Noise Trading and Asset Pricing Factors*

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Abstract

We demonstrate that a large set of asset pricing factors (anomalies) are significantly exposed to "noise trader" risk, which arises from uninformative demand shifts of mutual fund investors. Mutual fund investors are largely ignorant of systematic factors and respond to simple signals when allocating capital to mutual funds. We measure the uninformed demand of factors by aggregating flow-induced trades of individual stocks underlying the factors. We find that mutual funds' flow-induced trading significantly determines average returns, volatilities, and comovements among the well-studied factors, indicating that these factors are exposed to "noise trader" risk. Importantly, we show that this flow-driven "noise trader" risk is significantly priced by arbitrageurs and other investors.

1 Introduction

In the past decades, asset pricing literature has documented dozens of factors (anomalies) that arguably explain cross-sectional returns among individual stocks.[1] Understanding the source and variation of these factors is an important question. While risk-based explanations are often provided for these factors, there is considerable debate over their economic plausibility and statistical reliability.[2]

This paper provides a new perspective on asset pricing factors. In particular, we show that mutual funds' flow-induced trading significantly determines average returns, volatilities, and comovements among a large set of well-studied factors,[3] although fund flows are hard to be reconciled with an asset pricing theory with rational investors. That is, these factors are heavily exposed to "noise trader" risk à-la De Long, Shleifer, Summers, and Waldmann (1990), which arises from uninformative demand shifts of mutual fund investors. Importantly, we find that this noise trader risk is significantly priced by arbitrageurs and other investors: In the time series, average factor premia are much higher when flow-driven trades are expected to be more correlated across factors; Cross-sectionally, the required return of a factor is higher when its flow-driven trading is more correlated with that of other factors.

The majority of mutual fund investors are households with limited information readily available to them. For example, according to the 2011 ICI Fact Book, 93.7% of mutual fund assets in the U.S. were held by households at the end of 2010. Not surprisingly, recent research documents that mutual fund investors are largely ignorant of systematic factors (anomalies) and respond to simple and uninformative signals when allocating capital to mutual funds.[4] In a fully rational world, however, investors should consider exposures to factors that explain cross-sectional variation in fund performance and only reward fund managers with "real" alphas (Grinblatt and Titman, 1989; Pástor and Stambaugh, 2002).

[1]We use factors and anomalies interchangablely in this paper.

[2]See, for example, Cochrane (2011), Nagel (2013), McLean and Pontiff (2016), Harvey, Liu, and Zhu (2016), Hou, Xue, and Zhang (2018), and Harvey and Liu (2019).

[3]Because the construction of flow-induced trading does not use contemporaneous stock returns, our results are not subject to the critique in Wardlaw (2018).

[4]See Berk and van Binsbergen (2016), Barber, Huang, and Odean (2016), and Ben-David, Li, Rossi, and Song (2018). There is also a large literature showing that mutual fund investors exhibit behavior that is generally considered unsophisticated. For example, mutual fund investors prefer funds that report holdings of recent winners and lottery stocks (Solomon, Soltes, and Sosyura (2014) and Agarwal, Jiang, and Wen (2018)); invest in funds that advertise a lot (Jain and Wu (2000)) or appear in the media (Solomon, Soltes, and Sosyura (2014) and Kaniel and Parham (2017)); prefer funds that recently experienced an extremely positive monthly return (Akbas and Genc (2019)); and time the market poorly (Frazzini and Lamont (2008) and Akbas, Armstrong, Sorescu, and Subrahmanyam (2015)). Song (2018) shows that investors' unsophisticated behaviors lead to a mismatch between managerial skill and scale of active funds.

In such a world, fund flows would have little influence on factor returns as factors are constructed to be well-diversified long-short portfolios. Due to investors' actual behaviors, we hypothesize and verify that the uninformative flow-driven trades of mutual funds strongly influence average returns, volatilities, and comovements among asset pricing factors. We also find that, both in the time series and cross-sectionally, average factor premia are significantly higher when flow-induced trades of factors are expected to be more correlated, suggesting that this flow-driven noise trader risk is priced by arbitrageurs and other investors.

In our empirical exercise, we use 70 characteristic-based factors including size, book-to-market ratio, profitability, and momentum. To construct a characteristic-based factor, we sort all NYSE-AMEX-NASDAQ stocks into quintile portfolios based on the NYSE breakpoints for that characteristic. The factor return in a given month is the spread between the value-weighted returns of the top-quintile and the bottom-quintile stocks. We use NYSE breakpoints and value-weighted returns to mitigate the impact of microcaps (Hou, Xue, and Zhang, 2018).

We use a bottom-up approach to measure mutual funds' flow-driven demand of a given factor π at a quarterly frequency. That is, we first estimate mutual fund flow-induced trading for individual stock in a given quarter using the FIT measure of Lou (2012). In a nutshell, FIT measures the magnitude of flow-driven trading by the aggregate mutual fund industry on a particular shock over a quarter. Then we value weight FIT of the stocks underlying the long leg and the short leg of factor π, respectively, using the market capitalization as the weights. The difference between the value-weighted FIT of the long and short legs is our measure of flow-induced trading of factor π, which we denote as FITOF_{π}. In total, we use 208,419 fund-quarter observations with 4,999 active equity mutual funds in the US from 1980 to 2017.

We start our analysis by showing that flow-induced trading of factor (FITOF) strongly influences return dynamics of the 70 well-studied factors. For example, in a given quarter, the top 20 factors by FITOF over the same quarter significantly *outperform* the bottom 20 factors by 3.6% on average (14.4% on an annual basis), in terms of the Fama-French five-factor (FF5) alpha. This indicates that the flow-induced price impact does not wash out at the factor level, but rather largely determines contemporaneous factor returns.

We further show that this flow-driven price pressure strongly reverts over time, confirming that mutual fund flow-induced trades are largely uninformative as argued in the literature. For example, when we sort the 70 factors by contemporaneous FITOF and track their performance over a longer horizon, the top 20 factors by inflows significantly *underperform* the bottom 20 factors. The short-term price impact is completely reverted over the following two years. We further confirm our results through panel regressions with fixed effects. We also find that the flow-induced effects on factor returns are stronger in the second half of our sample period, consistent with the growth of mutual fund assets over time.

Having demonstrated a large influence of mutual fund flows on factor average returns, we then link variations of flow-induced trading to factor return volatilities and factor return comovements.[5] Intuitively, when mutual fund trading of a factor is expected to be more volatile, return volatility of this factor should be higher; when flow-induced trades across factors are expected to be more correlated, factor returns should covary more with each other.

To test this, we estimate expected variance and expected covariance of flow-induced trading of factors by extending the approach of Greenwood and Thesmar (2011), which we refer to as "factor fragility" and "factor co-fragility," respectively. Indeed, we find that factor fragility strongly forecasts factor return variance in the future, while factor co-fragility strongly forecasts future factor return comovements.[6] For example, in the Fama-Macbeth regression of quarterly frequency, a one-standard-deviation increase in factor co-fragility predicts an increase of 41% of a standard deviation in factor return covariance over the next quarter, even after controlling for lagged factor covariance. The results change little when excluding the crisis periods (2000 to 2001 and 2007 to 2008). Forecasting variance-covariance matrix of factor returns is also of practical importance as one may use this information to construct portfolios of factors (Moskowitz, 2003), especially given the growing popularity of factor (smart-beta) investing.

Taken together, our findings indicate that even the asset pricing factors are heavily exposed to "noise trader" risk (De Long, Shleifer, Summers, and Waldmann, 1990), which arises from uninformed mutual fund flow movements. A natural follow-up question is whether the flow-driven noise trader risk is being "priced" by arbitrageurs and other sophisticated investors who trade these factors.[7] Intuitively, if mutual funds' flow-induced trading is a real concern, then other investors would demand higher average compensation to trade these factors when flow-driven demand shocks are more correlated across factors as diversification opportunities deteriorate in those times.[8] Cross-sectionally, the required

[5] Greenwood and Thesmar (2011), Lou (2012), and Anton and Polk (2014) show that mutual fund ownership structure plays an important role in determining volatilities and comovement among individual stocks.

[6] Here, factor return volatility and return covariance are calculated by weekly factor returns over the subsequent quarter.

[7] Hanson and Sunderam (2014) and McLean and Pontiff (2016), for example, provide evidence that many asset pricing factors found in the literature have been exploited by sophisticated investors.

[8] Intuitively, the expected variance of flow-induced trading of a diversified factor portfolio is mainly determined by the average factor co-fragility. Pollet and Wilson (2010), for example, show that the

return of a factor should also be higher if the flow-driven trading of that factor is more correlated with noise trading of other factors.

Consistent with this intuition, we find that average factor co-fragility, that is, the average covariance of flow-induced trading of factors, significantly and positively forecasts average factor premia in the future. For example, in the time-series regression, a one-standard-deviation increase of average co-fragility forecasts an increase of about 54 bps in average factor premia over the next quarter. This is economically significant as the average premium across the set of factors is about 78 bps per quarter.[9] The out-of-sample (OOS) tests (Welch and Goyal, 2007) further confirm the strong predictive power of factor co-fragility. In the cross-sections, we also find that a factor's required return increases by 48 bps per quarter with a one-standard-deviation increase in the average co-fragility with other factors. Both the time-series and cross-sectional results indicate that the flow-driven noise trader risk is priced by arbitrageurs and other factor investors.

This paper contributes to several strands of the literature. First, our paper is closely related to the recent literature that investigates the seemingly high dimensionality of cross-sectional asset pricing models. Examples include Baz, Granger, Harvey, Le Roux, and Rattray (2015), Harvey, Liu, and Zhu (2016), Harvey (2017), McLean and Pontiff (2016), Kozak, Nagel, and Santosh (2017), Hou, Xue, and Zhang (2018), Kelly, Pruitt, and Su (2018), Feng, Giglio, and Xiu (2019), among some others.[10] We offer a new perspective by emphasizing the important influence of the uninformed mutual funds' flow-driven trading on average return, variation, and comovement among these factors. Our results highlight that asset pricing factors are heavily exposed to "noise trader risk," which we find is significantly priced by other investors.

A vast empirical literature shows that investor demand unrelated to fundamentals can significantly impact asset prices. For example, Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012) show that mutual fund flow-induced demand shocks have a considerable price impact on individual stock prices.[11] This paper complements the prior literature by comprehensively analyzing the impact of uninformative demand shocks on a large collection of asset pricing factors.

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aggregate risk is higher when stocks comove more with each other.

[9]The results are also unchanged when adjusting for the Stambaugh bias (Stambaugh (1999)) and when controlling for lagged average return covariance and other sentiment measures, e.g.. investor sentiment of Baker and Wurgler (2006). The results are robust when factors are constructed as equal-weighted long-short portfolios.

[10]See Feng, Giglio, and Xiu (2019) for a more comprehensive litereature review.

[11]Other examples include Shleifer (1986), Harris and Gurel (1986), Mitchell, Pedersen, and Pulvino (2007), Gârleanu, Pedersen, and Poteshman (2009), Barber, Odean, and Zhu (2009), Greenwood and Vayanos (2010), Foucault, Sraer, and Thesmar (2011), Huang, Song, and Xiang (2019), and Li (2018), among many others.

This paper is also related to Teo and Woo (2004), who find evidence of stock price reversion at the style level and also document that mutual fund flows negatively predict style-level stock returns, consistent with the "style investing" hypothesis in Barberis and Shleifer (2003). We go much beyond mutual funds' price pressure on style average returns as we show that expected variations of mutual fund flows strongly influence variance and covariance of future factor returns. More importantly, we emphasize that flow-induced noise trader risk is being priced at factor/anomaly levels.

The rest of the paper is organized as follows. Section 2 introduces the dataset, the set of asset pricing factors, and our measure of flow-induced trading of factors (FITOF). Section 3 analyzes how demand shifts induced by the uninformative fund flows affect factor return dynamics. Section 4 links (co)variance of fund-induced trades of factors to factor return (co)variance. Section 5 shows that the flow-driven risk is significantly priced. Section 6 concludes. Robustness checks and supplementary results are found in the appendices.

2 Data and Methodology

In this section, we describe the dataset, the list of asset pricing factors (anomalies), and the methodology in estimating mutual fund flow-induced trades of factors.

2.1 Factor construction

We use CRSP and Compustat to construct 70 asset pricing factors. Table C.1 shows the list of factors, which includes size, book-to-market ratio, profitability, and momentum, among many others. Our sample stocks include all ordinary common shares (CRSP share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. In addition, to include a stock in our sample in a given quarter, we require the stock to be held by at least one mutual fund with non-missing holding data from Thomson Reuters CDA/Spectrum database and valid fund flow (calculated using CRSP mutual fund database) in that quarter. To avoid microstructure issues, we follow Hou, Xue, and Zhang (2018) to form quintile portfolios based on NYSE breakpoints. Then, we long and short the two extreme quintiles and track value-weighted returns of the long-short portfolio.

The universe of factors consists of 70 annually or quarterly rebalanced factors based on firm characteristics.[12] For annually rebalanced factors, at June-end of each calendar year, we sort all stocks into quintiles based on NYSE breakpoints of sorting variables

[12]We transform several typical monthly rebalancing factors (e.g., momentum) into quarterly rebalancing factors in order to match with the quarterly mutual fund holdings data in later analysis.

(e.g., book-to-market ratio) at the fiscal year ending in the previous calendar year, and then we track value-weighted portfolio returns from this July to next June. For quarterly rebalanced factors that rely on Compustat quarterly fundamentals data, we skip one quarter between the portfolio formation date and the start of the portfolio holding period to ensure all information is available upon portfolio formation. Specifically, at the end of each quarter, we form quintile portfolios based on sorting variables as of the fiscal quarter ending in the previous calendar quarter, and then we hold the portfolios in the next calendar quarter. More details of factor construction are provided in Appendix C.

2.2 Mutual fund flow-induced trades of factors

To measure flow-induced trades of each of the 70 factors, we first estimate flow-induced trades of individual stocks. To this end, we merge the Thomson Reuters CDA/Spectrum database with the CRSP Survivorship-bias-free mutual fund database. In particular, we obtain mutual funds' holding data from the CDA/Spectrum database. Mutual funds' total net assets (TNA), monthly net returns (after fee), and annual expense ratios are from the CRSP database. For mutual funds with multiple share classes, we use the sum of TNA across all share classes as the TNA of the fund, and we take TNA-weighted average net returns and expense ratios across all share classes. We compute mutual fund monthly gross returns (before fee) as the sum of monthly net returns and 1/12 of the annual expense ratio.

We focus on actively-managed equity mutual funds. Specifically, we filter out non-equity funds based on investment objective codes reported in the CDA/Spectrum database and the CRSP mutual fund database.[13] In addition, we require the ratio of common stock holdings to TNA to be between 80% and 105% on average over the sample period. Finally, we exclude fund-quarter observations with less than $1 million TNA. Our fund sample includes 4,999 distinct US domestic equity funds with 208,419 fund-quarter observations during 1980-2017.

[13] We follow Kacperczyk, Sialm, and Zheng (2008) to screen funds in the following steps. First, we screen funds by investment objectives reported by CDA/Spectrum database. We exclude funds with Investment Objective Codes in 1, 5, 6, or 7, in CDA/Spectrum database. Then, we screen funds by investment objectives reported by CRSP mutual funds database. For funds with non-missing "Type of Securities Mainly Held by Fund" variable (policy variable), we remove those with policy in C&I, Bal, Bonds, Pfd, B&P, GS, MM, or TFM. We then require remaining funds to have Lipper Classification Code in EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, or Missing. For funds with missing Lipper Classification Code, we require them to have Strategic Objective Insight Code in AGG, GMC, GRI, GRO, ING, SCG, or missing. If a fund has both missing Lipper Classification Code and Strategic Objective Insight Code, we screen them through Wiesenberger Fund Type Code and retain funds with objective codes in G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, SCG, or Missing.

We take two steps to construct the stock-level flow-induced trading. We first calculate quarterly mutual fund flows, which is defined as the percentage change of total net assets after adjusting for the appreciation of fund holdings (Sirri and Tufano (1998)):

$$\mathrm{Flow}_{k,t} = \frac{\mathrm{TNA}_{k,t} - \mathrm{TNA}_{k,t-1} \times (1 + R_{k,t})}{\mathrm{TNA}_{k,t-1}},$$

where $\mathrm{TNA}_{k,t}$ is the total net assets of fund k at the end of quarter t and $R_{k,t}$ is the gross return of fund k in quarter t.

Second, we measure quarterly aggregate mutual fund trading of each individual stock in response to fund flows. We use the flow-induced-trading (FIT) measure of Lou (2012):

$$\mathrm{FIT}_{j,t} = \frac{\sum_k \mathrm{Shares}_{k,j,t-1} \times \mathrm{Flow}_{k,t} \times \mathrm{PSF}_{k,t}}{\sum_k \mathrm{Shares}_{k,j,t-1}}, \tag{1}$$

where $\mathrm{Shares}_{k,j,t-1}$ is the number of shares of stocks j held by fund k at the end of quarter $t-1$, $\mathrm{Flow}_{k,t}$ is the percentage flow of fund k in quarter t, and PSF is the partial scaling factor. The scaling factor reflects how fund managers, on average, increase and liquidate their holdings in response to capital inflows and outflows, respectively. Lou (2012) estimates $\mathrm{PSF}_{k,t}$ to be 0.970 for outflows and 0.858 for inflows, and we use the same estimates of the partial scaling factor in our study.[14] Moreover, we use FIT rather than the entire realized trading of mutual funds because FIT only captures those trades that are driven by the demand shifts from mutual fund investors, which are largely uninformative (Ben-David, Li, Rossi, and Song, 2018).

Based on stock-level flow-induced trading, we measure flow-induced trading of a factor π as the value-weighted average FIT of stocks in the factor's long leg minus the value-weighted average FIT of stocks in the short leg. That is,

$$\mathrm{FITOF}_{\pi,t} = \sum_{j \in \mathcal{N}_L^\pi} \mu_{j,t-1}^\pi \mathrm{FIT}_{j,t} - \sum_{j \in \mathcal{N}_S^\pi} \mu_{j,t-1}^\pi \mathrm{FIT}_{j,t}, \tag{2}$$

where $\mathcal{N}_L^\pi$ and $\mathcal{N}_S^\pi$ are the set of stocks consisting of the long-leg and short-leg of factor π at time t, respectively, and $\mu_{j,t-1}^\pi$ is the weight of stock j in factor π. In short, FITOF measures the flow-induced trades of the long-leg stocks relative to the flow-induced trades of the short-leg stocks.

[Table 1 Here]

From Panel A of Table 1, at the beginning of the sample period, our sample covers

[14] Our results are not sensitive to the choices of PSF.

46.30% of all CRSP common stocks, and those stocks represent 94.45% of the dollar value of the market. This is because mutual funds tend to avoid stocks with tiny capitalizations (Frazzini and Lamont (2008)). The sample coverage steadily rises as the relative size of the mutual fund sector grows substantially over time. For example, the fraction of the market held by mutual funds in our sample increases from 2.62% to 20.1%. At the end of the sample period, our sample covers 94.34% in terms of the number of stocks and 99.15% in terms of market capitalization. Because we use the value-weighted scheme when constructing factor returns, stocks that are not held by mutual funds have little influence on our results.

Panel B of Table 1 shows that the average quarterly return of the 70 factors is 0.78%, with a standard deviation of 6.54%. It also shows that the 25th and 75th percentiles of the stock-level FIT are −1.95% and 3.02%, respectively. This suggests that, in response to retail investors' demand shifts, mutual funds adjust their stock holdings relative to their existing holdings at a scale between −1.95% and 3.02% within a quarter in the 25th to 75th percentile range. The 25th and 75th percentiles of FITOF are −0.53% and 0.55%, respectively.

3 Flow-induced trading and factor return dynamics

In this section, we examine how mutual funds' flow-induced demand shifts influence factor returns. While some earlier work, such as Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012), shows that mutual fund flows generate price pressure on individual stocks, it is not clear whether the flow-induced price impact would cancel out at the factor level, as factors are constructed to be diversified long-short portfolios. Indeed, in a hypothetical market where mutual fund investors account for anomalies (factors) and only reward funds with "real" alphas, fund flows should have little impact on factor returns. However, we show in this section that flow-induced trades significantly and positively influence contemporaneous factor returns, followed by strong reversals over longer horizons. This return pattern confirms the findings in prior studies that mutual fund investors are largely ignorant of asset pricing anomalies and make uninformed decisions when allocating capital among funds (Barber, Huang, and Odean, 2016; Ben-David, Li, Rossi, and Song, 2018).

To examine the return pattern associated with flow-induced trading of factors (FITOF), at each quarter-end, we sort the 70 factors into three groups based on FITOF over the same quarter, with 20/30/20 factors in each group respectively. We then track the equal-weighted portfolio returns in the following 12 quarters. Table 2 reports the monthly (adjusted) returns of the three portfolios of factors sorted by FITOF.

[Table 2 Here]

The first pattern to note is that FITOF generates a strong price effect on factors over the contemporaneous quarter (Qtr 0). For example, Panel D of Table 2 reports that the low-FITOF group earns an average monthly Fama-French five-factor (FF5) alpha of -0.42% in the formation quarter, while the high-FITOF group earns a monthly FF5 alpha of 0.82%. The high-minus-low return spread is associated with an average monthly FF5 alpha of 1.25% with a t-statistic of 5.93.

Second, the short-term return effect strongly reverts in the subsequent two years. For example, when we adjust the returns for the FF5 factors (Panel D), the high-minus-low spread is indistinguishable from zero in the first post-formation year, but it is -0.33% per month in the second year. In the third year, there is not further reversal associated with portfolios ranked by FITOF.

[Figure 1 Here]

To visualize the return pattern, Figure 1 plots the cumulative FF5 alpha of a long-short portfolio that longs the high-FITOF group and shorts the low-FITOF group. As one can see, the positive FF5 alpha of the long-short portfolio in the formation quarter is almost entirely reversed by the end of the second year. This flow pattern validates the argument that flow-induced trades of factors are mostly uninformed. In addition, by exploiting the reversal effect associated with FITOF, we find a tradable strategy that longs the factors with low flow-induced trades in the past 8 quarters and shorts the factors with high past FITOF generates annualized alphas of 7.3% to 11.6% depending on the benchmark (see Table B.5).

We also conduct a comprehensive robustness check in Appendix B. First, to account for time and factor fixed effects that might be correlated with factor returns, we also estimate panel regressions of factor returns on flow-induced trading of factors. The regression exercise confirms the strong influence of fund flows on factor returns (see Table B.3). Furthermore, we conduct the regression exercises in the first- and second-half sample period (1982-1998 versus 1999-2017), respectively. We find that the effects of FITOF on factor returns are stronger in the second-half sample. This is consistent with the rapid growth of the mutual fund industry over time.

We also have several placebo tests in Appendix B. First, to ensure that the above return dynamics are not driven by the mean reversion of factor returns, we conduct a similar portfolio-sorting exercise but instead sort on factor returns. We do not find any return patterns (see Panels A and B Table B.4). We also analyze the influence of mutual fund trades of factors that are not driven by fund flows.[15] We find that non-flow-induced trades do not lead to factor return reversals, suggesting that these trades of mutual funds could be driven by information (see Panel C of Table B.4).

In summary, the results in this section and in Appendix B indicate that flow-driven price impact does not wash out at the factor level. Rather, these uninformed demand shifts are statistically strong and economically significant drivers of factor returns. Furthermore, our findings are also consistent with the mounting evidence that mutual fund flows are largely uninformative.

4 Flow-induced trading, factor volatility, and factor comovement

In this section, we link variations of flow-induced factor trading to return volatilities and return comovements among the set of factors. Given that fund flows generate large price pressure on average factor returns, we expect that factor return volatilities are higher when mutual fund trades are more volatile. Moreover, when mutual fund trades are expected to be more correlated across factors, factors would comove more with each other.

To test this argument, we extend the approach of Greenwood and Thesmar (2011) to estimate the variance-covariance matrix of flow-induced factor trading. We find that (*i*) the expected volatility of flow-induced trading strongly forecasts factor return volatility and (*ii*) the expected covariance of flow-induced trading of factors strongly forecasts factor comovement in the future. Together with the results in Section 3 that the fund flow-induced price pressure is largely uninformed, we conclude that these 70 asset pricing factors are significantly exposed to "noise trader" risk (De Long, Shleifer, Summers, and Waldmann, 1990), which arises from uninformative fund flow movement. In Section 5, we will show that this flow-driven noise trader risk is in fact significantly "priced" by arbitrageurs and other investors.

[15] The non-flow-induced trades are the difference between mutual funds' realized trades and the flow-induced trades. To calculate mutual funds' realized trades on factors, we first compute mutual funds' aggregate realized trades on each stock (RT) in a similar way as we compute FIT. Then we compute mutual funds' realized trades on factors as portfolio-weighted average RT on stocks that constitute a factor.

4.1 Estimate (co)variance of flow-induced trading of factors

We first describe how we estimate the variance-covariance matrix of flow-induced trading of factors. Following the idea of Greenwood and Thesmar (2011), we show in Appendix A that the expected variance of flow-induced trading of a given factor π over quarter $t+1$, which we refer to as "factor fragility," can be estimated by

$$G_t^\pi = W_t^{\pi\prime} E_t(\Omega_{t+1}) W_t^\pi. \tag{3}$$

Here, $E_t(\Omega_{t+1})$ is the conditional variance-covariance matrix of mutual fund flows in quarter $t+1$ and $W_t^\pi = \left(w_{1,t}^\pi, \ldots, w_{K,t}^\pi\right)$ is the vector of mutual fund weights in factor π. In particular, the weight of mutual fund k in factor π is calculated as

$$w_{k,t}^\pi = \sum_j \mu_{j,t}^\pi \frac{\text{Shares}_{k,j,t}}{\text{Shrout}_{j,t}},$$

where $\mu_{j,t}^\pi$ is the weight[16] of stock j in factor π and $\text{Shrout}_{j,t}$ is shares outstanding of stock j.

Likewise, we estimate the expected covariance of flow-induced trading of factors π_1 and π_2 over quarter $t+1$, refered to as "factor co-fragility," by

$$G_t^{\pi_1,\pi_2} = W_t^{\pi_1\prime} E_t(\Omega_{t+1}) W_t^{\pi_2}. \tag{4}$$

As one can see, factor fragility and factor co-fragility depend on mutual fund ownership concentration and the expected variance-covariance matrix of mutual fund flows. To estimate $E_t(\Omega_{t+1})$, we calculate the variance-covariance matrix of mutual fund flows using observations in the past two years and the results are not sensitive to this choice.

To illustrate the role of flow variation on factor return variation, we calculate the factor fragility for the Fama-French size and value factors and plot the return volatility of the Fama-French size and value factors and the square root of lagged factor fragility in Figure 2. At first glance, there is a clear positive correlation between future factor return volatility and volatility of flow-induced trading of factors. We formally explore the association between factor fragility (co-fragility) and factor volatilities (co-variance) in the next subsection.

[Figure 2 Here]

[16] For a long-leg stock, $\mu_{j,t}^\pi$ simply equals its original weight in the long leg. For a short-leg stock, $\mu_{j,t}^\pi$ is its original weight in the short leg multiplied by negative one.

4.2 Influences of flow-induced trading on factor (co)variances

We now examine how factor fragility and factor co-fragility, our measure of expected variance and expected covariance of flow-induced trades of factors, respectively, can forecast future variance and covariance of factor returns.

To this end, we first estimate the following regression:

$$\sigma_{t+1}^{\pi_1,\pi_2} = \alpha + \beta G_t^{\pi_1,\pi_2} + \tau \sigma_t^{\pi_1,\pi_2} + \gamma \mathbf{Z}_t^{\pi_1,\pi_2} + \epsilon_{t+1}^{\pi_1,\pi_2}, \tag{5}$$

where $\sigma_{t+1}^{\pi_1,\pi_2}$ is the return covariance between factors π_1 and π_2 over quarter $t+1$ and is estimated based on weekly factor returns in quarter $t+1$, and $G_t^{\pi_1,\pi_2}$ is the estimated co-fragility between factors π_1 and π_2 in equation (4). To account for persistence in factor return covariance, we include lagged factor return covariance. We also have a set of control variables, $\mathbf{Z}_t^{\pi_1,\pi_2}$, that include the factor-pairwise difference in size, book-to-market, and momentum as in Anton and Polk (2014).[17] Panel A of Table 3 presents the results based on the Fama-Macbeth regressions. For easy interpretation, all variables are normalized to have a standard deviation of one.

[Table 3 Here]

As one can see, the expected covariance of flow-induced trades between factors strongly predicts future factor return comovements. In the univariate regression, a one-standard-deviation increase of factor co-fragility predicts an average increase of 80% of a standard deviation of factor return covariance over the next quarter. Even after controlling for lagged factor return covariance, a one-standard-deviation increase of factor co-fragility still predicts an increase of 46% of a standard deviation of factor return covariance. In Columns (3) and (4), we also exclude the crisis periods (from 2000 to 2001 and from 2007 to 2008) and we confirm that our results are not driven by these crisis periods. (In fact, we get even stronger effects.) These results indicate that the correlation in flow-induced trading is an important determinant of factor return comovement.

We then estimate the predictive power of factor fragility on future factor return variation through the following regression:

$$\sigma_{t+1}^{\pi} = a + b\sqrt{G_t^{\pi}} + c\sigma_t^{\pi} + \eta_{t+1}. \tag{6}$$

[17] We construct factor pairwise characteristics difference as follows. First, following Anton and Polk (2014), we construct stock-level NYSE percentile ranking of characteristics. Second, we take value-weighted NYSE percentile rankings for long leg and short leg, and compute factor-level NYSE percentile ranking as the long-short difference. The factor pair-level difference is the absolute value of difference in factor-level NYSE percentile ranking of characteristics.

Here, the dependent variable σ^{π}_{t+1} is the one-quarter-ahead factor volatility, estimated as the standard deviation of weekly factor returns over the next quarter. The independent variable of interest is the square root of factor fragility. We also control for past factor return volatility. Panel B of Table 3 reports the results.

Under all specifications, we find that the square root of factor fragility, $\sqrt{G_t}$, positively and significantly forecasts the one-quarter-ahead factor return volatility. For example, in the univariate regression excluding the crisis period (Column (3)), a one-standard-deviation increase in $\sqrt{G_t}$ predicts an increase of 37% of a standard deviation of factor volatility in the next quarter. After controlling for past volatilities, a one-standard-deviation increase in $\sqrt{G_t}$ still leads to an average increase of 17% of a standard deviation of factor return volatility (Column (4)).

In summary, the results in Sections 3 and 4.2 indicate that flow-induced trading of mutual funds, while being driven by uninformative demand shifts, significantly determines average returns, variations, and comovements among the set of asset pricing factors (anomalies). In other words, this large set of well-studied factors are significantly exposed to "noise trader" risk arising from retail investors' capital reallocation among mutual funds. We further explore the asset pricing implications of the flow-driven risk in the next section.

5 The flow-driven "noise trader" risk is priced

We have shown that a large portion of variations in factor returns is driven by the uninformative fund flow movement. In this section, we further study the implications of the flow-driven "noise trader" risk. Specifically, we explore whether the flow-driven risk is priced by arbitrageurs and other sophisticated investors who trade these factors.[18] Through both in-sample and out-of-sample time-series tests, we find that average factor premia are much higher when flow-driven mutual fund trades are expected to be more correlated across factors. Cross-sectionally, we find that the required return of a factor is higher when its flow-driven demand is expected to be more correlated with that of other factors. We also find that the effect is mainly driven by large-cap stocks within factors where institutional investors trade more extensively. Taken together, the evidence indicates that the flow-driven noise trader risk is indeed priced by other investors and confirms the theory of De Long, Shleifer, Summers, and Waldmann (1990).

[18] Hanson and Sunderam (2014) and McLean and Pontiff (2016), for example, provide evidence that asset pricing factors are exploited by sophisticated investors.

5.1 In-sample time-series tests

If mutual fund flows are a real concern of other investors who trade factors, then they should require higher average factor premia when the average flow-driven "noise trader" risk is expected to be higher. Our exercise in the section confirms this intuition.

Specifically, we use the average pairwise factor co-fragility, which measures the average expected covariances of flow-induced trading across factors, as the proxy for the average "noise trader" risk. Intuitively, the expected variance of flow-induced trading on a diversified (equal-weighted) factor portfolio is mostly determined by the average factor co-fragility. As higher average co-fragility implies a deterioration in diversification opportunities among these factors, we expect that average co-fragility positively predicts average factor premia in the future.

[Table 4 Here]

To set the stage, Table 4 reports the correlation between average factor co-fragility and some other indicators that could potentially predict future factor premia, including the Baker-Wurgler (BW) sentiment index (Baker and Wurgler, 2006) and average value spread of factors (Ilmanen, Israel, Moskowitz, Thapar, and Wang, 2019). Table 4 shows that the correlation between average factor co-fragility and average return covariance of factors is 0.19, and the correlation with the BW sentiment is 0.23, and the correlation with average value spread is 0.27. These fairly low correlations indicate that average factor co-fragility captures information beyond return covariance, the BW sentiment index and the factor value spreads.

[Table 5 Here]

Table 5 presents the time-series regression of future average factor premia on average factor co-fragility. For easy interpretation, all independent variables are normalized to have a standard deviation of one. From column (1), average factor co-fragility positively and significantly forecasts future average factor premia ($t = 3.14$). In terms of the magnitude, a one-standard-deviation increase in average factor co-fragility is associated with an increase of 54 bps in the average factor premia over the next quarter. This effect is economically significant as the average factor premia is about 78 bps per quarter throughout our sample period.

In column (2), we also use average covariance of factor returns to forecast future factor premia. We find that average return covariance also positively forecasts future average factor returns. This result is consistent with the finding of Pollet and Wilson (2010) that average comovement of individual stock returns predicts average stock returns. Columns (3) and (4) show that the BW sentiment and average value spread of factors are also strong predictors of future average factor premia, consistent with Stambaugh, Yu, and Yuan (2012) and Ilmanen, Israel, Moskowitz, Thapar, and Wang (2019).

To confirm the predictability of average co-fragility is not driven by the correlation with other predictors, we further conduct pairwise horse-race regressions. Column (5) of Table 5 shows that the predictive power of average co-fragility is not subsumed by average factor covariance. In contrast, the lagged average return covariance becomes statistically insignificant with the presence of average factor co-fragility. Meanwhile, average co-fragility remains statistically significant with mild reductions in coefficient estimates when controlling for the BW sentiment or average value spread. Finally, we put all these predictors together into the predictive regression. Column (8) shows that average co-fragility remains statistically significant while other predictors lose the power of predicting future average factor premia.

[Table 6 Here]

To adjust for the potential small-sample bias in the predictive regressions (Stambaugh, 1999), we apply the bias-reduction estimation approach proposed in Amihud and Hurvich (2004). Table 6 reports the results. Panel A shows that average co-fragility has low autocorrelation, and Panel B shows that the innovation in the predictive regression by average co-fragility is almost uncorrelated with the innovation in the AR(1) regression of average co-fragility. Hence, the predictive regression is unlikely to suffer from the small sample bias. Panel C confirms that the results are almost unchanged after bias-correction.

[Table 7 Here]

To check robustness, we also detrend average factor co-fragility to alleviate the effect of time trend on our regression analysis.[19] We find the results are almost unchanged (Columns (3)-(6) of Table 7). To further confirm that the results are not specific to the particular way that we construct factors, we also form factors with the NYSE decile breakpoints of characteristic variables and repeat the in-sample regression.[20] Under this alternative factor construction method, average factor co-fragility remains a statistically significant predictor of future average factor premium, and its magnitude is even larger (Columns (1)-(2) of Table 7).[21]

[19]In our sample period 1982Q1-2017Q4, we take residuals from OLS regression of Avg Co-Fragility on year-quarter indicator as linearly-detrended Avg Co-Fragility. Similarly, quadratic trend are excluded through regressing Avg Co-Fragility on both level and square term of year-quarter indicator.

[20]All factor-related variables are also re-constructed based on the decile portfolios.

[21]We also conduct several other robustness checks and placebo tests in Appendix B . In Table B.6,

5.2 Out-of-sample time-series tests

Welch and Goyal (2007) point out that many variables with in-sample forecasting power cannot forecast returns out-of-sample. To further validate the role of average factor co-fragility in predicting future factor premia, we also have the out-of-sample (OOS) test in Welch and Goyal (2007). In particular, our OOS test uses only real-time data of a given predictor to forecast future average factor premia. The OOS predictive power of the predictor is evaluated against that of the historical average factor premia. We find that factor co-fragility strongly forecasts future average factor premia in a series of OOS tests, despite that most of the suggested predictors of the equity premium fail to do so.

Specifically, we conduct the OOS test through estimating the following predictive regression recursively:

$$R_{t+1} = \alpha + \beta A_t + \epsilon_t. \tag{7}$$

Here, R_{t+1} is the average factor return over quater $t+1$ and A_t refers to a specific return predictor (e.g., average co-fragility). Starting with an initial in-sample estimation period, we estimate the above predictive regression and obtain the OLS estimates $(\hat{\alpha}_t,\ \hat{\beta}_t)$ of (α, β). We then forecast average factor premia over the next quarter by

$$\hat{R}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t A_t. \tag{8}$$

Each quarter we expand the estimation window by one quarter until we reach the end of our sample period.

To evaluate the OOS performance for a given predictor of future average factor premia, we follow Welch and Goyal (2007) to compute the following OOS statistics:

$$R^2_{\text{OOS}} = 1 - \frac{\text{MSE}_A}{\text{MSE}_N} \text{ and } \Delta\text{RMSE} = \sqrt{\text{MSE}_\text{N}} - \sqrt{\text{MSE}_\text{A}}.$$

Here,

$$\text{MSE}_A = \sum_{t=n}^{T-1} \left(R_{t+1} - \hat{R}_{t+1}\right)^2, \quad \text{MSE}_N = \sum_{t=n}^{T-1} \left(R_{t+1} - \bar{R}_{t+1}\right)^2,$$

we demonstrate the relation between average co-fragility and future average factor premium in a non-parametric approach. Specifically, we sort all quarters into terciles based on average co-fragility in previous quarter and compute average factor returns in the three sub-periods. We find average quarterly factor premium is only 0.34% following low average co-fragility period, but it is 1.39% following high average co-fragility periods. In Table B.7, we conduct a placebo test and show that average co-fragility can not predict stock market returns and bond market returns. In contrast, the BT sentiment index or the stock market variance can significantly predict the long-term yield or the default yields. This comforts us that the "noise trader" risk from equity mutual fund flow does not capture the information contained in some variables (e.g., BW sentiment or stock market variance).

T is the total number of quarters in our sample, n is the number of in-sample quarters used for the first forecast, R_{t+1} is the actual average factor premium, $\hat{R}_{t+1}$ is the forecast of average factor premium in (8), and $\bar{R}_{t+1}$ is the historical mean of the average factor premia. Intuitively, R^2_{OOS} and ΔRMSE are positive when the forecast errors based on the predictor A_t, MSE_A, are smaller than the forecast errors of the historical mean, MSE_N. To test the hypothesis, we also compute the MSE-F statistic by $(T-h+1)\times\left(\frac{\text{MSE}_N-\text{MSE}_A}{\text{MSE}_A}\right)$, and we compare it against the asymptotic critical values in McCracken (2007).

[Table 8 Here]

Table 8 reports the OOS performance of average factor co-fragility, average covariance, and other predictors of average factor premia used in Table 5. We choose a long enough evaluation period from 1992Q1 to 2017Q4, which starts 10 years after the first quarter in our sample.[22] As one can see, average factor co-fragility, the BW sentiment, and average value spread all have superior OOS predictive power of future average factor premia. For instance, R^2_{OOS} of average co-fragility is 6.91% in the evaluation period. By comparison, average factor return covariance fails to beat the historical mean in the OOS tests, despite it has positive in-sample predictability (Table 5).

Taken together, the results in Tables 5 to 8 demonstrate that average co-fragility positively forecasts future average factor premia both in-sample and out-of-sample. As higher average co-fragility implies higher average flow-driven noise trader risk, other investors are requiring higher average premia trading these factors.

5.3 Decomposition of factors by stock capitalization

In this section, we further corroborate the claim that flow-driven "noise-trader" risk is priced by arbitrageurs and other sophisticated investors. If the positive relationship between average co-fragility and average factor premium arises as compensation for bearing noise trader risk, then the effect should only exist among assets that are indeed traded by arbitrageurs and other investors. Previous literature sheds light on which types of stocks are more likely to be traded by arbitrageurs and institutional investors. For example, hedge funds, who often make use of long-short equity strategies, trade much more intensively on larger stocks rather than smaller stocks (Gompers and Metrick, 2001). Thus, if

[22] Hansen and Timmermann (2012) suggest that the the power of forecast evaluation tests is strongest with long out-of-sample periods. Our choice of evaluation period ensures that the out-of-sample period is long enough relative to the initial estimation period. We also report OOS test results based on alternative choices of evaluation periods in Table B.8, and the results are robust.

we construct factors by stocks with similar factor-characteristics but different market capitalization, we should expect to find a stronger relationship between average co-fragility and average factor premium when factors are constructed with larger stocks.

To test this argument, for each factor, we further sort the stocks in the long leg or short leg into terciles based on their market capitalization at previous year-end (grouped by size tercile 1, 2, and 3 from smallest to largest). We then construct value-weighted long-short portfolios using stocks in each size tercile separately. Take momentum factor as an example. We construct a so-called "Momentum Size Tercile 1" factor by longing the winner stocks that are in the size tercile 1 and shorting the loser stocks that are also in the size tercile 1. Within the size group, we repeat the in-sample and out-of-sample tests of average co-fragility and future average factor premia. Table 9 reports the results.

[Table 9 Here]

Panel A of Table 9 shows the in-sample predictive regressions of average factor premia on average factor co-fragility. We see a sharp difference in the coefficient estimates of across size terciles. For example, in univariate regressions, the coefficients of average co-fragility is -0.01 (t-statistic = -0.04) for size tercile 1, while it is 0.52 (t-statistic = 2.73) for size tercile 3. This comparison is even more striking given that the unconditional factor returns are higher for factors constructed by small-cap stocks.[23] By contrast, the influence of the BW sentiment on factor returns is mostly through small-cap stocks. Panel B reports the out-of-sample tests as in Table 8 across size tercile. Consistent with the in-sample regression results, the out-of-sample performance of average factor co-fragility is positively significant in size tercile 3 while it is slightly negative among the other two size terciles.

5.4 Evidence from cross-sectional factor returns

The above time-series analysis shows that arbitrageurs and other investors require higher average factor premia when flow-driven trades of factors are more correlated. Cross-sectionally, when a factor's flow-driven demand is expected to be more correlated with other factors, arbitrageurs and other investors should also require a higher premium for trading this factor. We formally test this prediction in this section.

To measure the expected covariance of flow-driven demand between a given factor and other factors, we compute the average pairwise co-fragility between that factor and other factors (dubbed by $\overline{\text{Co-Fragility}}$) in each quarter. Intuitively, a higher $\overline{\text{Co-Fragility}}$ implies

[23] Average quarter factor returns in size tercile 1, 2, and 3 are 0.74%, 0.59%, 0.37%, respectively.

that a factor is expected to covary more with other factors due to more correlated flow-induced trading. We test the cross-sectional relationship between $\overline{\text{Co-Fragility}}$ and factor returns in predictive Fama-MacBeth regressions. Specifically, the dependent variable is the return of factor π in a given month $m+1$, and the independent variable of interest is the average co-fragility between factor π and other factors in the nearest quarter prior to month $m+1$. To alleviate the concerns of outliers, we also use the quintile ranking of $\overline{\text{Co-Fragility}}$ in each quarter as the regressor. For control variables, we include average return covariance between factor π and other factors in the nearest quarter prior to month $m+1$ ($\overline{\text{Covariance}}$), past one-quarter factor returns, factor value spread at previous quarter-end, and average FITOF in past eight quarters. Table 10 reports the results.

[Table 10 Here]

Across all specifications, higher factor-level average co-fragility is associated with higher future factor return. Column (1) of Table 10 shows that a one-standard-deviation increase in $\overline{\text{Co-Fragility}}$ is associated with an increase in monthly factor return of 16 bps and the effect is statistically significant at the 99% confidence level.[24] This magnitude is also economically relevant given that our sample average monthly factor return is around 26 bps. Furthermore, the predictive power is not subsumed by other control variables (see column (2)). By comparison, factor-level average return covariance has limited predictability on future factor returns. In columns (3) and (4), we replace $\overline{\text{Co-Fragility}}$ by the quintile ranking of $\overline{\text{Co-Fragility}}$ in each quarter, and the results remain statistically significant.

To give an easy interpretation of the economic magnitude, each quarter we only retain factors assigned to the lowest or highest quintile of $\overline{\text{Co-Fragility}}$ and regress factor returns on a dummy variable which indicates the highest quintile ranking (Dummy_Rank5). Column (5) shows that the coefficient of Dummy_Rank5 is 0.52 (t = 2.76), which means a long-short strategy that longs (shorts) factors in the highest (lowest) quintile of $\overline{\text{Co-Fragility}}$ produces monthly returns of 0.52% per month.

We also show the positive return predictability of factor-level average co-fragility ($\overline{\text{Co-Fragility}}$) through portfolio analysis. Each quarter-end, we sort factors into quintiles based on $\overline{\text{Co-Fragility}}$ in the quarter and hold the quintile portfolios in the next quarter. As shown in Table B.9, the CAPM alpha (FFC four-factor alpha or FF five-factor alpha) increases monotonically with $\overline{\text{Co-Fragility}}$. For example, the CAPM alpha

[24] In the Fama-Macbeth regression, we standardize all independent variables, except Rank and Dummy_Rank5, by their standard deviation in each time period. Hence, the coefficient reported here represents the change in monthly factor returns associated with a one-cross-sectional-standard-deviation increase in the independent variable.

increases from 0.02 % to 0.68% from the bottom to the top quintile. The spread of CAPM alpha is 0.66% ($t = 3.68$). This return pattern is also clearly shown in Figure 3.

[Figure 3 Here]

In summary, the results in Sections 5.1 to 5.4 strongly suggest that the noise trader risk due to mutual fund flow movements is an important state variable priced by other investors, consistent with the theory of De Long, Shleifer, Summers, and Waldmann (1990).

6 Conclusion

Asset pricing literature has documented a large set of stock market factors/anomalies over the past several decades. Understanding the source and variation of these factors is an important question and is also subject to considerable debate. In this paper, we offer a new perspective by showing that a large set of well-studied factors are heavily exposed to "noise-trader risk," which arises from the uninformative demand shifts of retail mutual fund investors.

Specifically, we take a bottom-up approach to measure mutual funds' flow-induced trading of asset pricing factors. We find that the influences of mutual fund flow on factors are both statistically and economically significant. For example, mutual fund trades driven by the uninformative capital allocation of retail investors strongly determine average returns, volatilities, and comovements among the asset pricing factors. That is, these factors are heavily exposed to "noise trader" risk à-la De Long, Shleifer, Summers, and Waldmann (1990). Importantly, we find that the flow-driven "noise trader" risk is significantly priced by arbitrageurs or other sophisticated investors.

References

Agarwal, Vikas, Lei Jiang, and Quan Wen, 2018, Why do mutual funds hold lottery stocks?, Working paper. Available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3164692`.

Akbas, Ferhat, Will J. Armstrong, Sorin Sorescu, and Avanidhar Subrahmanyam, 2015, Smart money, dumb money, and capital market anomalies, *Journal of Financial Economics* 118, 355–382.

Akbas, Ferhat, and Egemen Genc, 2019, Do mutual fund investors overweight the probability of extreme payoffs in the return distribution?, *Journal of Financial and Quantitative Analysis* p. forthcoming.

Amihud, Yakov, and Clifford M. Hurvich, 2004, Predictive regressions: A reduced-bias estimation method, *Journal of Financial and Quantitative Analysis* 39, 813–841.

Ang, Andrew, 2014, *Asset management: A systematic approach to factor investing* (Oxford University Press).

Anton, Miguel, and Christopher Polk, 2014, Connected stocks, *Journal of Finance* 69, 1099–1127.

Arnott, Robert D., Mark Clements, Vitali Kalesnik, and Juhani T. Linnainmaa, 2019, Factor momentum, .

Asness, Clifford S., Antti Ilmanen, Ronen Israel, and Tobias J. Moskowitz, 2015, Investing with style, *Journal of Investment Management* 13, 27–63.

Bai, Jushan, and Kunpeng Li, 2012, Statistical analysis of factor models of high dimension, *The Annals of Statistics* 40, 436–465.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645–1680.

Barber, Brad M., Xing Huang, and Terrance Odean, 2016, Which factors matter to investors? Evidence from mutual fund flows, *Review of Financial Studies* 29, 2600–2642.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Systematic noise, *Journal of Financial Markets* 12, 547–569.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

——— , and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Baz, Jamil, Nicolas Granger, Campbell R. Harvey, Nicolas Le Roux, and Sandy Rattray, 2015, Dissecting investment strategies in the cross section and time series, Working paper. Available at SSRN: `https://ssrn.com/abstract=2695101`.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song, 2018, What do mutual fund investors really care about?, Working paper.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

——— , and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

Berk, Jonathan B., and Jules H. van Binsbergen, 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics* 119, 1–23.

Bogousslavsky, Vincent, 2016, Infrequent rebalancing, return autocorrelation, and seasonality, *Journal of Finance* 71, 2967–3006.

Bollen, Nicolas P.B., and Jeffrey A. Busse, 2001, On the timing ability of mutual fund managers, *Journal of Finance* 56, 1075–1094.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.

Chan, Yeung Lewis, and Leonid Kogan, 2002, Catching up with the joneses: Heterogeneous preferences and the dynamics of asset prices, *Journal of Political Economy* 110, 1255–1285.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015, Regression discontinuity and the price effects of stock market indexing, *Review of Financial Studies* 28, 212–246.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 94, 1276–1302.

Chen, Long, Robert Novy-Marx, and Lu Zhang, 2011, An alternative three-factor model, Working paper. Available at SSRN: `https://ssrn.com/abstract=1418117`.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Christoffersen, Susan E.K., and Mikhail Simutin, 2017, On the demand for high-beta stocks: Evidence from mutual funds, *Review of Financial Studies* 30, 2596–2620.

Cochrane, John H., 2011, Presidential address: Discount rates, *Journal of finance* 66, 1047–1108.

Cohen, Randolph B., Christopher Polk, and Bernhard Silli, 2010, Best ideas, Working paper. Available at SSRN: `https://ssrn.com/abstract=1364827`.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Cremers, Martijn, Antti Petajisto, and Eric Zitzewitz, 2013, Should benchmark indices have alpha? Revisiting performance evaluation, *Critical Finance Review* 2, 1–48.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

Del Guercio, Diane, and Jonathan Reuter, 2013, Mutual fund performance and the incentive to generate alpha, *Journal of Finance* 69, 1673–1704.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *Journal of Finance* 65, 1237–1267.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *Journal of Finance* 67, 933–971.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

———, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–155.

———, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

———, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491–518.

———, 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915–1947.

———, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Feng, Guanhao, Stefano Giglio, and Dacheng Xiu, 2019, Taming the factor zoo: A test of new factors, Working paper. Available at SSRN: `https://ssrn.com/abstract=2934020`.

Ferreira, Miguel A., Aneel Keswani, António F Miguel, and Sofia B. Ramos, 2013, The determinants of mutual fund performance: A cross-country study, *Review of Finance* 17, 483–525.

Financial Times, 2017, Smart beta funds pass $1tn in assets, `https://www.ft.com/content/bb0d1830-e56b-11e7-8b99-0191e45377ec` Accessed: 2018-09-11.

Foucault, Thierry, David Sraer, and David J. Thesmar, 2011, Individual investors and volatility, *Journal of Finance* 66, 1369–1406.

Frazzini, Andrea, and Owen A. Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

French, Kenneth R., 2008, Presidential address: The cost of active investing, *Journal of Finance* 63, 1537–1573.

Froot, Kenneth, and Melvyn Teo, 2008, Style investing and institutional investors, *Journal of Financial and Quantitative Analysis* 43, 883–906.

Fung, William, and David A Hsieh, 2000, Performance characteristics of hedge funds and commodity funds: Natural vs. spurious biases, *Journal of Financial and Quantitative analysis* 35, 291–307.

Fung, William, and David A. Hsieh, 2001, The risk in hedge fund strategies: Theory and evidence from trend followers, *Review of financial studies* 14, 313–341.

———, 2004, Hedge fund benchmarks: A risk-based approach, *Financial Analysts Journal* 60, 65–80.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009, Demand-based option pricing, *Review of Financial Studies* 22, 4259–4299.

Gomes, Joao, Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

Gompers, Paul A., and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–259.

Greenwood, Robin, Samuel G. Hanson, and Gordon Y. Liao, 2018, Asset price dynamics in partially segmented markets, *Review of Financial Studies* 31, 3307–3343.

Greenwood, Robin, and David Thesmar, 2011, Stock price fragility, *Journal of Financial Economics* 102, 471–490.

Greenwood, Robin, and Dimitri Vayanos, 2010, Price pressure in the government bond market, *American Economic Review* 100, 585–90.

Grinblatt, Mark, and Tobias J. Moskowitz, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.

Grinblatt, Mark, and Sheridan Titman, 1989, Mutual fund performance: An analysis of quarterly portfolio holdings, *Journal of Business* 62, 393–416.

Gruber, Martin J., 2011, Another puzzle: The growth in actively managed mutual funds, in *Investments And Portfolio Performance* . pp. 117–144 (World Scientific).

Guercio, Diane Del, and Jonathan Reuter, 2014, Mutual fund performance and the incentive to generate alpha, *Journal of Finance* 69, 1673–1704.

Gupta, Tarun, and Bryan T. Kelly, 2019, Factor momentum everywhere, Working paper. Available at SSRN: `https://ssrn.com/abstract=3300728`.

Hansen, Peter, and Allan Timmermann, 2012, Choice of sample split in out-of-sample forecast evaluation, Working paper. Available at SSRN: `https://econpapers.repec.org/paper/aahcreate/2012-43.htm`.

Hanson, Samuel G., and Adi Sunderam, 2014, The growth and limits of arbitrage: Evidence from short interest, *Review of Financial Studies* 27, 1238–1286.

Harris, Lawrence, and Eitan Gurel, 1986, Price and volume effects associated with changes in the s&p 500 list: New evidence for the existence of price pressures, *Journal of Finance* 41, 815–829.

Harvey, Campbell R., 2017, Presidential address: The scientific outlook in financial economics, *Journal of Finance* 72, 1399–1440.

——— , and Yan Liu, 2017a, Decreasing returns to scale, fund flows, and performance, Working paper. Available at SSRN: `https://ssrn.com/abstract=2990737`.

——— , 2017b, Does scale impact skill?, Working paper. Available at SSRN: `https://ssrn.com/abstract=2872385`.

Harvey, Campbell. R, and Yang Liu, 2019, A census of the factor zoo, Working paper. Available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3341728`.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, . . . and the cross-section of expected returns, *The Review of Financial Studies* 29, 5–68.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets?, *Journal of Accounting and Economics* 38, 297–331.

Hou, Kewei, Chen Xue, and Lu Zhang, 2018, Replicating anomalies, forthcoming, *Review of Financial Studies*.

Huang, Shiyang, Yang Song, and Hong Xiang, 2019, Fragile factor premia, Working paper. Available at SSRN: https://ssrn.com/abstract=3312837.

Ilmanen, Antti, 2011, *Expected returns: An investor's guide to harvesting market rewards* (John Wiley & Sons).

———, Ronen Israel, Tobias J. Moskowitz, Ashwin K. Thapar, and Franklin Wang, 2019, Do factor premia vary over time? a century of evidence, Working paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3400998.

Investment Company Institute, 2017, *Investment company fact book (2017)* (Investment Company Institute).

Jain, Prem C., and Joanna S. Wu, 2000, Truth to mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937–958.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Kaniel, Ron, and Robert Parham, 2017, WSJ category kings - the impact of media attention on consumer and mutual fund investment decisions, *Journal of Financial Economics* 123, 337–356.

Kelly, Bryan, Seth Pruitt, and Yinan Su, 2018, Characteristics are covariances: A unified model of risk and return, Working paper. https://www.nber.org/papers/w24540.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2017, Shrinking the cross section, Working paper. https://www.nber.org/papers/w24070.

———, 2018, Interpreting factor models, *Journal of Finance* 73, 1183–1223.

Kumar, Alok, 2009, Dynamic style preferences of individual investors and stock returns, *Journal of Financial and Quantitative Analysis* 44, 607–640.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Lettau, Martin, Sydney C. Ludvigson, and Paulo Manoel, 2018, Characteristics of mutual fund portfolios: Where are the value funds?, Working paper. https://www.nber.org/papers/w25381.

Lewis, Ryan, 2015, Finding fund scale, Working paper, University of Colorado.

Li, Jiacui, 2018, Slow-moving liquidity provision and flow-driven common factors in stock returns, Working paper. Available at SSRN: `https://ssrn.com/abstract=2909960`.

Linnainmaa, Juhani T., and Michael R. Roberts, 2018, The history of the cross-section of stock returns, *Review of Financial Studies* 31, 2606–2649.

Lou, Dong, 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25, 3457–3489.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

Lyandres, Evgeny, Le Sun, and Lu Zhang, 2008, The new issues puzzle: Testing the investment-based explanation, *Review of Financial Studies* 21, 2825–2855.

Malkiel, Burton G., 1995, Returns from investing in equity mutual funds 1971 to 1991, *Journal of Finance* 50, 549–572.

McCracken, Michael W., 2007, Asymptotics for out of sample tests of granger causality, *Journal of Econometrics* 140, 719–752.

McLean, R. David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32.

McQuade, Timothy J., 2018, Stochastic volatility and asset pricing puzzles, Working paper. Available at SSRN: `https://ssrn.com/abstract=3222902`.

Mitchell, Mark, Lasse Heje Pedersen, and Todd Pulvino, 2007, Slow moving capital, *American Economic Review* 97, 215–220.

Moskowitz, Tobias J., 2003, An analysis of covariance risk and pricing anomalies, *Review of Financial Studies* 16, 417–457.

Nagel, Stefan, 2013, Empirical cross-sectional asset pricing, *Annual Review of Financial Economics* 5, 167–199.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

——— , and Mihail Velikov, 2016, A taxonomy of anomalies and their trading costs, *Review of Financial Studies* 29, 104–147.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* pp. 109–131.

Pástor, Luboš, and Robert F. Stambaugh, 2002, Investing in equity mutual funds, *Journal of Financial Economics* 63, 351–380.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Patton, Andrew J., and Tarun Ramadorai, 2013, On the high-frequency dynamics of hedge fund risk exposures, *Journal of Finance* 68, 597–635.

Pollet, Joshua M., and Mungo Wilson, 2008, How does size affect mutual fund behavior?, *Journal of Finance* 63, 2941–2969.

———, 2010, Average correlation and stock market returns, *Journal of Financial Economics* 96, 364–380.

Ratcliffe, Ronald, Paolo Miranda, and Andrew Ang, 2017, Capacity of smart beta strategies: A transaction cost perspective, *Journal of Index Investing* 8, 39–50.

Reuter, Jonathan, and Eric Zitzewitz, 2015, How much does size erode mutual fund performance? a regression discontinuity approach, Working paper.

Ritter, Jay R., 1991, The long-run performance of initial public offerings, *Journal of Finance* 46, 3–27.

Schwert, G. William, 2003, Anomalies and market efficiency, *Handbook of the Economics of Finance* 1, 939–974.

Shleifer, Andrei, 1986, Do demand curves for stocks slope down?, *Journal of Finance* 41, 579–590.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* pp. 289–315.

Solomon, David H., Eugene Soltes, and Denis Sosyura, 2014, Winners in the spotlight: Media coverage of fund holdings as a driver of flows, *Journal of Financial Economics* 113, 53–72.

Song, Yang, 2018, The mismatch between mutual fund scale and skill, Working paper. Available at SSRN: https://ssrn.com/abstract=3065700.

Spiegel, Matthew, and Hong Zhang, 2013, Mutual fund risk and market share-adjusted fund flows, *Journal of Financial Economics* 108, 506–528.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

———, Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Stein, Jeremy C., 2009, Presidential address: Sophisticated investors and market efficiency, *Journal of Finance* 64, 1517–1548.

Teo, Melvyn, and Sung-Jun Woo, 2004, Style effects in the cross-section of stock returns, *Journal of Financial Economics* 74, 367–398.

Titman, Sheridan, and Cristian Tiu, 2010, Do the best hedge funds hedge?, *Review of Financial Studies* 24, 123–168.

Wahal, Sunil, and M. Deniz Yavuz, 2013, Style investing, comovement and return predictability, *Journal of Financial Economics* 107, 136–154.

Wardlaw, Malcolm, 2018, Measuring mutual fund flow pressure as shock to stock returns, Working paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3248750.

Welch, Ivo, and Amit Goyal, 2007, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655–1695.

Yan, Xuemin Sterling, 2008, Liquidity, investment style, and the relation between fund size and fund performance, *Journal of Financial and Quantitative Analysis* 43, 741–767.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Table 1: **Summary Statistics.**

This table reports the summary statistics of mutual funds, stocks, and factors in our sample. Panel A reports the summary statistics of the US equity mutual funds in our study. # Funds is the number of distinct mutual funds in each period. TNA is the average fund total net assets (in million \$). % Coverage of stock (EW) is the number of distinct stocks held by mutual funds in our sample, divided by total number of CRSP stocks. % Coverage of stock (VW) is the total market capitalization of distinct stocks held by mutual funds in our sample, divided by total market capitalization of CRSP stocks. % market is the average percentage of the US common stocks held by the mutual funds in our sample. Panel B reports the stock and factor characteristics. Size and book-to-market ratio of our sample stocks are shown in NYSE percentiles. Stock-level flow-induced trading (FIT) is defined in (1). Flow-induced trading of factor (FITOF) is defined as the value-weighted FIT of a factor's long-leg stocks minus that of the short-leg stocks in (2). The definition of factor-level square root of fragility ($\sqrt{G}$) and factor pairwise co-fragility are in Section 4.1. The list of factors is in Table C.1.

Panel A: Summary statistics of mutual funds

Period	# Funds	TNA		% Coverage of stock		% Market
		Median	Mean	EW	VW	
1980-1984	370	64.43	159.62	46.30	94.45	2.62
1985-1989	610	79.18	264.52	58.58	97.15	4.33
1990-1994	1,453	71.81	299.02	65.76	98.51	7.51
1995-1999	2,699	110.79	698.13	72.56	98.40	13.19
2000-2004	3,461	120.31	837.97	86.77	99.54	15.35
2005-2009	3,636	172.73	1,097.92	92.77	99.61	18.52
2010-2014	2,875	297.49	1,664.22	91.29	98.44	18.61
2014-2017	2,216	479.88	2,757.40	94.34	99.15	20.07

Panel B: Summary statistics of stocks and factors

Variables	Mean	SD	Q1	Median	Q3
Stock level:					
Size	0.3105	0.2923	0.0547	0.2143	0.5190
Book-to-Market	0.4839	0.3033	0.2088	0.4801	0.7534
FIT	0.0157	0.1196	−0.0195	0.0017	0.0302
Factor level:					
Quarterly Ret	0.0078	0.0654	−0.0270	0.0048	0.0388
FITOF	0.0003	0.0177	−0.0053	0.0001	0.0055
SD of Daily Ret	0.0060	0.0041	0.0037	0.0049	0.0068
$\sqrt{\text{Fragility}}$	0.0012	0.0014	0.0005	0.0008	0.0015
Factor-pair level:					
Cov of Daily Ret (10^{-6})	0.4683	6.0821	−0.5313	0.1116	0.8814
Co-Fragility (10^{-6})	0.0097	0.7377	−0.0377	0.0021	0.0514

Table 2: **Return pattern of flow-induced trading of factors**

This table reports calendar-time performance of factor portfolios sorted by flow-induced trading of factor (FITOF). FITOF is the portfolio-weighted flow-induced trading (FIT) of a factor's long-leg stocks minus that of the short-leg stocks (see (2)). In each quarter t, we sort the 70 factors into three groups based on their FITOF in quarter t, with 20/30/20 factors in the low/mid/high group respectively. Each factor is given equal-weight in the respecitve portfolio. The portfolios are rebalanced every quarter and held for three years. Quarter 0 is the portfolio formation quarter. We track the monthly calendar-time returns of factor portfolios from quarter 0 to quarter 12. To deal with overlapping portfolios in each holding month, we follow Jegadeesh and Titman (1993) to take equal-weighted returns of portfolios formed in different quarters. Panel A to Panel D reports monthly raw returns, monthly CAPM alpha, monthly Fama-French-Carhart four-factor alpha, and monthly Fama-French five-factor alpha, respectively. The returns and alphas are reported in percents. The t-statistics in parentheses are computed based on standard errors with Newey-West correction for twelve lags.

Portfolio	**Qtr 0**	**Qtr 1-4**	**Qtr 5-8**	**Qtr 9-12**	**Portfolio**	**Qtr 0**	**Qtr 1-4**	**Qtr 5-8**	**Qtr 9-12**
Panel A: Monthly Raw Return					**Panel B: Monthly CAPM Alpha**				
Low	−0.22	0.41***	0.49***	0.27***	Low	−0.10	0.55***	0.63***	0.42***
	(−1.61)	(3.42)	(3.86)	(2.70)		(−0.70)	(4.12)	(4.87)	(4.79)
Mid	0.26***	0.25***	0.27***	0.25***	Mid	0.35***	0.34***	0.35***	0.35***
	(4.55)	(4.48)	(4.57)	(4.18)		(6.65)	(6.49)	(6.30)	(5.71)
High	0.76***	0.16**	0.05	0.24***	High	0.85***	0.23***	0.13**	0.33***
	(8.04)	(2.21)	(0.81)	(3.41)		(8.53)	(3.50)	(2.00)	(3.73)
H−L	0.97***	−0.25*	−0.44***	−0.03	H−L	0.95***	−0.32*	−0.50***	−0.08
	(5.18)	(−1.74)	(−2.87)	(−0.27)		(4.51)	(−1.90)	(−3.04)	(−0.66)
Panel C: Monthly FFC4 Alpha					**Panel D: Monthly FF5 Alpha**				
Low	−0.19*	0.36***	0.39***	0.26***	Low	−0.42***	0.20***	0.36***	0.23***
	(−1.72)	(4.98)	(4.13)	(2.85)		(−4.43)	(2.83)	(3.38)	(2.68)
Mid	0.21***	0.21***	0.22***	0.22***	Mid	0.18***	0.18***	0.18***	0.18***
	(4.54)	(5.30)	(5.07)	(4.78)		(3.16)	(4.18)	(4.35)	(3.42)
High	0.65***	0.10	0.05	0.18***	High	0.82***	0.19***	0.03	0.12*
	(5.66)	(1.57)	(0.87)	(3.26)		(6.55)	(2.59)	(0.51)	(1.75)
H−L	0.84***	−0.26**	−0.33**	−0.08	H−L	1.25***	−0.01	−0.33**	−0.12
	(3.99)	(−2.40)	(−2.48)	(−0.65)		(5.93)	(−0.05)	(−2.25)	(−0.89)

Table 3: **Predicting factor return comovement and volatility**

Panel A reports the Fama-Macbeth regressions of one-quarter-ahead factor pairwise return covariance ($\sigma_{t+1}^{\pi_1,\pi_2}$) on the factor pairwise co-fragility ($G_t^{\pi_1,\pi_2}$). $\sigma_{t+1}^{\pi_1,\pi_2}$ is the covariance of weekly returns between factor π_1 and π_2 in quarter t+1. $G_t^{\pi_1,\pi_2}$ is the co-fragility between factor π_1 and π_2 measured at the end of quarter t, following the definition in equation 5. The control variables include one-quarter lagged pairwise return covariance and pairwise difference in size, book-to-market, and momentum characteristics. Panel B reports the Fama-Macbeth regressions of one-quarter-ahead factor return volatility (σ_{t+1}) on the factor fragility ($\sqrt{G_t}$). σ_{t+1} is the standard deviation of weekly factor returns in quarter t+1 and $\sqrt{G_t}$ is the square root of factor fragility, which is defined in equation 4. In Column (1)-(2), we report Fama-Macbeth estimates in the full sample period from 1981Q1 to 2017Q4. In Column (3)-(4), we exclude observations in the crisis period (year 2000, 2001, 2007, and 2008) and report Fama-Macbeth estimates in this sub-period. For easy interpretation, all variables are standardized to have unit variance. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Predict pairwise factor return covariance

DepVar: $\sigma_{t+1}^{\pi_1,\pi_2}$	(1)	(2)	(3)	(4)
	Full Sample		*Exclude Crisis Period*	
$G_t^{\pi_1,\pi_2}$	0.80***	0.46***	1.06***	0.60***
	(4.96)	(5.64)	(4.55)	(5.51)
$\sigma_t^{\pi_1,\pi_2}$		0.53***		0.53***
		(16.18)		(15.53)
Size Diff		−0.03***		−0.04***
		(−7.26)		(−7.14)
BM Diff		0.01		0.02**
		(1.50)		(2.27)
MOM Diff		−0.00		−0.01
		(−0.40)		(−1.38)
No. Obs.	347,760	347,760	309,120	309,120
Adj. R^2	0.10	0.34	0.10	0.34

Panel B: Predict factor return volatility

DepVar: σ_{t+1}	(1)	(2)	(3)	(4)
	Full Sample		*Exclude Crisis Period*	
$\sqrt{G_t}$	0.27***	0.12***	0.37***	0.17***
	(7.49)	(5.10)	(9.26)	(5.77)
σ_t		0.63***		0.62***
		(25.54)		(26.04)
No. Obs.	10,080	10,080	8,960	8,960
Adj. R^2	0.07	0.41	0.07	0.39

Table 4: **Correlation between average factor co-fragility and other sentiment measures**

This table reports pairwise correlations among average co-fragility and sentiment measures. Avg Co-Fragility is the average pairwise co-fragility of the 70 factors in a given quarter, where co-fragility is defined in equation 4. Avg Covariance is the average pairwise daily return covariance of the factors in a given quarter. BW Sentiment is the investor sentiment index orthogonalized to macroeconomic indicators from Baker and Wurgler (2006) in the last month of a given quarter. Avg Value Spread is the average value spread of the factors at the end of a given quarter. The value spread of a factor is computed as the log difference between portfolio-weighted book-to-market ratio of the long-leg and the short-leg. Avg Factor Ret is the average quarterly returns of the factors in a given quarter.

	(1)	(2)	(3)	(4)	(5)
(1) Avg Co-Fragility	1.00				
(2) Avg Covariance	0.19	1.00			
(3) BW Sentiment	0.23	0.33	1.00		
(4) Avg Value Spread	0.27	0.41	0.75	1.00	
(5) Avg Factor Ret	0.02	0.47	0.39	0.33	0.06

Table 5: **Average factor co-fragility and future average premium**

This table reports the estimation results from predictive regressions of average factor return. The dependent variable is equal-weighted average quarterly returns (in percents) of the 70 factors in a given quarter $t+1$. The independent variables include the average pairwise co-fragility of the 70 factors in quarter t (Avg Co-Fragility), the average pairwise daily return covariance of the factors in quarter t (Avg Covariance), the investor sentiment index from Baker and Wurgler (2006) in the last month of quarter t (BW Sentiment), the average value spread of the factors at the end of quarter t, and average quarterly returns of the factors in quarter t. The sample period is 1982Q1-2017Q4. For easy interpretation, all independent variables are standardized to have unit variance. The t-statistics in parentheses are computed based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg Co-Fragility	0.54***				0.50***	0.40***	0.37***	0.38**
	(3.14)				(3.21)	(2.65)	(2.89)	(2.47)
Avg Covariance		0.32*			0.23			−0.07
		(1.83)			(1.60)			(−0.34)
BW Sentiment			0.70***			0.61***		0.27
			(3.60)			(2.95)		(0.88)
Avg Value Spread				0.74***			0.64***	0.42
				(3.02)			(2.82)	(1.02)
Avg Factor Ret								0.13
								(0.60)
No. Obs.	144	144	144	144	144	144	144	144
Adj. R^2	0.07	0.02	0.11	0.13	0.08	0.15	0.16	0.17

Table 6: **Bias adjustment of the predictive regression**

This table reports analysis of bias in the predictive regression. The dependent variable is equal-weighted average quarterly returns (in percents) of the 70 factors in a given quarter $t+1$, and the independent variable is average pairwise co-fragility of the 70 factors in quarter t (Avg Co-Fragility). The sample period is 1982Q1-2017Q4. Panel A reports the OLS estimates from the following two equations: Avg Factor $\text{Ret}_{t+1} = a + b \times$ Avg $\text{Co-Fragility}_{t+1} + u_{t+1}$, Avg $\text{Co-Fragility}_{t+1} = c + d \times$ Avg $\text{Co-Fragility}_{t+1} + v_{t+1}$. Panel B reports correlations or standard deviations (shown in brackets) of innovations in above two regressions. In Panel C reports the coefficient estimates and t-statistics (shown in parentheses) of the predictive regression based on bias-reduction estimation approach in Amihud and Hurvich (2004). *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Original OLS estimates			
a	b	c	d
0.68***	0.54***	0.28***	−0.02
(3.94)	(3.26)	(3.18)	(−0.24)
Panel B: Correlation [SD]			
	u	v	
u	[2.00]	0.02	
v		[1.00]	
Panel C: Bias-adjusted estimates			
a^c	b^c		
0.68***	0.55***		
(3.93)	(3.25)		

Table 7: **Robustness check for predicting average factor premium**

This table reports several robustness checks for predictive regressions of average factor premium. First, we construct factors through forming value-weighted long-short portfolios with NYSE decile breakpoints of characteristic variables. All factor-level variables are defined following Table 5 but are constructed using NYSE decile long-short portfolios. The regression results are reported in Column (1)-(2). We also detrend the key independent variable Avg Co-Fragility in the regressions. Specifically, in the sample period of 1982Q1-2017Q4, we regress Avg Co-Fragility on a year-quarter time indicator and use the residuals as linear-detrended Avg Co-Fragility. Similarlly, we regress Avg Co-Fragility on a year-quarter time indicator together with its square term and use the residuals as quadratic-detrended Avg Co-Fragility. Regression results with the detrended Avg Co-Fragility are reported in Column (3)-(6). All independent variables are standardized to have unit variance. The *t*-statistics in parentheses are computed based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	NYSE Decile		*Detrend-Linear*		*Detrend-Quadratic*	
Avg Co-Fragility	0.68***	0.46**	0.56***	0.38**	0.56***	0.38**
	(3.19)	(2.53)	(3.34)	(2.43)	(3.39)	(2.42)
Avg Covariance		0.02		−0.06		−0.06
		(0.09)		(−0.30)		(−0.28)
BW Sentiment		0.57*		0.26		0.24
		(1.77)		(0.85)		(0.80)
Avg Value Spread		0.31		0.42		0.43
		(0.75)		(1.00)		(1.03)
Avg Factor Ret		0.04		0.13		0.13
		(0.18)		(0.59)		(0.60)
No. Obs.	144	144	144	144	144	144
Adj. R^2	0.07	0.15	0.07	0.14	0.07	0.14

Table 8: **Out-of-sample tests of forecasting average factor premia**

This table reports statistics on out-of-sample forecast errors for average factor return at quarterly frequency. We calculate out-of-sample test statistics, R^2_{OOS} and ΔRMSE, following Welch and Goyal (2007) to compare the predictive regression forecast against unconditional mean forecast. A star next to the R^2_{OOS} is based on critical values of MSE-F statistic given by McCracken (2007). The MSE-F statistic tests the equivalence of MSE of the unconditional mean forecast and the conditional forecast. The definition of each predictor refer to Table 5. All numbers are in percents. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Predictor	R^2_{OOS}	ΔRMSE	MSE_F
Avg Co-Fragility	6.91***	8.99	5.92
Avg Covariance	−17.83	−19.84	−16.11
BW Sentiment	11.16***	14.96	9.47
Avg Value Spread	9.42***	12.48	8.03
Avg Factor Ret	0.12	0.15	0.11

Table 9: **Predict Avg Factor Premium for factors in different size groups**

This table reports the estimation results from predictive regressions of average factor return for factors constructed using stocks with different sizes. In each holding period, we sort the stocks in the long or short leg of a factor into terciles based on their market cap at previous year-end (size tercile 1, 2, and 3 from smallest to largest tercile). For each factor, we re-construct value-weighted long-short portfolios using stocks in size tercile 1, 2, and 3, respectively. For example, "Momentum factor-Size Tercile 1" refers to the long-short portfolio that goes long in size tercile 1 stocks within original momentum winner group and goes short in size tercile 1 stocks within original momentum loser group. All factor-level and factor-pair level variables follow the same definitions as in Table 5 but are constructed based on the size-sorted factor long-short portfolio. For easy interpretation, all independent variables are standardized to have unit variance. The *t*-statistics in parentheses are computed based on standard errors with Newey-West correction of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: In-sample predictive regression

	(1)	(2)	(3)	(4)	(5)	(6)
	Size Tercile 1		Size Tercile 2		Size Tercile 3	
Avg Co-Fragility	−0.01	−0.08	0.22	0.05	0.52***	0.37**
	(−0.04)	(−0.59)	(0.95)	(0.28)	(2.73)	(2.29)
Avg Covariance		−0.37*		−0.22		−0.04
		(−1.90)		(−1.08)		(−0.17)
BW Sentiment		0.88***		0.46		0.25
		(4.59)		(1.56)		(0.85)
Avg Value Spread		0.19		0.61**		0.41
		(0.93)		(2.01)		(0.99)
Avg Factor Ret		−0.32		−0.19		0.14
		(−1.25)		(−0.74)		(0.62)
No. Obs.	144	144	144	144	144	144
Adj. R^2	−0.01	0.15	0.00	0.13	0.06	0.13

Panel B: Out-of-sample test

	(1)	(2)	(3)	(4)	(5)	(6)
	Size Tercile 1		Size Tercile 2		Size Tercile 3	
	R^2_{OOS}	ΔRMSE	R^2_{OOS}	ΔRMSE	R^2_{OOS}	ΔRMSE
Avg Co-Fragility	−1.12	−1.25	−0.49	−0.59	5.11***	5.98

Table 10: **Cross-sectional predictive regressions of factor returns**

This table reports the Fama-MacBeth regressions of factor returns. The independent variable is monthly return (in percents) of a factor in month $m+1$. All independent variables are at the nearest quarter prior to month $m+1$. $\overline{\text{Co-Fragility}}$ is the average of pariwise co-fragility between a given factor and all other factors in the nearest quarter prior to month $m+1$. Rank is the quintile ranking of $\overline{\text{Covariance}}$ in a given quarter. Dummy_Rank5 is a dummy that equals one for factors in the highest $\overline{\text{Covariance}}$ quintile, and it equals zero elsewhere. $\overline{\text{Covariance}}$ is the average of pariwise daily return covariance between a given factor and all other factors in the nearest quarter prior to month $m+1$. Other regressors include factor returns in the nearest quarter prior to month $m+1$, value spread of a given factor at the end of the nearest quarter, and average FITOF in the nearest eight quarters. In each month, we standardize the independent variables by their cross-sectional standard deviations, except for Rank and Rank5. Column (1)-(4) reports the regression results in full sample. Column (5)-(6) reports the regression results among factors in the lowest and highest $\overline{\text{Co-Fragility}}$ quintile. t-statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample				*Extreme Quintiles*	
$\overline{\text{Co-Fragility}}$	0.16***	0.10**				
	(2.63)	(2.30)				
Rank			0.11**	0.06**		
			(2.48)	(2.17)		
Dummy_Rank5					0.52***	0.29**
					(2.76)	(2.15)
$\overline{\text{Covariance}}$		0.05		0.05		0.02
		(0.70)		(0.68)		(0.23)
Past one-quarter return		0.09		0.09		0.11*
		(1.57)		(1.59)		(1.68)
Value Spread		−0.00		0.01		0.01
		(−0.07)		(0.13)		(0.17)
Past eight-quarter FITOF		−0.08		−0.09*		−0.13*
		(−1.63)		(−1.74)		(−1.95)
Adj. R^2	0.11	0.44	0.11	0.43	0.19	0.49

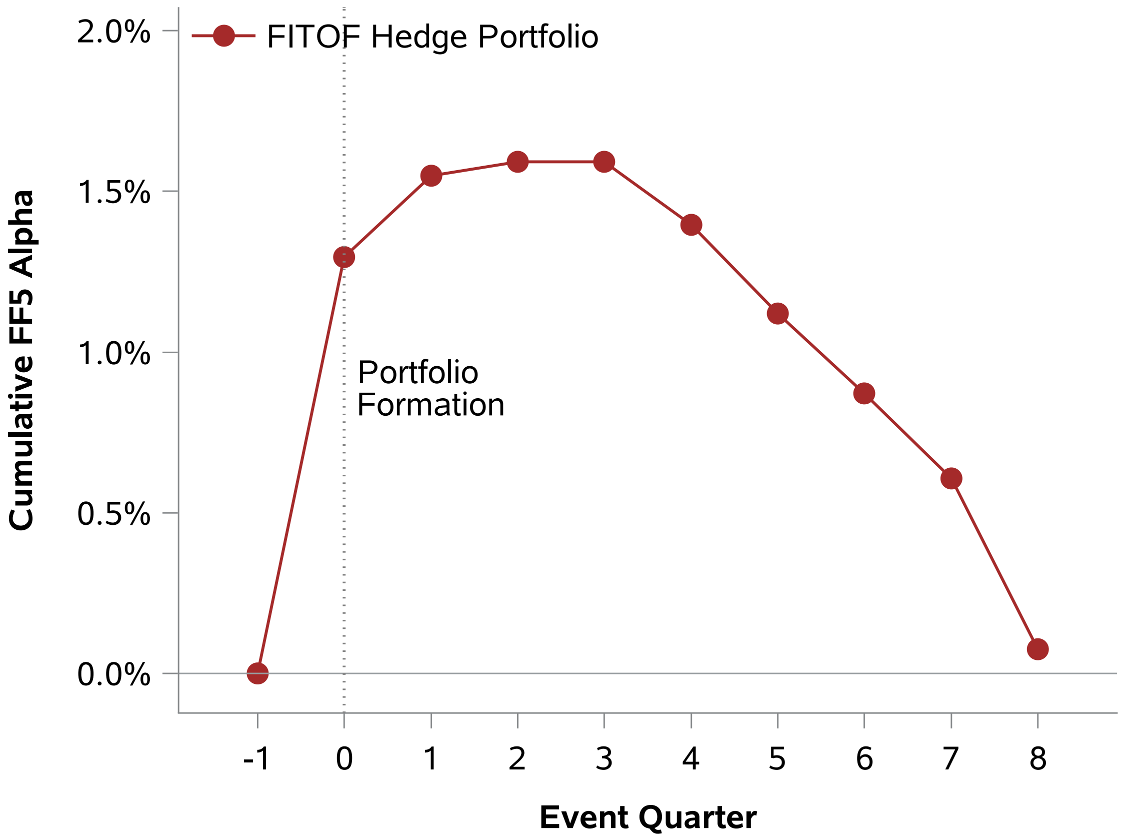

Figure 1: **Cumulative FF5 alpha of the FITOF-hedge portfolio.** This figure plots cumulative FF5 alpha of the hedge portfolio ranked by FITOF. FITOF measures the mutual fund flow-induced trading for a given factor (see 2). At each quarter end, the 70 factors are sorted into three groups based on FITOF in ascending order (20/30/20 factors are assigned into the low/mid/high group, respectively). Each factor is given equal weight in the portfolios, and the portfolios are held for three years. The hedge portfolio goes long in the high FITOF group and short in the low FITOF group. Quarter 0 is the portfolio formation quarter.

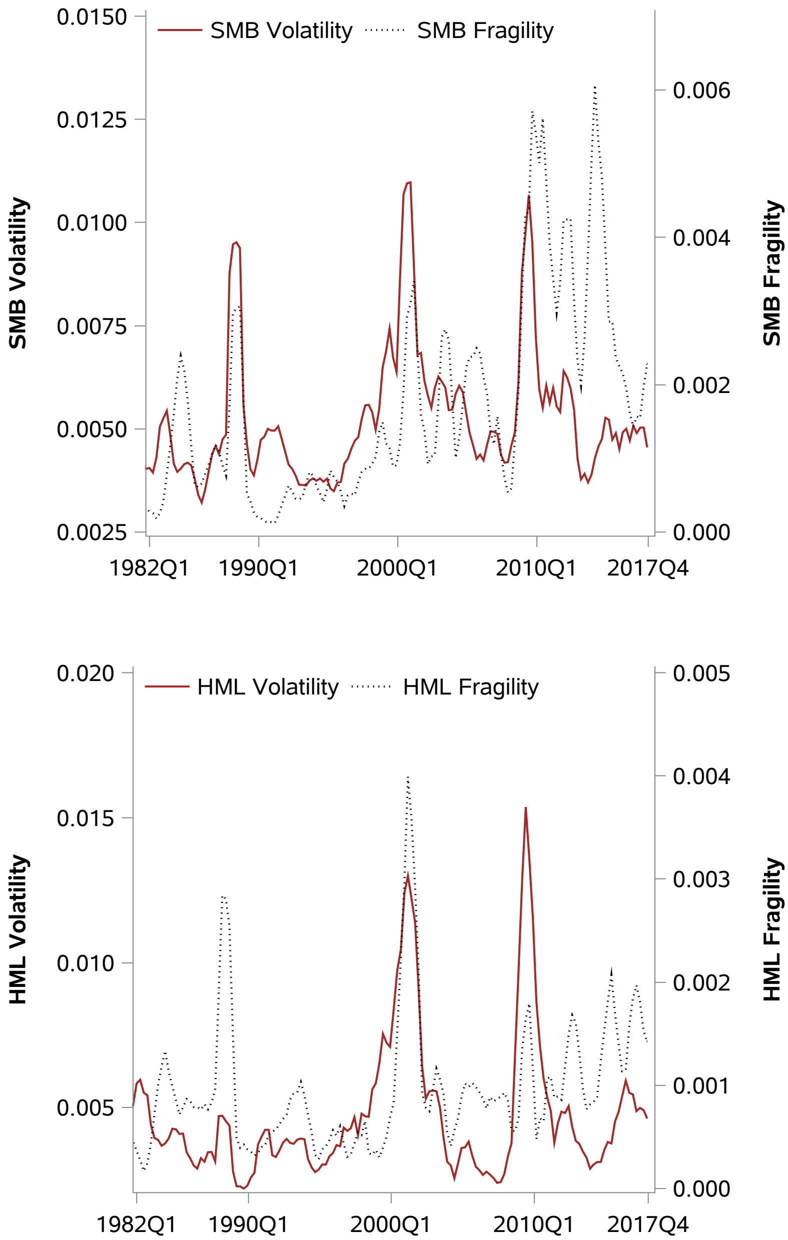

Figure 2: **Factor volatility and square root of lagged factor fragility.** This figure plots the return volatility of the Fama-French size and value factors and the square root of lagged factor fragility. Factor return volatility is measured as standard deviation of weekly factor returns over the quarter and factor fragility is defined in equation (3).

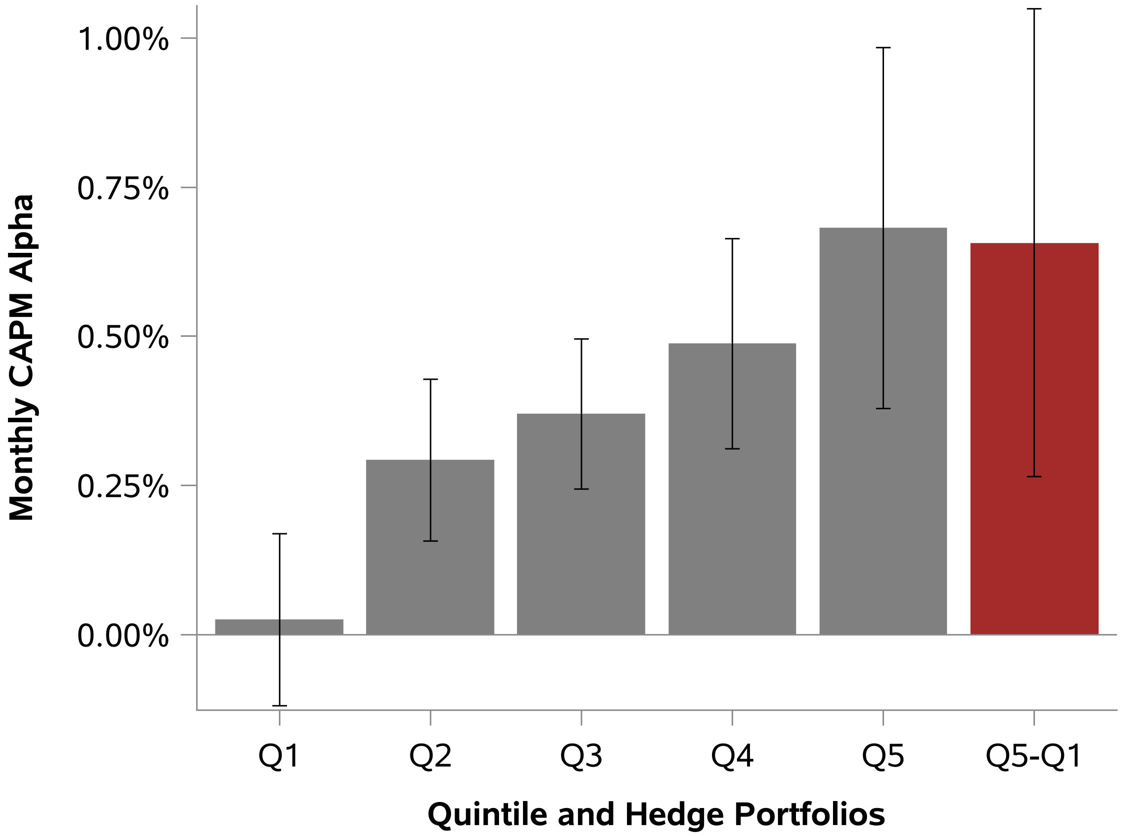

Figure 3: **Monthly CAPM Alpha of portfolios sorted on factor-level Avg Co-Fragility.** Each quarter end, we sort the 70 factors into quintiles based on their average co-fragility with other factors ($\overline{\text{Co-Fragility}}$) in the quarter and hold the portfolios in the next quarter. This figure shows the average monthly CAPM alpha of the quintile portfolios (leftmost five bars) and the "quintile five minus quintile one" long-short portfolio (rightmost bar) in the holding period of January 1982 to December 2017. Limit lines around the bars show the 95% confidence intervals for estimates of monthly CAPM alpha.

Appendix

A Derivation of Factor fragility and factor co-fragility

In this section, we explain how we derive the measures of factor fragility and factor co-fragility. Similar to Greenwood and Thesmar (2011) (GT), we assume the following relationship between mutual fund flow-induced trading and return of stock j:

$$r_{j,t} = \alpha_j + \lambda_j \frac{\sum_k \text{Shares}_{k,j,t-1} f_{k,t} \text{PSF}_{k,t}}{\sum_k \text{Shares}_{k,j,t-1}} + \varepsilon_{j,t}. \tag{9}$$

Here, $r_{j,t}$ is the return of stock j in quarter t, $\text{Shares}_{k,j,t-1}$ is the number of shares of stocks j held by fund k at the end of quarter $t-1$, $f_{k,t}$ is the percentage flow of fund k in quarter t, and PSF is the partial scaling factor as in (1). α_j and λ_j are two parameters. In our implementation, we assume that $\lambda_j = \lambda \sum_k \text{Shares}_{k,j,t-1}/\text{Shrout}_{j,t-1}$, where λ is the unconditional price impact factor and $\text{Shrout}_{j,t-1}$ is shares outstanding of stock j at the end of quarter $t-1$. The residual term, $\varepsilon_{j,t}$, has a conditional mean of zero and may capture other sources of variation of returns (e.g., news about fundamentals).

Since factors are effectively value-weighted portfolios of stocks, returns of factor π can be expressed as:

$$r_{\pi,t} = \sum_j \mu^{\pi}_{j,t-1} r_{j,t}, \tag{10}$$

where $\mu^{\pi}_{j,t-1}$ is the weight of stock j in factor π in quarter t.[25] Combining (9) and (10), we get

$$r_{\pi,t} = \sum_j \mu^{\pi}_{j,t-1}\alpha_j + \lambda \left(\sum_k w^{\pi}_{k,t-1} f_{k,t} \text{PSF}_{k,t} \right) + \sum_j \mu^{\pi}_{j,t-1}\varepsilon_{j,t}, \tag{11}$$

where $w^{\pi}_{k,t-1} = \sum_j \mu^{\pi}_{j,t-1}\text{Shares}_{k,j,t-1}/\text{Shrout}_{j,t-1}$ can be regarded as the weight of mutual fund k in factor π in quarter t.

Based on equation (11), the conditional variance and covariance of $r_{\pi,t+1}$ at the end of quarter t are

$$\text{Var}_t(r_{\pi,t+1}) = \lambda^2 W^{\pi'}_t E_t(\Omega_{t+1}) W^{\pi}_t + \text{Var}_t\left(\sum_j \mu^{\pi}_{j,t}\varepsilon_{j,t+1} \right) \tag{12}$$

[25] For a long-leg stock, $\mu^{\pi}_{j,t}$ simply equals its original weight in the long leg. For a short-leg stock, $\mu^{\pi}_{j,t}$ is its original weight in the short leg multiplied by negative one.

and

$$\mathrm{Cov}_t(r_{\pi_1,t+1}, r_{\pi_2,t+1}) = \lambda^2 W_t^{\pi_1 \prime} E_t(\Omega_{t+1}) W_t^{\pi_2} + \mathrm{Cov}_t\left(\sum_j \mu_{j,t}^{\pi_1}\varepsilon_{j,t+1}, \sum_j \mu_{j,t}^{\pi_2}\varepsilon_{j,t+1}\right), \quad (13)$$

respectively. Here, $E_t(\Omega_{t+1})$ is the conditional variance-covariance matrix of mutual fund flows in quarter $t+1$ and $W_t^\pi = \left(w_{1,t}^\pi, \ldots, w_{K,t}^\pi\right)$ is the vector of mutual fund weights in factor π.

Similar to GT, we define "factor fragility" of factor π in quarter t as

$$G_t^\pi = W_t^{\pi\prime} E_t(\Omega_{t+1}) W_t^\pi. \quad (14)$$

Likewise, we define co-fragility between factor π_1 and factor π_2 to be

$$G_t^{\pi_1,\pi_2} = W_t^{\pi_1\prime} E_t(\Omega_{t+1}) W_t^{\pi_2}. \quad (15)$$

To estimate $E_t(\Omega_{t+1})$, we calculate the variance-covariance matrix of mutual fund flows using observations in the most recent eight quarters (including quarter t). The summary statistics of fragility and co-fragility are reported in Table 1.

B Additional Results

B.1 Flow-driven effect on factor return momentum

In this section, we analyze the role of mutual fund flow-induced trading in explaining the so-called *factor momentum*. Recent work of Gupta and Kelly (2019) and Arnott, Clements, Kalesnik, and Linnainmaa (2019) shows that return momentum also exists at the factor level. That is, factors performing well in the recent past continue to outperform poorly-performing factors in the next one to three months. Moreover, factor momentum cannot be explained by either stock momentum (Jegadeesh and Titman, 1993) or industry momentum (Grinblatt and Moskowitz, 1999).

We propose a flow-based explanation for factor momentum: For those winning factors, stocks in their long legs perform relatively well recently, so do mutual funds that concentrate in these stocks. Because mutual fund investors do not account for factor exposures and chase unadjusted returns (Ben-David, Li, Rossi, and Song, 2018), these funds are likely to receive additional capital inflows, with which they largely scale up existing holdings. Due to positive price pressure of flow-induced trades, stocks in the long leg of the winning factors will experience higher returns in the near future. Consequently, the winning factors continue to perform well over a short horizon. The opposite effect would apply to those losing factors.

To examine the extent to which our proposed mechanism can explain factor momentum, we run a horse-race test between the expected flow-induced trading of factors ($\mathbb{E}$[FITOF]) and recent factor returns in predicting future factor returns. Based on (1) and (2), the expected flow-induced trades of factor π is given by

$$\mathbb{E}_t[\text{FITOF}_{\pi,t+1}] = \sum_{j\in\mathcal{N}_L^\pi} \frac{1}{\mathcal{N}_L^\pi}\mathbb{E}_t\left[\text{FIT}_{j,t+1}\right] - \sum_{j\in\mathcal{N}_S^\pi} \frac{1}{\mathcal{N}_S^\pi}\mathbb{E}_t\left[\text{FIT}_{j,t+1}\right], \tag{16}$$

where

$$\mathbb{E}_t[\text{FIT}_{j,t+1}] = \frac{\sum_k \text{Shares}_{k,j,t} \times \mathbb{E}_t[\text{Flow}_{k,t+1}] \times \text{PSF}}{\sum_i \text{Shares}_{k,j,t}}$$

and $\mathbb{E}_t[\text{Flow}_{k,t+1}]$ is the expected flow to mutual fund k at the end of quarter t. In particular, we use Fama-French-Carhart four-factor alpha and market-adjusted returns to predict future fund flows.

Table B.1 reports the results of the horse-race tests using Fama-Macbeth regressions. In Panel A of Table B.1, the dependent variable is the factor return at month $m+1$ and the independent variables include the factor return at month m and the most recent $\mathbb{E}$[FITOF] before month $m+1$. ($\mathbb{E}$[FITOF] is estimated at a quarterly frequency.) In Panel B, the dependent variable is the factor return at quarter $t+1$ and the independent variables include the factor return at quarter t and $\mathbb{E}$[FITOF] at the end of quarter t. In both panels, the forecasts of equal-weighted factor return and value-weighted factor return are examined seperately.

From the Column (1)-(2) and (4)-(5) of Panel A, one can see that the past one-quarter factor return and $\mathbb{E}$[FITOF], each alone, positively predicts factor returns in the next quarter. For example, a one-standard-deviation increase in $\mathbb{E}$[FITOF] is associated with an increase in quarterly equal-weighted factor by 1.14% (t=2.35) or an increase in value-weighted factor returns of 0.88% ($t = 2.19$). When both the past-one-quarter factor return and $\mathbb{E}$[FITOF] are included, the coefficient estimate of the past one-quarter return drops by about 50% and becomes insignificant for both the forecast of equal-weighted and value-weighted factor return, while the coefficient estimate of $\mathbb{E}$[FITOF] is slightly reduced and remain statistically significant. Panel B reports the forecast of one-month-ahead factor returns with past-one-month factor return and $\mathbb{E}$[FITOF] in the nearest quarter prior to month $m+1$. Past-one-month return and $\mathbb{E}$[FITOF] each alone can significantly predict one-month-ahead factor returns. Moreover, in the horse race of the two predictors, the coefficient estimates and statistical significance of both variables are

Table B.1: **Expected flow-induced trading and factor momentum**

This table reports the Fama-Macbeth regressions of factor returns on past factor returns and the expected flow-induced trading of factors ($\mathbb{E}$[FITOF]) defined in (16). The sample period is from 1980-2017. We use the 50 factors listed in Table C.1. In Panel A, the dependent variable is factor return in month $m+1$ and the independent variables are the factor return in month m and the most recent $\mathbb{E}$[FITOF] as of month m end. In Panel B, the dependent variable is the factor return in quarter $t+1$ and the independent variables are the factor return in quarter t and $\mathbb{E}$[FITOF] at quarter t end. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Regression in Quarterly Observations						
	(1)	(2)	(3)	(4)	(5)	(6)
DepVar:	EW Factor Return			VW Factor Return		
$\mathbb{E}_t[\text{FITOF}_{k,t+1}]$	1.06**		0.82**	0.82**		0.62*
	(2.35)		(2.10)	(2.19)		(1.67)
Past 1-Qtr Ret		0.12**	0.07		0.08*	0.04
		(2.27)	(1.33)		(1.81)	(0.99)
Intercept	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(9.84)	(7.44)	(10.61)	(5.03)	(4.23)	(5.34)
No. Obs.	7,500	7,500	7,500	7,500	7,500	7,500
Adj. R^2	0.25	0.24	0.40	0.18	0.15	0.29
Panel B: Regression in Monthly Observations						
	(1)	(2)	(3)	(4)	(5)	(6)
DepVar:	EW Factor Return			VW Factor Return		
$\mathbb{E}_t[\text{FITOF}_{k,t+1}]$	0.35***		0.26**	0.27**		0.24**
	(2.72)		(2.27)	(2.20)		(2.18)
Past 1-Month Ret		0.21***	0.18***		0.11***	0.09***
		(7.79)	(7.31)		(4.37)	(3.79)
Intercept	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(11.14)	(7.43)	(8.33)	(5.36)	(4.18)	(4.70)
No. Obs.	22,600	22,600	22,600	22,600	22,600	22,600
Adj. R^2	0.25	0.24	0.40	0.19	0.20	0.33

slightly reduced. The distinction in horse race results between Panel A and Panel B are likely due to: 1) $\mathbb{E}$[FITOF] has less overlap with past-one-month return than with past-one-quarter return, and 2) factor momentum is strongest at one-month horizon (see Arnott, Clements, Kalesnik, and Linnainmaa (2019)).

B.2 Robustness Check

This section reports supplementary information and robustness checks for our main results.

Table B.2 reports the quarterly transition matrix for the factor quintile portfolios sorted on FITOF. The probability that a factor stays in the same quintile over two consecutive quarters is 31% to 50%. This suggests that FITOF is not highly persistent.

Table B.3 shows the relation between FITOF and factor returns in Panel and Fama-MacBeth regressions. After accounting for factor and time fixed effects, we still find a strong positive relation between factor return and contemporaneous FITOF and a sizeable negative relation between factor return and FITOF in past five- to eight-quarter. This result confirms our findings in Table 2. Furthermore, we run the regressions of factor returns on contemporaneous or past FITOF in the first- and second-half sample period seperately. We find the price effect of FITOF is stronger in the second-half sample period (1999-2017). This is consistent with the dramatic growth of mutual fund industries which is also documneted in the summary statistics (see Table 1).

Table B.4 examines return pattern of factor portfolios sorted on factor returns or mutual funds' non-FIT trade. The portfolio analysis procedure is the same as that in Table 2 and the only difference is the sorting variable. When sorting on factor returns, we didn't find reversals in the three years after portfolio formation. This ensures that the reversal pattern associated FITOF is not driven by mean-reversion of factor returns. We also sort on mutual funds' non-FIT trade. We take a bottom-up approach to compute mutual funds' non-FIT trade of factors. First, at stock-level, we calculate mutual funds's non-FIT trade on a stock as mutual funds'aggregate realized trade scaled by total number of shares held by mutual funds (dubbed by RT) minus flow-induced trading (see 1). Second, we compute mutual funds' non-FIT trade of a factor as the portfolio-weighted average RT of stocks that constitute the factor. We find no statistically significant return patterns associated with mutual funds' realized trades on factors. This highlights the unique non-fundamental feature of mutual funds' flow-induced trading on factors.

Table B.5 shows the performance of a trading strategy that longs factors with low past FITOF and shorts factors with high past FITOF. We compute past FITOF for a given factor as follows. For each stock in the long-short portfolio of the factor in a holding period that belongs to quarter t, we compute its average FIT during Qtr $t-5$ to Qtr $t-8$. Then we compute portfolio-weighted average past FIT for each factor based on its portfolio composition in quarter t as past FITOF. At the begining of each quarter, we sort the 70 factors into quintiles by their past FITOF and long (short) the lowest (highest) past FITOF quintile for one quarter. Each factor is given equal-weight in the portfolio and the portfolios are rebalanced quarterly. During April 1982 to December 2017, such a trading strategy generates an average monthly raw returns of 0.79% (t-statistic = 3.05) and a CAPM alpha of 0.97% (t-statistic = 3.53).

We conduct several other robustness checks for the main results in Table 5. First, we demonstrate the relation between average co-fragility and future average factor premium in a non-parametric approach (see Table B.6). Specifically, we sort all quarters into terciles based on average co-fragility in previous quarter and compute average factor returns in the three sub-periods. We find average quarterly factor premium is only 0.34% following low average co-fragility period, but it is 1.39% following high average co-fragility periods. The difference in average factor premium is 1.05% per quarter with a t-statistic of 2.28. In Table B.7, we conduct a placebo test using average co-fragility to predict stock market returns and bond market returns. We find no results in placebo tests.

For out-of-sample test, main Table 8 evaluates the OOS performance of average co-fragility in the evaluation period that starts in 1992Q1 (10 years from sample start) and ends in 2017Q4. As a robustness check, in Table B.8, we choose alternative evaluation periods and find that OOS performance are robust. We find OOS performance of average co-fragility is stronger in the later periods.

Finally, we show the positive return predictability of factor-level average co-fragility in portfolio analysis. Each quarter-end, we sort factors into quintiles based on factor-level average co-fragility in the quarter and hold the quintile portfolios in the next quarter. Table B.9 shows that factor returns (alphas) increases monotonically with factor-level average co-fragility.

Table B.2: **Transition matrix of FITOF quintile portfolios**

In each quarter, we sort factors into quintiles based on FITOF in current quarter. This table reports the quarter-to-quarter transition likelihood for FITOF quintile ranking.

	Rank Qtr $t+1 \rightarrow$				
Rank Qtr $t \downarrow$	1	2	3	4	5
1	0.49	0.22	0.12	0.08	0.08
2	0.22	0.33	0.22	0.13	0.10
3	0.11	0.23	0.31	0.23	0.11
4	0.08	0.13	0.22	0.35	0.20
5	0.09	0.09	0.12	0.20	0.50

Table B.3: **Regressions of factor returns on FITOF in subsamples**

This table reports the regression of factor return on contemporaneous and past FITOF. The dependent variable is monthly factor return (in percents) in month $m+1$. Panel A reports the regressions of monthly factor returns on the flow-induced trading of factor (FITOF) in contemporaneous quarter. FITOF is the value-weighted flow-induced trading (FIT) of a factor's long-leg stocks minus that of the short-leg stocks. Panel B reports the regressions of monthly factor returns on past FITOF. In a given quarter, past FITOF refers to the average FITOF in the period of qtr $t-5$ to qtr $t-8$. Column (1)-(2) report regression results in full sample period of Apr 1982 to Dec 2017. Column (3)-(6) report regression results in two sub-periods: 1982-1999 (first-half) and 1999-2017 (second-half).Regression method "Panel" refers to panel regression where time and factor fixed effects are included and t-statistics are computed based on standard errors double clustered by factor and time. Regression method "FM" refers to the Fama-MacBeth regression. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Factor return and contemporaneous FITOF						
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		First	Second	First	Second
Contemporaneous FITOF	0.24***	0.44***	0.15***	0.53**	0.27***	0.59***
	(3.29)	(3.97)	(3.14)	(2.48)	(3.33)	(3.01)
Factor FE	Yes		Yes	Yes		
Year-Month FE	Yes		Yes	Yes		
Regression Method	Panel	FM	Panel	Panel	FM	FM
No. Obs.	30,030	30,030	14,070	15,960	14,070	15,960
Adj. R^2	0.09	0.17	0.07	0.11	0.15	0.09

Panel B: Factor return and past FITOF						
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		First	Second	First	Second
Past FITOF	−0.20***	−0.35***	−0.15***	−0.28**	−0.29***	−0.41***
	(−3.29)	(−4.03)	(−2.65)	(−2.13)	(−3.28)	(−2.81)
Factor FE	Yes		Yes	Yes		
Year-Month FE	Yes		Yes	Yes		
Regression Method	Panel	FM	Panel	Panel	FM	FM
No. Obs.	30,030	30,030	14,070	15,960	14,070	15,960
Adj. R^2	0.08	0.10	0.06	0.09	0.19	0.08

Table B.4: **Return pattern of portfolios sorted by factor returns or non-FIT trades.** This table reports calendar-time performance of factor portfolios sorted by factor return or non-FIT trades. We conduct following portfolio analysis with different sorting variables across Panels: At the end of each quarter t, we sort the 70 factors into three groups based on a given sorting variable, with 20/30/20 factors in the low/mid/high group respectively. Each factor is given equal-weight in the respecitve portfolio. The portfolios are rebalanced every quarter and held for three years. Qtr 0 is the portfolio formation quarter. We track the monthly calendar-time returns of factor portfolios from Qtr 1 to 12. We deal with overlapping portfolios in each holding month following Jegadeesh and Titman (1993). Monthly FF5 alpha (%) are reported. The t-statistics in parentheses are computed based on standard errors with Newey-West correction for twelve lags. In Panel A, the sorting variable is factor return in Qtr 0. In Panel B, the sorting variable is cumulative factor return from Qtr -3 to Qtr 0. In Panel C, the sorting variable is mutual funds' non-FIT trade of factors. At stock-level, we calculate mutual funds's non-FIT trade on a stock as mutual funds'aggregate realized trade scaled by total number of shares held by mutual funds (dubbed by RT) minus flow-induced trading (see 1). Then we compute mutual funds' non-FIT trade of a factor as the portfolio-weighted average RT of stocks that constitute the factor.

Portfolio	**Qtr 1-4**	**Qtr 5-8**	**Qtr 9-12**
Panel A: Sort on current-quarter ret			
Low	0.10 (2.51)	0.18 (2.72)	0.21 (3.37)
Mid	0.18 (3.82)	0.19 (4.54)	0.19 (3.80)
High	0.30 (2.79)	0.21 (3.67)	0.13 (2.79)
H-L	0.20 (1.44)	0.03 (0.42)	-0.08 (-1.08)
Panel B: Sort on past four-quarter ret			
Low	0.09 (1.52)	0.24 (2.81)	0.21 (2.55)
Mid	0.18 (4.17)	0.21 (4.64)	0.17 (3.53)
High	0.31 (2.73)	0.12 (1.80)	0.16 (2.71)
H-L	0.23 (1.45)	-0.11 (-0.98)	-0.06 (-0.49)
Panel C: Sort on mutual funds' non-FIT trades			
Low	0.25 (2.78)	0.20 (2.70)	0.16 (2.20)
Mid	0.17 (4.58)	0.21 (3.86)	0.19 (3.36)
High	0.16 (3.75)	0.15 (4.10)	0.19 (5.54)
H-L	-0.09 (-0.90)	-0.05 (-0.60)	0.03 (0.42)

Table B.5: **Trading strategy based on flow-induced trades on factors.**

This table reports the performance of factor portfolios sorted by past FITOF. We compute past FITOF for a given factor as follows. For each stock in the long-short portfolio of the factor in a holding period that belongs to quarter t, we compute its average FIT during Qtr $t-5$ to Qtr $t-8$. Then we compute portfolio-weighted average past FIT for each factor based on its portfolio composition in quarter t as past FITOF. At the begining of each quarter, we sort the 70 factors into quintiles by their past FITOF and hold the portfoios for one quarter. Each factor is given equal-weight in the portfolio. This table reports the average monthly raw returns, CAPM alpha, Fama-French-Carhart four-factor alpha, and Fama-French five-factor alpha for each factor portfolio in the holding period of April 1982 to December 2017. t-statistics are computed based on standard errors with Newey-West correction for twelve lags.

Portfolio	Excess	CAPM	FFC4	FF5
1 (L)	0.63	0.81	0.53	0.48
	(3.66)	(4.58)	(3.81)	(3.07)
2	0.46	0.61	0.38	0.33
	(3.83)	(5.19)	(4.09)	(3.66)
3	0.28	0.38	0.19	0.17
	(3.85)	(4.89)	(3.87)	(2.04)
4	0.14	0.22	0.14	0.12
	(2.59)	(4.14)	(2.52)	(1.74)
5 (H)	−0.16	−0.16	−0.12	−0.13
	(−1.51)	(−1.43)	(−1.15)	(−1.07)
1 − 5	0.79	0.97	0.64	0.61
	(3.05)	(3.53)	(2.82)	(2.24)

Table B.6: **Predict average factor premium in non-parametric approach**

All quarters during 1982Q1-2017Q4 are sorted into terciles based on average co-fragility in previous quarter. This table reports average quarterly factor premim (%) and one-quarter lagged average co-fragility (10^{-7}) in the three sub-periods, respectively.

Period	Avg Factor Ret	Avg Co-Fragility
Low	0.34	−0.05***
	(1.32)	(−3.23)
Medium	0.77***	0.02***
	(3.36)	(10.05)
High	1.39***	0.23***
	(3.60)	(4.57)
H−L	1.05**	0.28***
	(2.28)	(5.37)

Table B.7: **Placebo test: Predicting other returns**

This table reports the predictive regressions of one-quarter-ahead quarterly S&P500 excess return, Long-term yield, T-bill rate, and default yield on average co-fragility. Definitions for the dependent variables follow Welch and Goyal (2007). *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
DepVar:	S&P 500	Long-term yield	T-bill rate	Defaul yield
Avg Co-Fragility	-0.76	-0.00	-0.00	0.00
	(-1.12)	(-1.64)	(-0.98)	(0.82)
Avg Covariance	-1.61*	-0.01***	-0.01***	0.00
	(-1.91)	(-5.68)	(-5.26)	(0.14)
BW Sentiment	-0.33	0.02***	0.02***	-0.00**
	(-0.46)	(10.93)	(9.67)	(-2.29)
Stock market variance	0.38	0.01**	0.00*	-0.00***
	(0.48)	(2.58)	(1.74)	(-5.09)
No. Obs.	144	144	144	144
Adj. R^2	0.04	0.46	0.40	0.21

Table B.8: **OOS tests of forecasting average factor premia with different evaluation periods**

This table reports OOS performance of average co-fragility in the forecasts of one-quarter-ahead average factor premia. We report OOS performance in three different evaluation periods as indicated in the first column. All numbers are in percents. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

OOS Period	R^2_{OOS}	ΔRMSE	MSE_F
1987Q1-2017Q4 (5 years from sample start)	6.29***	8.65	5.71
1997Q1-2017Q4 (15 years from sample start)	8.07***	9.60	6.29
2000Q1-2017Q4	8.72***	9.85	6.44

Table B.9: **Performance of factor portfolios sorted on $\overline{\text{Co-Fragility}}$**

This table reports the performance of factor portfolios sorted by past $\overline{\text{Co-Fragility}}$. The definition of $\overline{\text{Co-Fragility}}$ follows Table 10. At the begining of each quarter, we sort the 70 factors into quintiles by their $\overline{\text{Co-Fragility}}$ in previous quarters and hold the portfoios for one quarter. Each factor is given equal-weight in the portfolio. This table reports the average monthly raw returns, CAPM alpha, Fama-French-Carhart four-factor alpha, and Fama-French five-factor alpha for each factor portfolio in the holding period of January 1982 to December 2017. t-statistics are computed based on standard errors with Newey-West correction for twelve lags.

Portfolio	Excess	CAPM	FFC4	FF5
1	0.01	0.02	−0.08	−0.01
	(0.11)	(0.27)	(−0.84)	(−0.13)
2	0.23	0.29	0.19	0.21
	(4.09)	(4.86)	(3.40)	(3.30)
3	0.27	0.37	0.24	0.20
	(4.03)	(6.28)	(4.42)	(3.50)
4	0.33	0.49	0.30	0.20
	(3.72)	(6.24)	(4.35)	(2.83)
5	0.51	0.68	0.47	0.36
	(4.19)	(5.96)	(4.74)	(3.28)
5-1	0.50	0.66	0.55	0.38
	(2.71)	(3.68)	(3.20)	(2.04)

C List of factors

Table C.1 lists the 50 factors studied in our paper. We compute the sorting variables for the 70 factors (anomalies) following Hou, Xue, and Zhang (2018), Linnainmaa and Roberts (2018), and Arnott, Clements, Kalesnik, and Linnainmaa (2019). Since our study requires the factor long-short portfolio to be rebalanced quarterly or annually to match with the quarterly mutual fund holdings data, we convert several typically monthly rebalanced factors into quarterly rebalanced ones. These factors include: 52-week high; Industry momentum; Intermediate momentum; Long-term reversals; Maximum daily returns; Momentum; Customer Momentum; Geographic Momentum; Industry Lead-lag; Segment Momentum; Residual Momentum; Frazzini-Pedersen beta; Idiosyncratic volatility. For these variables, we use the latest possible sorting variables at each quarter end to form portfolios and hold the portfolios in the next quarter. For the rest of the factors, see Hou, Xue, and Zhang (2018), Linnainmaa and Roberts (2018), and Arnott, Clements, Kalesnik, and Linnainmaa (2019) for definitions.

Table C.1: **List of factors**

This table lists the 70 factors studied in our paper. Definitions of sorting variables for the construction factors follows Hou, Xue, and Zhang (2018), Linnainmaa and Roberts (2018), and Arnott, Clements, Kalesnik, and Linnainmaa (2019). The factors are constructed with NYSE quintile breakpoints and value-weights. We report average monthly raw returns and Fama French five-factor alpha in percents during January 1980 to December 2017.

	Factor	Raw Ret	CAPM	FF5		Factor	Raw Ret	CAPM	FF5
1	52-week high	0.51	1.01	0.50	21	Earnings Persistence	0.39	0.53	0.46
2	Abnormal capital investment	0.18	0.12	0.25	22	Earnings Timeliness	0.06	-0.06	0.07
3	Accruals	0.21	0.33	0.08	23	Earnings-to-price	0.32	0.59	0.01
4	Advertising Expense	0.39	0.46	-0.01	24	Enterprise multiple	0.25	0.25	0.41
5	Altman's Z-score	0.07	-0.08	0.25	25	Firm age	-0.01	-0.32	0.28
6	Amihud Illiquidity	0.30	0.22	0.18	26	Five-year share issuance	0.40	0.54	0.21
7	Analyst earnings forecast Revision	0.26	0.30	0.24	27	Frazzini-Pedersen beta	0.23	0.91	0.48
8	Asset Growth	0.25	0.39	-0.15	28	Geographic Momentum	0.32	0.37	0.37
9	Book-to-june-end-market	0.20	0.28	-0.10	29	Gross profitability	0.18	0.24	0.32
10	Book-to-market	0.19	0.28	-0.08	30	Growth in Inventory	0.38	0.48	0.21
11	Capital turnover	0.19	0.14	0.23	31	Growth score	0.11	0.27	0.31
12	Cash-based profitability	0.18	0.29	0.52	32	Idiosyncratic volatility	0.36	0.88	0.22
13	Cashflow-to-price	0.24	0.46	-0.01	33	Industry adjusted CAPX growth	0.18	0.29	0.06
14	Change in asset turnover	0.14	0.17	0.01	34	Industry Concentration	0.26	0.16	0.54
15	Change in Long-term net operating assets	0.29	0.35	0.00	35	Industry Lead-lag	0.32	0.37	0.37
16	Customer Momentum	0.55	0.66	0.56	36	Industry Momentum	0.44	0.26	0.36
17	Debt issuance	0.14	0.17	0.01	37	Intermediate momentum	0.47	0.45	0.62
18	Discretionary accruals	0.27	0.20	0.42	38	Investment growth	0.19	0.30	0.02
19	Distress risk	0.61	0.89	0.68	39	Investment-to-assets	0.13	0.12	-0.10
20	Earnings Forecast to Price	0.37	0.61	0.09	40	Investment-to-capital	0.08	0.40	-0.28

	Factor	Raw Ret	CAPM	FF5		Factor	Raw Ret	CAPM	FF5
41	Long-term reversals	0.25	0.26	0.03	56	Profit margin	-0.05	0.16	-0.10
42	M/B and accruals	0.34	0.43	0.19	57	QMJ Profitability	0.40	0.49	0.29
43	Maximum daily return	0.30	0.93	0.09	58	R&D Expense	0.44	0.26	0.36
44	Momentum	0.18	0.28	0.26	59	Real estate ratio (indsutry-adj)	0.30	0.22	0.42
45	Net operating assets	0.33	0.31	0.27	60	Residual Momentum	0.56	0.67	0.55
46	Net Payout Yield	0.34	0.68	0.01	61	Return on assets	0.35	0.58	0.27
47	Number of earnings increase	0.23	0.91	0.48	62	Return on equity	0.35	0.56	0.15
48	Ohlson's O-score	0.16	0.32	0.31	63	Sales growth	-0.14	-0.35	0.17
49	One-year share issuance	0.37	0.57	0.05	64	Sales-minus-inventory growth	0.15	0.15	0.09
50	Operating cash flow-to-price	0.31	0.46	-0.03	65	Sales-to-price	0.35	0.33	-0.18
51	Operating Leverage	0.34	0.43	0.19	66	Segment Momentum	0.28	0.35	0.29
52	Operating profitability	0.35	0.60	0.17	67	Size	0.17	0.05	0.04
53	Organizational capital-to-book (industry-adjusted)	0.31	0.47	0.17	68	Sustainable growth	0.28	0.42	0.04
54	Percent accruals	0.22	0.31	0.09	69	Tax expense change	0.23	0.16	0.24
55	Piotroski's F-score	0.06	0.10	0.06	70	Total external financing	0.25	0.53	0.04
						Average	0.27	0.41	0.17