated values of $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ are amongst the highest 1% are dropped from the sample. T-statistics are reported in parentheses. We use Newey-West standard errors (lag = 1 month) for the regressions with abnormal returns as the dependent variable. Statistical significance at the 5% and 1% level is denoted by * and **.

Table 7: Fama-MacBeth regressions: Relationship between *FEV* and fund determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	$\sigma(\beta_{RMRF})$	$\sigma(\beta_{SMB})$	$\sigma(\beta_{HML})$	$\sigma(\beta_{UMD})$	*FEV Indicator*	*Economic Significance*
ln(tna)	-2.89e-4 (-0.56)	-1.47e-4 (-0.15)	-3.02e-3 (-1.27)	2.12e-3 (1.38)	1.06e-3 (0.10)	+0.00
ln(fund age)	2.18e-3 (1.47)	6.27e-4 (0.18)	6.67e-3 (1.86)	2.14e-3 (1.11)	3.43e-2 (1.55)	+0.02
ln(manager tenure)	2.55e-3* (2.45)	8.77e-3** (4.57)	7.28e-3** (2.86)	6.44e-3** (7.46)	6.37e-2** (6.51)	+0.05
Expenses (in %)	2.78e-2** (6.78)	6.61e-2** (18.35)	5.99e-2** (8.25)	3.99e-2** (8.46)	5.14e+1** (9.42)	+0.20
Turnover ratio	5.19e-3** (3.09)	1.39e-2** (5.82)	1.23e-2** (3.05)	1.56e-2** (11.71)	1.21e-1** (8.01)	+0.08
Past Alpha	7.11e-3 (0.17)	-3.31e-2 (-0.69)	1.10e-2 (0.40)	4.93e-3 (0.18)	5.71e-2 (0.18)	+0.00
Fund Flows	1.98e-6** (3.26)	2.41e-3 (1.19)	1.50e-2* (2.52)	2.53e-3* (2.13)	4.75e-2** (4.86)	+0.03
Style dummy variables						
Growth and Income	–	–	–	–	–	–
Growth	0.013** (4.75)	0.030** (4.64)	0.033** (6.33)	0.017** (4.24)	0.239** (9.05)	–
Hedged	0.032* (2.49)	0.052* (2.24)	0.061 (1.71)	0.004 (0.44)	0.388** (3.48)	–
Income	0.003 (1.85)	-0.007 (-0.51)	0.007 (-0.83)	0.002 (0.32)	0.012 (0.21)	–
Micro	0.036** (6.35)	0.080** (4.36)	0.079** (6.24)	0.063** (5.02)	0.701** (7.87)	–
Mid	0.029** (3.25)	0.066** (8.31)	0.065** (3.53)	0.053** (6.56)	0.560** (6.85)	–
Small	0.021** (2.97)	0.057** (7.55)	0.062** (2.73)	0.034** (5.11)	0.432** (6.53)	–
R^2	0.24	0.17	0.23	0.26	0.24	–

This table reports the results of multivariate regressions of measures of *FEV* on lagged fund characteristics. We split our sample into non-overlapping 3-year subperiods, that is 1999-2001, 2002-2004, etc. up to 2014-2016. factor loadings obtained from a dynamic version of Carhart's (1997) four-factor model over the previous three years as introduced in Section 1.2. We assume factor exposures to follow a mean-reverting process. The *FEV Indicator* is the mean of the four cross-sectionally standardized measures of *FEV*. Fund size, age, management tenure, turnover ratio and total expense ratio are obtained from the CRSP survivorship bias free database and relative fund flows are calculated over the past year using $flow_t = (tna_t - tna_{t-1year})/(tna_{t-1year} * (1 + ret_{(t-1year,t)}))$. . In column (6) we report the economic effect of a one standard deviation increase in the respective fund characteristic on the overall *FEV Indicator*. Fund styles are mainly determined by a fund's CRSP objective code. Funds are aggregated on a portfolio level and size is the sum of all share classes' total assets, fund age is the age of the oldest share class and all other characteristics as well as returns are calculated as the size-weighted mean of all share classes. . Data on age, tenure, turnover, expense ratio, flows, and total net assets are winsorized at the 1%-level and observations for which the estimated values of $\sigma(\beta_{RMRF})$, $\sigma(\beta_{SMB})$, $\sigma(\beta_{HML})$ and $\sigma(\beta_{UMD})$ are amongst the highest 1% are dropped from the sample. T-statistics are reported in parentheses. We use Newey-West standard errors (lag = 1 month) for the regressions with abnormal returns as the dependent variable. Statistical significance at the 5% and 1% level is denoted by * and **.

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