Noise Trading and Asset Pricing Factors*

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Abstract

We demonstrate that a broad set of asset pricing factors/anomalies are significantly exposed to "noise trader risk," and the noise trader risk is priced in factor premia. We first confirm that mutual funds' flow-induced trading of factors are uninformed as they generate a large price impact on factor returns, followed by a complete reversal. We then show asset pricing factors are subject to flow-driven noise trader risk in that expected variation (covariation) of flow-induced noise trading strongly forecasts variance (covariance) of factor returns. Importantly, factor premia are higher when flow-driven noise trader risk is expected to be more salient.

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1 Introduction

The asset pricing literature has discovered a large number of asset pricing factors (anomalies) that explain cross-sectional variations in stock returns.[1] Some argue that asset pricing factors reflect compensation for bearing fundamental economic risk, while others argue that asset pricing factors stem from systematic mispricings. Understanding the source and variations of these factors has been arguably one of the main themes of asset pricing research.

In this paper, we study asset pricing factors from a new perspective. We show that a broad set of asset pricing factors are heavily exposed to noise trader risk, which arises from uninformed capital allocations of mutual fund investors, as expected variations and co-variations of mutual funds' flow-induced trading of factors strongly forecast variations and co-variations of future factor returns. Importantly, we find that the flow-driven noise trader risk is significantly priced in factor premia: in the time series, the average premium across asset pricing factors is higher when the expected variance of flow-induced trading of the aggregate factor portfolio is higher; cross-sectionally, the expected return of a factor is higher when its flow-induced trading is expected to be more correlated with the flow-induced trading of the aggregate factor portfolio.

Our analyses show that a sizeable fraction of factor return variance-covariance is driven by variations of uninformed mutual fund flows, and factor premia reflect compensations for this noise trader risk. That is, the non-fundamental demand of mutual fund investors exerts a significant impact on systemic return patterns in the equities market (De Long, Shleifer, Summers, and Waldmann, 1990; Barberis and Shleifer, 2003; Koijen and Yogo, 2019; Gabaix and Koijen, 2020).

Our study is motivated by recent observations that mutual fund investors are ignorant of asset pricing factors as they fail to account for mutual fund exposures to factors when

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

allocating capital among equity mutual funds (Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016; Ben-David, Li, Rossi, and Song, 2022b).[2] This is not surprising since the majority of mutual fund investors are households with limited financial knowledge and limited information for them to make investment decisions. For example, according to the 2017 ICI Fact Book, more than 90% of mutual fund assets in the US were held by households and retails. Moreover, an extensive literature has also documented that mutual fund investors indeed exhibit unsophisticated behaviors.[3]

Meanwhile, the mutual fund sector is sufficiently large so that it can channel non-fundamental demand and generate systemic price impacts. As the primary conduit for equity investments by the US households, equity mutual funds held about 5% of the US equities when our sample begins in the 1980s, and their ownership has increased to about 30% by 2005 and has remained steady since then (Ben-David et al., 2022a). Meanwhile, the literature (e.g., Coval and Stafford, 2007; Lou, 2012) has well documented that mutual funds channel non-fundamental demand from fund investors (i.e., fund flows) into financial markets as they, to a large extent, scale their holdings mechanically in response to fund flows. Motivated by mutual fund investors' unsophisticated behaviors and their large holding of the stock market through mutual funds, we argue and verify that mutual funds' flow-induced trading of factors is mostly uninformed. More importantly, we demonstrate that the flow-driven noise trader risk is an important state variable in pricing factor premia.

To study how flow-induced noise trader risk affects factor premia, we construct 71 prominent asset pricing factors (anomalies) based on stock characteristics (e.g., size, value,

[2]As argued by Grinblatt and Titman (1989) and Pástor and Stambaugh (2002), in a fully rational world, mutual fund investors should consider all factors that explain cross-sectional variation in fund performance and only reward mutual funds with "real" alphas.

[3]For example, mutual fund investors prefer funds that report holdings of recent winners and lottery stocks (e.g., Solomon, Soltes, and Sosyura, 2014; Agarwal, Jiang, and Wen, 2018); invest in funds that advertise a lot (Jain and Wu, 2000) or appear in the media (Kaniel and Parham, 2017); prefer funds that recently experienced an extremely positive monthly return (Akbas and Genc, 2020); and time the market poorly (Frazzini and Lamont, 2008; Song, 2019).

momentum, profitability, and investment; refers to Appendix D for details).[4] To construct a characteristic-based factor, we sort all NYSE-AMEX-NASDAQ stocks into quintile portfolios based on the NYSE breakpoints and calculate factor returns as the spreads between the value-weighted returns of the top-quintile and the bottom-quintile portfolios. In total, we have 250,819 fund-quarter observations with 6,422 equity funds in the US from 1980 to 2021.

As a premise, we first justify that flow-induced trading at the factor level is largely uninformed and generates a large price impact. Although the literature has already documented stock-level evidence, it is not necessarily true that flow-induced trading could also impact asset pricing factors, which are diversified long-short portfolios of individual stocks. For example, if flow-induced trading is idiosyncratic, it would cancel out at the portfolio level and thus have no impact on asset pricing factors. Specifically, we first follow Lou (2012) to calculate flow-induced trading of individual stocks at each quarter and then aggregate the stock-level flow-induced trading to factor level (termed as flow-induced trading of factors). We show that flow-induced trading of factors (FITOF) is indeed uninformed as FITOF generates a large short-term price impact on factor returns, which reverts entirely afterward.

With this, we demonstrate that asset pricing factors are significantly exposed to the flow-driven noise trader risk, as expected variations (covariations) of flow-induced trading strongly forecast variations (covariations) of factor returns. To this end, we extend the approach of Greenwood and Thesmar (2011) and use mutual fund ownership and mutual fund flows to estimate expected variance and expected covariance of flow-induced trading of asset pricing factors, which we refer to as "factor fragility" and "factor co-fragility," respectively.

We find that when flow-induced trading of a factor is expected to be more volatile, the return volatility of this factor is higher; when flow-induced trading between two factors is

[4] We also conduct tests based on a smaller set of factors, like the 11 factors used in Stambaugh et al. (2012) or the 51 factors used in Arnott et al. (2019). Our conclusion still holds.

expected to be more correlated, factor returns comove more. For example, in the Fama-MacBeth regression of quarterly frequency, a one-standard-deviation increase in factor co-fragility predicts an increase of 60% of a standard deviation in factor return covariance over the next quarter after controlling for lagged factor return covariance. The results remain largely unchanged when excluding crisis periods. Together with the confirming evidence that flow-induced trading of factors is uninformed, our findings suggest that asset pricing factors are heavily exposed to noise trader risk. In our study, the noise trader risk arises from the non-fundamental demand shift of mutual fund investors.

Unlike Greenwood and Thesmar (2011) that focus more on stock price volatility and covariance, our ultimate goal is to understand whether and to what extent the flow-driven noise trader risk is "priced" by arbitrageurs and other sophisticated investors who trade these factors (anomalies).[5] Intuitively, when noise trader risk is higher (e.g., the flow-induced trading of factors is expected to be more volatile), arbitrageurs are less willing to exploit anomalies through buying the long-leg stocks or selling the short-leg stocks, and consequently, anomalies have higher expected returns. A similar argument that noise trader risk deters arbitrageurs from cross-asset arbitrage is explicitly modeled in Gromb and Vayanos (2010).

To this end, we use fragility of the aggregate factor portfolio, that is, the expected variation of flow-induced trading of the aggregate factor portfolio, to proxy for the aggregate flow-driven noise trader risk on the asset pricing factors in our study. We expect that the average premium across factors should be higher when the aggregate fragility is higher. Consistent with the intuition, aggregate fragility significantly and positively forecasts future average factor premium. For example, in the time-series regression, a one-standard-deviation increase in aggregate fragility of the 71 factors forecasts an increase of 61 bps in average factor premium over the next quarter. This is economically

[5]Hanson and Sunderam (2014), Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), McLean and Pontiff (2016), and Calluzzo, Moneta, and Topaloglu (2019) document that arbitrageurs, such as hedge funds, have widely exploited asset pricing anomalies.

significant as the average premium across the set of factors is about 79 bps per quarter.

We conduct several robustness tests. First, we find that the results still hold after controlling for the sentiment measure of Baker and Wurgler (2006), average value spread of factors, past average factor returns, market volatility, and average factor return covariance (Pollet and Wilson, 2010). This suggests that aggregate fragility indeed captures information beyond these predictors. Second, following Welch and Goyal (2008), we conduct out-of-sample (OOS) tests and further confirm the strong predictive power of aggregate fragility on future factor premia. Third, we also show that the results are robust to alternative definitions of the aggregate factor portfolio, such as the mean-variance optimal portfolio of factors.

Beyond the time-series evidence, we also conduct a cross-sectional analysis. In the cross-section, the return of a factor should also be higher if flow-induced trading of that factor is expected to be more correlated with flow-induced trading of the aggregate factor portfolio. Specifically, for each factor, we first calculate the co-fragility between this factor and the aggregate factor portfolio. Intuitively, this co-fragility (divided by the aggregate fragility) can be regarded as "noise trading beta." Then, we examine the cross-sectional relation between noise trading beta and future factor returns. We find that the expected return (alpha) of a factor is significantly higher when its noise trading beta is higher. For example, sorting all factors into quintiles by noise trading beta, the top quintile of factors outperforms the bottom quintile by 2.80% ($t = 3.42$) per quarter in terms of CAPM alpha.

Thus far, the evidence is consistent with our argument that when arbitrageurs or other sophisticated investors trade on factors (anomalies), they require compensation to bear the flow-driven noise trader risk. To further corroborate this argument, we explore the trading activities of hedge funds, the typical arbitrageurs. Specifically, we decompose each factor into two "sub-factors" based on the stock-level net arbitrage trading (NAT) of hedge funds in Chen et al. (2019). We find that the flow-driven noise trader risk only affects factor premia through stocks that are more likely to be traded by arbitrageurs and other sophisticated investors.[6] In contrast, we find that other predictors, such as sentiment (e.g., Baker and Wurgler, 2006), mainly predict factor premia through small-cap stocks and stocks that are not often traded by hedge funds, mutual funds, and other institutions. This sharp contrast also suggests that flow-induced noise trading is largely orthogonal to other predictors, particularly the sentiment measure of Baker and Wurgler (2006). In summary, all these results suggest that the flow-driven noise trader risk is priced in factor premia.

Our paper is closely related to the literature that studies the role of non-fundamental demand on asset prices. Examples include De Long, Shleifer, Summers, and Waldmann (1990), Lee, Shleifer, and Thaler (1991), Hirshleifer (2001), Barberis and Shleifer (2003), Greenwood and Thesmar (2011), Gao, Moulton, and Ng (2017), Cho (2018), Koijen and Yogo (2019), Chu, Hirshleifer, and Ma (2020), Gabaix and Koijen (2020), and Peng and Wang (2021). Moreover, we show that the effect of flow-driven noise trader risk on factor premia is fundamentally different from that of the sentiment measure of Baker and Wurgler (2006).[7] While the earlier sentiment measures mostly influence small-cap stocks, the flow-driven noise trader risk is priced through large-cap stocks, which are more likely to be traded by hedge funds and other institutional investors.

A related strand of the literature shows that mutual fund flows can have a sizeable temporary price impact on individual stocks (e.g., Teo and Woo, 2004; Coval and Stafford, 2007; Frazzini and Lamont, 2008; Froot and Teo, 2008; Lou, 2012). While these prior researches justify our paper's premise that flow-induced trading of factors is non-fundamental, we largely extend this literature by showing that the uninformed demand

[6] In similar exercises, we also decompose each factor based on stock-level hedge fund trading volume or market capitalization. We find that the effects are stronger if we construct factors using stocks that are traded more by hedge funds or large-cap stocks (which are more likely to be held by institutional investors (Gompers and Metrick, 2001)).

[7] Stambaugh, Yu, and Yuan (2012) compare the performance of asset pricing anomalies following periods of high and low sentiment. Specifically, they argue that the presence of short-sale constraints drives anomalies, particularly the short legs of anomalies, to be stronger following periods of high sentiment.

shift of mutual fund investors has much broader asset pricing implications. First, as factors are well-diversified portfolios of stocks, it is not clear whether the flow-induced price impact would cancel out at the factor level. Thus, whether the factor-level fragility has a significant impact on factor return volatility is also an empirical question. We are the first to study this question. Moreover, through quantifying the flow-driven noise trader risk, we show that higher noise trader risk is associated with higher future factor returns in both time-series and cross-section. This suggests that mutual funds' flow-induced trading is not merely a temporary demand shock, but also an important source of risk priced by arbitrageurs.

Our paper is also related to the literature that studies whether and how institutions trade stock market anomalies. Lewellen (2011) and Edelen, Ince, and Kadlec (2016) analyze aggregate institutional holdings (including banks, insurance companies, investment companies, and investment advisors) and show that institutions as a whole do not seem to take advantage of anomalies. Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) and Calluzzo, Moneta, and Topaloglu (2019) further explore the trading behaviors of different institutions and find that arbitrageurs, like hedge funds, actively exploit anomalies. Chen, Da, and Huang (2019) also find that hedge funds actively use long-short strategies to exploit anomalies. Our research question is different from these papers. We analyze the extent to which variations in factor returns are driven by variations in non-fundamental demand shift of mutual fund investors and whether factor premia reflect compensation for this flow-driven noise trader risk.

Lastly, our paper also contributes to the recent literature that investigates the high dimensionality of cross-sectional asset pricing models. Examples include Harvey, Liu, and Zhu (2016), Harvey (2017), McLean and Pontiff (2016), Kozak, Nagel, and Santosh (2018, 2020), Hou, Xue, and Zhang (2020), Kelly, Pruitt, and Su (2019), Feng, Giglio, and Xiu (2020), among others. We offer a new perspective on asset pricing factors by demonstrating the important influence of noise trading on factor premia and the variance-covariance structure among these factors.

The rest of the paper is organized as follows. Section 2 introduces the mutual fund data set and how we construct the set of asset pricing factors. Section 3 examines the price impact of flow-induced factor trading and the influence of flow-induced factor trading on return volatilities and return comovements among the factors. Section 4 shows that the flow-driven noise trader risk is significantly priced in factor premia. Section 5 concludes. Robustness checks and supplementary results are reported in the appendices.

2 Data and Methodology

In this section, we describe the data, the construction of the 71 asset pricing factors (anomalies), and how we estimate mutual fund flow-induced trading of factors. We note that the choices of these 71 asset pricing factors are not arbitrary. We closely follow Linnainmaa and Roberts (2018), Arnott, Clements, Kalesnik, and Linnainmaa (2019), and Hou, Xue, and Zhang (2020), but exclude some duplicated anomalies. Our results are robust if we only focus on the 51 anomalies in Arnott et al. (2019) or the 11 anomalies in Stambaugh et al. (2012) (see, for example, Appendix Table C.2).

It is worth noting that we exploit a large set of factors since our ultimate goal is to test whether flow-induced noise trader risk is priced by arbitrageurs who trade on the factors. Arbitrageurs usually combine a large set of asset pricing factors and signals to improve portfolio performance. Thus, to better examine the risk-return trade-off faced by arbitrageurs, we shall not limit our study to a few factors (e.g., value or momentum).

2.1 Factor Construction

We use the CRSP and Compustat datasets to construct asset pricing factors (anomalies). Our sample stocks include all ordinary common shares (CRSP share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. To be included in our sample in a given quarter, the stock is required to be held by at least one mutual fund with non-missing holding data from the Thomson Reuters S12 mutual fund holding database and valid fund flow (calculated using CRSP mutual fund database) in that quarter.

The universe of factors consists of 71 annually or quarterly rebalanced factors based on firm characteristics, including size, book-to-market ratio, profitability, and momentum, among many others (see Table D.1 for the detailed list).[8] To construct a characteristic-based factor, we follow the conventional approaches and use NYSE breakpoints of the characteristic to form quintile portfolios.For annually rebalanced factors, at the June-end of each calendar year, we sort all stocks into quintiles based on the NYSE breakpoints of sorting variables (e.g., book-to-market ratio) measured at the fiscal year ending in the previous calendar year. We then track the value-weighted portfolio returns from July to the 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 that all information is available upon portfolio formation. Specifically, at the end of each quarter, we form quintile portfolios based on sorting variables measured at the fiscal quarter ending in the previous calendar quarter and hold the portfolios for one quarter.

From Table 1, the average quarterly return of the 71 factors is 0.79%, with a standard deviation of 6.60%. It is also worth noting that because we use the value-weighting scheme to construct factor returns, our results are not affected by micro-cap and tiny stocks. More details of the factor construction are provided in Appendix D.

2.2 Mutual Fund Data

Now we describe how we construct the sample of mutual fund holdings. To this end, we merge the Thomson Reuters S12 mutual fund holding database with the CRSP

[8] We transform several typical monthly rebalanced factors (e.g., momentum) into quarterly rebalanced factors to match the quarterly mutual fund holdings data. Our results are unchanged when excluding those monthly rebalanced factors.

Survivorship-Bias-Free Mutual Fund database. Specifically, we obtain mutual funds' holding data from the CDA/Spectrum database. Mutual funds' total net assets (TNA), monthly net returns (after fees), 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 use the investment objective code from CRSP Mutual Fund database (*crsp_obj_cd*) to select equity funds. Specifically, we select US domestic equity funds by retaining funds with a *crsp_obj_cd* which begins with "ED." To ensure the sample funds are equity funds, we use *per_com* from CRSP fund summary file and require a fund to have 75% to 105% of the fund portfolio invested in common stocks on average. To mitigate the impact of small funds on our results, we exclude fund-by-quarter observations with TNA less than $1 million at the previous quarter-end. We use MFlinks from WRDS to merge mutual funds in CRSP Mutual Fund database and Thomson Reuters S12 mutual fund holding database. Our fund sample includes 6,422 distinct US domestic equity funds with 250,819 fund-quarter observations during 1980-2021.

[Table 1 Here]

Table 1 reports the basic statistics of our sample. As one can see, the stock coverage steadily increases as the size of the mutual fund sector relative to the aggregate market grows substantially over our sample period (from 2.99% to 23.13%). At the beginning of the sample period, our sample covers 45.92% in terms of the number of stocks and 94.88% in terms of market capitalization, suggesting that mutual funds tend to avoid tiny stocks, which is consistent with Gompers and Metrick (2001). At the end of the sample period, our sample covers 91.74% in terms of the number of stocks and 98.91% in terms of market capitalization.

3 Factors are Exposed to Noise Trader Risk

In this section, we demonstrate that the long list of asset pricing factors is significantly exposed to noise trader risk, which arises from uninformed flow-induced trades of mutual funds. Indeed, as explained in Lou (2012), whereas discretionary trading can reflect mutual fund managers' information about fundamentals, flow-induced trading isolates the nondiscretionary trading that is only attributable to fund flows and thus likely does not contain fundamental information.

We start by justifying the premise that mutual funds' flow-induced trading of factors are largely uninformed and can generate significant price impact.[9] We find that flow-induced trades significantly and positively influence contemporaneous factor returns, followed by full reversals over longer horizons. This return pattern confirms the prior findings that mutual fund flows are mostly uninformed and fail to account for mutual fund exposures to systematic factors (e.g., Barber et al., 2016; Ben-David et al., 2022b).

Next, we quantify the flow-driven noise trader risk by estimating the variance-covariance of flow-induced trading among the set of factors in our sample. We find that (*i*) the expected volatility of flow-induced trading of factor strongly forecasts future factor return volatility and (*ii*) the expected covariance of flow-induced trading of factors strongly forecasts future factor return covariance. Taken together, the findings in this section suggest that these 71 asset pricing factors are significantly exposed to flow-driven noise trader risk.

3.1 Estimates of Flow-Induced Trading of Factors

We use a bottom-up approach to estimate flow-induced trading of factors. We first measure quarterly aggregate mutual fund trading of an individual stock in response to

[9] While the literature has documented ample evidence that mutual fund flow-induced trading is non-fundamental at the stock-level (Coval and Stafford, 2007; Lou, 2012; Frazzini and Lamont, 2008), we need to make sure that the flow-induced price impact would not cancel out at the factor level as factors are constructed to be diversified long-short portfolios.

fund flows. Specifically, we follow Lou (2012) and estimate the flow-induced-trading (FIT) measure as follows:

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

where $\text{Shares}_{k,j,t-1}$ is the number of shares of stock j held by fund k at the end of quarter $t-1$, $\text{Flow}_{k,t}$ is the percentage flow of fund k in quarter t, and PSF is the partial scaling factor. The partial scaling factor reflects how fund managers, on average, increase and liquidate their holdings in response to capital inflows and outflows, respectively. Lou (2012) estimates $\text{PSF}_{k,t}$ to be 0.970 for outflows and 0.858 for inflows. We use the same estimates of the partial scaling factor, and our results are not sensitive to the choices of PSF. 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 et al., 2022b). For completeness, we also re-construct FIT using mutual fund flows that are not driven by fund alpha components, and the results remain largely unchanged.

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,

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

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 trading of the long-leg stocks relative to the flow-induced trading of the short-leg stocks.[10]

[10]Note that our empirical analysis only focuses on mutual funds' long positions without including the short positions of mutual funds. Having said that, a recent study (An, Huang, Lou, and Shi, 2022) finds that although regulatory restrictions on mutual fund short selling had been lifted in 1997, less than 10%

As shown in Panel B of Table 1, the 25th and 75th percentiles of the stock-level FIT are −1.64% and 3.38%, 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 −1.64% and 3.38% within a quarter in the 25th to 75th percentile range. For FITOF, the 25th and 75th percentiles are −0.49% and 0.56%, respectively. The time-series variation of FITOF is also quite large. For example, Table A.1 reports the transition matrix of FITOF. When we sort factors into quintiles based on FITOF, the likelihood that factors in the highest (lowest) quintile remain in the highest (lowest) quintile in the next quarter is 41%.

3.2 Flow-Induced Trading and Factor Return Patterns

To examine the return pattern associated with flow-induced trading of factors (FITOF), at each quarter-end, we sort the 71 factors into terciles based on FITOF over the same quarter, with 23/24/24 factors in each group respectively. We then track each group with equal-weighted factor returns in the next 12 quarters. Table 2 reports the quarterly (risk-adjusted) returns of the three portfolios of factors sorted by FITOF.

The first pattern to note is that FITOF generates a strong price impact on factors over the contemporaneous quarter (Qtr 0). For example, Panel D of Table 2 reports that the low-FITOF group earns an average quarterly Fama-French five-factor (FF5) alpha of −1.12% in the formation quarter, while the high-FITOF group earns a quarterly FF5 alpha of 2.33%. The high-minus-low return spread is associated with an average quarterly FF5 alpha of 3.49% with a t-statistic of 5.54.

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 −0.33% per quarter in the first post-formation year, and it is −0.70% per quarter in the second year. In the third year, no further reversal is associated with

of mutual funds have ever taken any short-selling activities in the post-2000 period. Their finding largely alleviates the concern of missing the short positions of mutual funds.

portfolios ranked by FITOF.

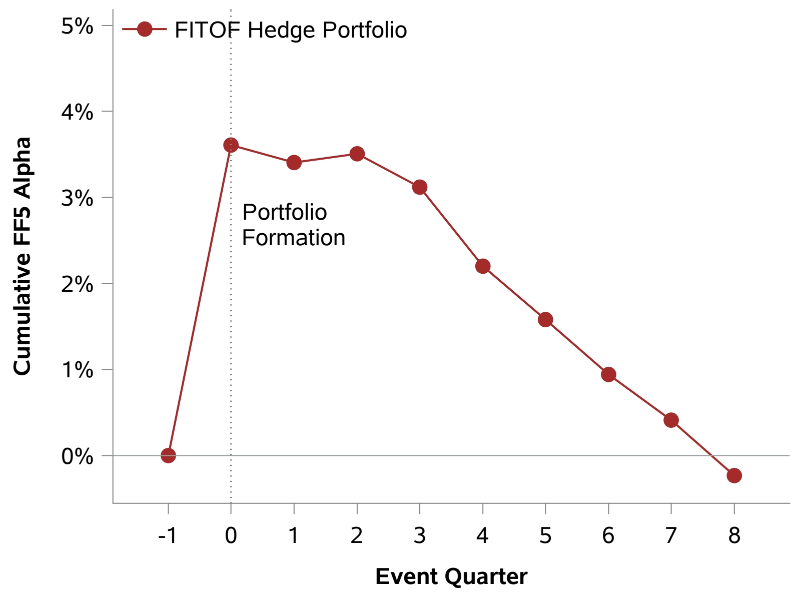

Figure 1: **Cumulative FF5 alpha of the FITOF-hedge portfolio.** This figure plots the cumulative FF5 alpha of the long-short factor portfolio sorted by FITOF (equation (2)). At each quarter-end, the 71 factors are sorted into three groups based on FITOF in ascending order (23/24/24 factors are assigned 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 long-short portfolio goes long in the high-FITOF group and short in the low-FITOF group. Quarter 0 is the portfolio formation quarter.

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 almost fully reverts by the end of the second year. This strong reversal validates our premis that flow-induced trading of factors are mostly uninformed and the mounting evidence that mutual fund investors are unsophisticated in allocating capital.

We also conduct several placebo tests. 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 in which we use factor returns as the sorting variable instead of FITOF. We do not find any return patterns (see Panels A and B of Table A.2). Second, we analyze the influence of mutual fund trades of factors that are not driven by fund flows.[11] We find that non-flow-induced trades do not generate return reversals (see Panel C of Table A.2). These placebo tests highlight the uniqueness of the return patterns associated with flow-induced factor trading.

In addition to the placebo tests, we conduct comprehensive robustness checks. First, in Table A.3, we isolate fund flows that are driven by fund alphas and re-construct FITOF with the alpha-isolated fund flows. We find that the return patterns are largely unchanged using these "alpha-free" fund flows. Second, to account for time and factor fixed effects that might be correlated with factor returns, we 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 A.4). Furthermore, we conduct the regression exercise in the earlier and later sample periods, respectively. We find that the effects of FITOF on factor returns are stronger in the later sample period, which is consistent with the rapid growth of the mutual fund industry over time.

In summary, the results in this section demonstrate that the flow-induced demand shifts are strong drivers of factor returns. More importantly, our findings confirm the large literature that mutual fund flows are largely uninformed.

3.3 Estimates of (Co)variation of Flow-Induced Factor Trading

We proceed to quantify the flow-driven noise trader risk. We first describe how we estimate the variance-covariance matrix of flow-induced trading of factors. Following the spirit of Greenwood and Thesmar (2011), 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

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

by

$$G_t^{\pi} = W_t^{\pi'} E_t(\Omega_{t+1}) W_t^{\pi}. \tag{3}$$

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. 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 of stock j in factor π,[12] and $\text{Shrout}_{j,t}$ is the number of shares outstanding of stock j.

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

$$G_t^{\pi_1,\pi_2} = W_t^{\pi_1'} E_t(\Omega_{t+1}) W_t^{\pi_2}. \tag{4}$$

As one can see, factor fragility and factor co-fragility depend on the weight of mutual funds on factors 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 eight quarters, and the results are similar if we use longer estimation windows, e.g., three to five years. We report the details of the derivation and estimation in Appendix B.1.[13]

From equations (3) and (4), one can see that factor fragility (co-fragility) is different from flow-induced trading (FIT) or expected flow-induced trading (E[FIT]) in Lou (2012). First, by construction, factor fragility (co-fragility) captures the second moment of flow-

[12] For a long-leg stock, $\mu_{j,t}^{\pi}$ 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.

[13] Note that we require past eight-quarter fund flows for the estimation of factor fragility and co-fragility. Thus, while our fund sample starts from 1980, the fragility and co-fragility measures are only available starting from 1981Q4. Our empirical analysis hereafter focuses on the sample period of 1982-2021.

induced trading, while FIT or E[FIT] captures the first moment. Second, unlike FIT, which affects asset pricing through price pressures, factor fragility affects asset pricing through a noise trader risk channel as modeled by De Long et al. (1990).

Although factor fragility (co-fragility) is constructed using a similar methodology as stock fragility (co-fragility) of Greenwood and Thesmar (2011), these two measures have significant differences. While stock fragility depends on mutual fund ownership of individual stocks, factor fragility hinges on the *difference* of mutual fund ownership of the long-leg and short-leg stocks. In addition, factor fragility captures investors' uninformed demand at factor-level, which is distinct from stock fragility. In Appendix Section B.2, we offer more discussions of the potential economic drivers of factor fragility.

To illustrate the role of flow variation on factor return variation, we plot the return volatility and the square root of *lagged* factor fragility of the Fama-French size and value factors 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 future factor volatility (covariance) in Section 3.4.

3.4 Variations of Flow-Induced Trading and Return Variations

In this section, we formally show that factor fragility and factor co-fragility, our measure of expected variance and expected covariance of flow-induced trading of factors, can significantly forecast future variation and covariation of factor returns, respectively. In other words, asset pricing factors are susceptible to noise trader risk that is caused by the uninformed capital allocation of mutual fund investors.

To this end, we first estimate the following Fama-MacBeth regression:

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

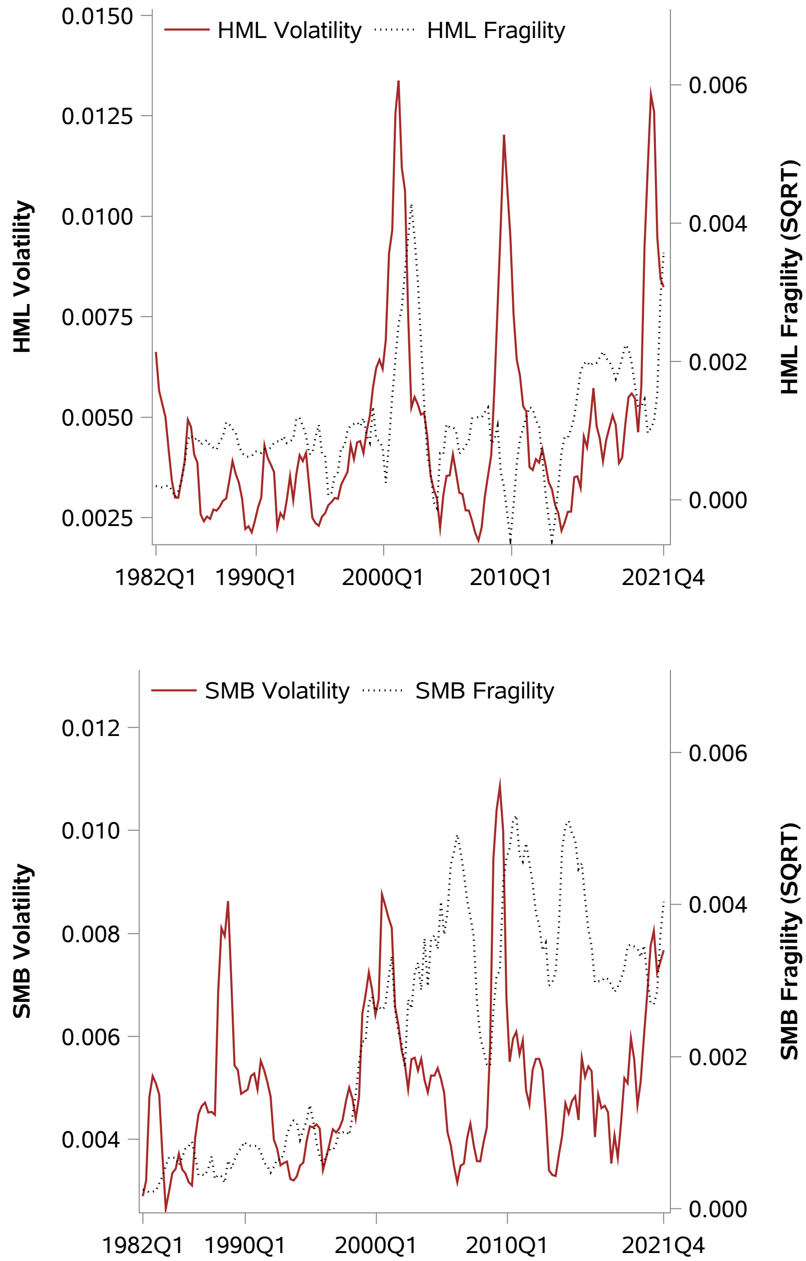

Figure 2: **Factor volatility and the square root of lagged factor fragility.** This figure plots the return volatility and the square root of one-quarter-lagged factor fragility of the Fama-French size and value factors. Factor return volatility is measured as the standard deviation of weekly factor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

where $\sigma_{t+1}^{\pi_1,\pi_2}$ is the return covariance between factors π_1 and π_2 in quarter $t+1$ and is estimated based on weekly factor returns, 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 control for lagged factor return covariance. We also include a set of control variables, $\mathbf{Z}_t^{\pi_1,\pi_2}$, that comprises the factor-pairwise difference in size, book-to-market, and momentum as in Antón and Polk (2014).[14] For ease of interpretation, all variables are normalized to have a standard deviation of one.

Panel A of Table 3 reports the results. The expected covariance of flow-induced trades between factors strongly predicts future factor return comovements. As shown in the univariate regression, a one-standard-deviation increase of factor co-fragility predicts an increase of 124% of a standard deviation of factor return covariance over the next quarter, which is 0.129% on an annualized basis. This effect of factor co-fragility is economically sizeable. For example, consider the aggregate factor portfolio that gives equal weight to the 71 factors. In our sample, the annualized variance of this factor portfolio, which largely depends on the average factor return covariance, is 0.157%. This suggests that factor co-fragility indeed plays an important role in determining the variance of the aggregate factor portfolio.

[Table 3 Here]

The effect of factor co-fragility is still highly significant in multivariate regressions or in sub-sample analysis. For example, after controlling for lagged factor return covariance and characteristics differences in column (2), a one-standard-deviation increase of factor co-fragility predicts an increase of 60% of a standard deviation of factor return covariance over the next quarter. In columns (3) and (4), we exclude the crisis periods (from 2000 to 2001 and from 2007 to 2008) and confirm that our results are not driven by the crisis periods. In fact, we get even stronger effects after excluding the crisis periods. These results suggest that the covariance in flow-induced trading is an important determinant of factor return comovement.

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

We then study the predictability of factor fragility on future factor return variation through the following Fama-MacBeth regression:

$$\sigma^{\pi}_{t+1} = \mu + \kappa \sqrt{G^{\pi}_t} + \nu \, \sigma^{\pi}_t + \eta_{t+1}. \tag{6}$$

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. Across 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 periods (column (3)), a one-standard-deviation increase in $\sqrt{G_t}$ predicts an increase of 53% of a standard deviation of factor volatility in the next quarter. After controlling for past volatility, a one-standard-deviation increase in $\sqrt{G_t}$ still leads to an average increase of 26% of a standard deviation of factor return volatility (column (4)).

It is worth noting that the explanatory power of flow-induced trading variation on factor return variation is largely consistent with the findings in the literature. For example, Ben-David et al. (2022a) estimate that mutual fund flows can explain, on average, 40% of the variation in style returns (e.g., value or growth) at a quarterly frequency. Li (2022) estimates that fund flow movements account for 30% of the Fama-French size and value factor return movements.

In summary, the results in this section show that flow-induced factor trading, while driven by uninformative capital allocation of mutual fund investors, significantly determines variations and covariations among the broad set of asset pricing factors. In other words, these asset pricing factors are significantly exposed to noise trader risk. We further explore the asset pricing implications of the flow-driven noise trader risk in the next section.

4 Is the Flow-Driven Noise Trader Risk Priced?

In this section, we demonstrate that the flow-driven noise trader risk is an important state variable that is priced in factor premia. Specifically, through in-sample and out-of-sample time-series tests, we find that the average premium across factors is higher when the flow-driven risk of the aggregate factor portfolio is expected to be more salient. Through cross-sectional tests, we find that the expected return of a factor is higher when its flow-induced trading is expected to be more correlated with the flow-induced trading of the aggregate factor portfolio. We also find that these "pricing" effects are mainly driven by stocks that are traded extensively by hedge funds and driven by large-cap stocks that mutual funds and other institutional investors mostly hold (e.g., Gompers and Metrick, 2001).

4.1 In-Sample Time-Series Tests

Intuitively, noise trader risk affects arbitrageurs' willingness to trade factors (anomalies). That is, when noise trader risk is higher, arbitrageurs are less willing to exploit factors (anomalies) by buying the long-leg stocks or selling the short-leg stocks, and consequently, factors (anomalies) have higher expected returns. A similar argument is explicitly modeled by Gromb and Vayanos (2010) in the case of cross-asset arbitrage with non-fundamental risk.[15]

We now show that the average expected return across factors is indeed higher when the flow-driven risk of the aggregate factor portfolio is expected to be higher. Specifically,

[15]Specifically, in the model of Gromb and Vayanos (2010), assets with similar payoffs can have different prices due to non-fundamental demand shocks. Arbitrageurs who exploit the mispricing have to bear the "noise trader risk" à-la De Long et al. (1990). Gromb and Vayanos (2010) show that future price volatility caused by non-fundamental demand shocks deters arbitrage so that higher noise trader risk leads to larger mispricing. Gromb and Vayanos (2018) further analyze cross-asset arbitrage with arbitrageurs facing financial constraints and show that expected returns on the long-short "arbitrage" increase with asset volatilities.

we estimate the following predictive time-series regression:

$$\frac{1}{71}\sum_{i=1}^{71} r_{\pi_i,t+1} = \alpha + \beta \underbrace{\text{Fragility}_t\left(\frac{1}{71}\sum_{i=1}^{71}\pi_i\right)}_{\text{Aggregate Fragility}} + \gamma' K_t + \eta_{t+1}. \tag{7}$$

Here, the dependent variable is the return of the equal-weighted portfolio of 71 factors (termed as aggregate factor portfolio) in quarter $t+1$. The independent variable of interest is the fragility of the aggregate portfolio of the 71 factors (termed as aggregate fragility), $G_t^{\bar{\pi}} \equiv \text{Fragility}_t\left(\sum_{i=1}^{71}\pi_i/71\right)$, which measures the expected variation of flow-induced trading of the aggregate factor portfolio. We take an equal-weighted combination of factors to construct the aggregate factor portfolio since equal-weighting is a transparent yet powerful factor combination strategy.[16] K_t is a vector of controls that potentially predicts future factor returns, including the sentiment measure of Baker and Wurgler (2006) (BW), average value spread of factors (Ilmanen, Israel, Moskowitz, Thapar, and Wang, 2019), average pairwise factor return covariance (Pollet and Wilson, 2010), and past average factor returns. We also control for aggregate market volatility, estimated by daily market returns in quarter t.

To set the stage, Table 4 reports the correlations between aggregate fragility and other predictors in equation (7). We do not find high correlations between aggregate fragility and other predictors, such as average return covariance. While aggregate fragility measures the expected variations of future flow-induced trading, average return covariance measures contemporaneous return comovements that can be driven by other economic

[16]This approach is motivated by prior studies evaluating the performance of equal-weighting against other portfolio strategies. For instance, DeMiguel et al. (2009) evaluate the out-of-sample performance of the simplest $1/N$ (equal-weighting) portfolio strategy against 14 other more sophisticated portfolio strategies. None of the 14 portfolio strategies can beat the $1/N$ strategy. We also compare the performances of this simple equal-weight portfolio of factors and other portfolios using sophisticated approaches (i.e., standard mean-variance efficient portfolio of factors; mean-variance efficient portfolio of factors constructed using the methodology of Kozak et al. (2020)). We confirm that the $1/N$ portfolio strategy at least has a similar performance as the other two strategies. Specifically, the $1/N$ portfolio strategy has a CAPM alpha of 35 bps per month, the standard mean-variance efficient portfolio has a CAMP alpha of 31 bps per month, and the mean-variance efficient portfolio of factors constructed using the methodology of Kozak et al. (2020)) has a CAMP alpha of 27 bps per month.

forces, such as arbitrageurs' trading activity.[17] In short, these low correlations suggest that aggregate fragility, as a measure of flow-driven noise trader risk, contains information beyond these other predictors.[18]

[Table 4 Here]

Table 5 presents the time-series regression of future average factor premium on aggregate fragility in equation (7). For ease of interpretation, all independent variables are normalized to have a standard deviation of one. One can see that aggregate fragility positively and significantly forecasts future average factor premium.[19] Columns (2) to (4) of Table 5 report the predictability of other predictors on future factor premia. In column (2), we find that average factor return covariance can positively forecast future average factor returns but with marginal significance ($t = 1.72$). This result is consistent with the finding of Pollet and Wilson (2010) that the average comovement of individual stock returns predicts average stock returns. Columns (3) and (4) show that the BW sentiment and the average value spread of factors are also strong predictors of future average factor premium, consistent with Stambaugh, Yu, and Yuan (2012) and Ilmanen, Israel, Moskowitz, Thapar, and Wang (2019).

[Table 5 Here]

To confirm that the predictability of aggregate fragility is not driven by its correlation with other predictors, we further conduct horse-race regressions in columns (5) to (7) of Table 5. Column (5) shows that aggregate fragility subsumes the predictive power of average return covariance. Columns (6) and (7) show that aggregate fragility remains

[17] As documented in Huang, Lou, and Polk (2018) and Lou and Polk (2020), arbitrageurs' trading activity can generate excess return comovements.

[18] In Appendix Table B.2, we also examine the correlations between aggregate fragility and other economic variables related to arbitrage activity (e.g., funding liquidity) and find their correlations are fairly low.

[19] In Appendix Table C.1, we find that the aggregate fragility positively predicts factors' long-leg returns and negatively predicts factors' short-leg returns, suggesting that arbitrageurs are reluctant to buy long-leg stocks or sell short-leg stocks in the presence of high noise trader risk.

statistically significant with mild reductions in coefficient estimates when controlling for the BW sentiment or the average value spread. Finally, we put all these predictors together into the predictive regression while controlling for past average factor return and aggregate market volatility. Column (8) shows that aggregate fragility remains statistically significant when all predictors are included in the predictive regression. In terms of the economic magnitude, a one-standard-deviation increase in aggregate fragility is associated with an increase of about 60 bps in the average factor premium over the next quarter. Considering that the average factor premium is about 79 bps per quarter in our sample, the effect of noise trader risk on factor premia is economically important.[20]

To adjust for potential small-sample bias in the predictive regressions (Stambaugh, 1999), we also apply the bias-reduction estimation approach proposed in Amihud and Hurvich (2004). Table 6 reports the results. Panel B shows that the innovation in the predictive regression of future factor premium on aggregate fragility is almost uncorrelated with the innovation in the AR(1) regression of aggregate fragility. Hence, the predictive regression does not have small sample bias. Panel C confirms that the results are almost unchanged after bias-correction.[21]

[Table 6 Here]

We further conduct several robustness tests. First, we detrend aggregate fragility to alleviate the potential effect of time trends on our regression analysis. We find that the results are almost unchanged (columns (3) to (6) of Table 7). Second, we confirm that

[20]We conduct a back-of-envelope calculation for the proportion of average factor premia that reflects compensation for flowed-induced noise trader risk. According to summary statistics in Appendix Table B.3, the mean (standard deviation) of aggregate fragility is 2.26×10^{-7} (4.68×10^{-7}), and the mean of average factor premia is 79bps per quarter. Based on column (8) of Table 5, a one-standard-deviation increase in aggregate fragility is associated with an increase in average factor premia by 61 bps per quarter. Compared with the counterfactual with zero aggregate fragility, the aggregate fragility in an average month ($= 2.26 \times 10^{-7}$) contributes to 29 bps factor premia ($=(2.26 \times 10^{-7}/4.68 \times 10^{-7}) \times 61$bps), which is about 36.7% (= 29bps/79bps) of the sample mean of average factor premia.

[21]Here, the coefficient estimate of b is slightly different from that in column (1) of Table 5. The reason is that when we implement small-sample bias adjustment based on the sample from Table 5, Aggregate Fragility$_{t+1}$ is not available in the observation of 2021Q4. Thus, we need to drop the observation of 2021Q4, which generates a small difference in coefficient b compared with that in Table 5.

the results are not sensitive to the particular way that we construct factors. Specifically, we form factors with the NYSE decile breakpoints of characteristic variables and repeat the in-sample regression. All factor-related variables are also re-constructed based on the decile portfolios. Under this alternative factor construction method, aggregate fragility remains a statistically significant predictor of future average factor premium, and its magnitude is even higher (columns (1) and (2) of Table 7).

[Table 7 Here]

Moreover, the results are robust under alternative construction of aggregate factor portfolios. In Appendix Table C.2, we consider three different ways to construct aggregate factor portfolios: (*i*) equal-weighted combination of 11 factors in Stambaugh et al. (2012); (*ii*) standard mean-variance efficient portfolio of the 71 factors; (*iii*) mean-variance efficient portfolio of factors constructed using the methodology of Kozak et al. (2020). In each specification, we re-construct aggregate fragility based on the corresponding aggregate factor portfolio and use it to forecast one-quarter-ahead returns of the aggregate factor portfolio. We find aggregate fragility positively and significantly predicts future factor premia in all specifications.[22]

We have also conducted other robustness tests. In Appendix Table C.3, we follow Greenwood and Thesmar (2011) to compute stock fragility and generate aggregate fragility of stocks as average stock fragility in each quarter. We find aggregate fragility of stocks fails to predict average factor premia. In Appendix Table C.4, we additionally control for aggregate mutual fund ownership and funding liquidity and find the predictability of aggregate factor fragility unchanged. These findings again highlight the difference

[22]In untabulated results, we also find the return predictability of Aggregate Fragility is not sensitive to dropping certain factors from our factor sample. We re-run the regression as in column (8) of Table 5 for 1,000 times. Each time, we randomly drop ten factors from our sample and use the equal-weighted combination of the rest of the factors as the aggregate factor portfolio. Then, we re-perform the regression as in column (8) of Table 5, where the dependent variable is the return of the new aggregate factor portfolio, and the independent variables are the same as those in Table 5. Finally, we obtain the empirical distribution of the coefficient estimates and t-statistics of the Aggregate Fragility variable. For the coefficient estimates of Aggregate Fragility, the 5^{th} and the 95^{th} percentile values are 0.526 and 0.698, respectively. For the t-statistics, the 5^{th} and the 95^{th} percentile values are 2.54 and 3.09, respectively.

between factor fragility and stock fragility. In Appendix Table C.6, we conduct placebo tests and show that aggregate fragility cannot predict stock market returns and bond market returns. In Appendix Table C.7, we use aggregate fragility to predict future average returns of price-based and fundamentals-based factors separately. We find the pricing effect of noise trader risk is stronger among price-based factors, which echos the argument that price-based factors have larger volatilities and are more vulnerable to investors' uninformed trading at factor level.

In summary, the time-series regressions indicate that when the flow-driven risk of the aggregate factor portfolio is expected to be higher, the average return across these factors is also higher.

4.2 Out-of-sample Time-Series Tests

Welch and Goyal (2008) point out that many predictors with in-sample forecasting power do not work in the out-of-sample tests. To further validate the role of aggregate fragility in predicting future factor premium, we conduct out-of-sample (OOS) tests as in Welch and Goyal (2008). In particular, our OOS test uses only real-time data of a given predictor to forecast future average factor premium. Then the OOS predictive power of the predictor is evaluated against that of the historical average factor premium. We find that aggregate fragility strongly forecasts future average factor premium in a series of OOS tests.

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

$$R_{t+1} = \alpha + \beta A_t + \epsilon_t. \tag{8}$$

Here, R_{t+1} is the average factor return over quarter $t + 1$, and A_t refers to a specific return predictor (e.g., aggregate fragility in equation (7)). 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 the average factor premium over the next quarter by

$$\hat{R}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t A_t. \tag{9}$$

At 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 premium, we follow Welch and Goyal (2008) and 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,

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

where 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 (9), 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 $(T - h + 1) \times ((\text{MSE}_N - \text{MSE}_A)/\text{MSE}_A)$, where h is the degree of overlap ($h = 1$ for no overlap). We compare it against the asymptotic critical values in McCracken (2007).

Table 8 reports the OOS performance of aggregate fragility and other predictors of average factor premium used in Table 5. We choose a long enough evaluation period from 1992Q1 to 2021Q4, which starts ten years after the first quarter in our sample.[23] As one can see, aggregate fragility, the BW sentiment, and average value spread all have superior OOS predictive power for future average factor premium. For instance, R^2_{OOS} of

[23]Hansen and Timmermann (2012) suggest that the power of forecast evaluation tests is stronger with longer 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 C.5, and the results are robust.

aggregate fragility is 7.74% in the evaluation period. By comparison, the average factor return covariance fails to beat the historical mean in the OOS tests, although it has positive in-sample predictability (Table 5).

[Table 8 Here]

Taken together, the results in Tables 5 to 8 show that aggregate fragility positively forecasts future average factor premium both in-sample and out-of-sample. As higher aggregate fragility implies higher noise trader risk, this evidence indicates that arbitrageurs and other investors demand higher average premium trading these factors (anomalies) when the flow-driven noise trader risk is more salient.

4.3 Exploring Arbitrageurs' Trading Activities

In this section, we further corroborate the claim that flow-driven "noise trader" risk is priced by arbitrageurs and other sophisticated investors. Specifically, we explore arbitrageurs' trading activities. If arbitrageurs that trade on factors/anomalies require compensation to bear the flow-driven noise trader risk, then noise trader risk should only affect factor premia through stocks that are indeed traded by arbitrageurs. In other words, if we construct factors using stocks with similar factor-characteristics but different likelihood to be traded by arbitrageurs, we should expect to find a stronger relationship between noise trader risk and factor premia when factors are constructed with stocks that are more likely to be traded by arbitrageurs.

To this end, we conduct two exercises. First, we utilize stock-level net arbitrage trading (NAT) in Chen et al. (2019). NAT combines hedge fund holdings with short interest and thus captures arbitrageurs' trading activities. Based on our argument above, the return predictability of the aggregate factor fragility should be more pronounced if we construct factors using stocks with high NAT. To test this, we follow Chen et al. (2019) and use stock NAT in the contemporaneous quarter of the aggregate fragility measure to identify arbitrageurs' trading on stocks.

Second, motivated by previous literature that institutional investors trade larger stocks more than smaller stocks (Gompers and Metrick, 2001), we also take size as a potential proxy for arbitrageurs' trading intensity. On the other hand, large stocks are also more liquid and more resilient to flow-induced price pressures, which alleviates arbitrageurs' concerns about flow-driven noise trader risk. Thus, we construct factors within size and liquidity double-sorted stock portfolios. We hypothesize that the predictability of aggregate fragility should be strongest among factors constructed using large but illiquid stocks, as these stocks are more heavily exploited by arbitrageurs and they are less resilient to flow-induced price effects.

Our first exercise is based on NAT. Specifically, in each quarter, we sort stocks into two even groups based on their NAT at the end of the quarter (i.e., the contemporaneous quarter of the aggregate fragility measure). A higher NAT indicates that a stock experienced more intense trading by arbitrageurs. We then reconstruct two "sub" factors by only using long-leg/short-leg stocks in the low or the high NAT group. Take the momentum factor as an example. We construct the so-called "Low-NAT" momentum factor by longing the winner stocks in the low NAT group and shorting the loser stocks that are also in the low NAT group. Similarly, the "High-NAT" momentum factor is constructed by longing the winner stocks in the high NAT group and shorting the loser stocks in the high NAT group.

Within the low NAT factors or the high NAT factors, we repeat the in-sample predictability tests of aggregate fragility on future average factor premia. That is, similar to equation (7), we estimate

$$\frac{1}{71}\sum_{i=1}^{71} r_{\pi_i,t+1}^{\text{high NAT}} = \hat{\alpha} + \hat{\beta}\,\text{Fragility}_t \left(\frac{1}{71}\sum_{i=1}^{71} \pi_i^{\text{high NAT}}\right) + \hat{\gamma}'\,K_t + \hat{\eta}_{t+1}, \tag{10}$$

and

$$\frac{1}{71}\sum_{i=1}^{71} r_{\pi_i,t+1}^{\text{low NAT}} = \tilde{\alpha} + \tilde{\beta}\,\text{Fragility}_t \left(\frac{1}{71}\sum_{i=1}^{71}\pi_i^{\text{low NAT}}\right) + \tilde{\gamma}'\,K_t + \tilde{\eta}_{t+1}, \tag{11}$$

where the factors are constructed by stocks with high and low hedge fund NAT, respectively.

Panel A of Table 9 reports the in-sample predictive regressions in equations (10) and (11). We find a sharp contrast in the coefficient estimates of aggregate fragility between the low and high NAT factors (columns (1) to (4)). For example, after controlling for sentiment and other factor return predictors, the coefficient of aggregate fragility is 0.07 ($t = 0.40$) for low-NAT group, while it is 0.57 ($t = 2.75$) for high-NAT group.

[Table 9 Here]

In the second exercise, we examine the predictability of aggregate fragility on returns of factors constructed using stocks in different size-liquidity sorted portfolios. In each quarter, we independently double-sort stocks into two-by-two portfolios based on their market capitalization and liquidity at the previous quarter-end, where the liquidity measure is Corwin and Schultz (2012) bid-ask spread. For each factor, we then reconstruct four "sub" factors by only using factor long-leg/short-leg stocks in one of the four size-liquidity sorted portfolios. For each subset of factors, we then compute quarterly average factor returns and regress it on the lagged aggregate fragility.[24]

Panel B of Table 9 reports the results. We find that the return predictability of aggregate fragility is strongest among factors constructed using large-illiquid stocks, with a coefficient estimate of 0.82 (t-statistic = 2.51). For factors with large-liquid stocks, the coefficient estimate of aggregate fragility drops to 0.27 (t-statistic = 1.66). By sharp

[24] For this analysis, we do not re-generate aggregate fragility for each subset of factors but use the aggregate fragility in the original factors as in Table 5. This is because factor portfolios in this analysis are effectively size-liquidity-factor characteristics three-way sorted portfolios, and these portfolios are too thin to estimate factor fragility.

contrast, the coefficient estimates of aggregate fragility are not even positive among factors built with small stocks.[25] This pattern is consistent with our conjecture that noise trader risk is priced by arbitrageurs who trade on these factor portfolios.

4.4 Evidence from Cross-Sectional Factor Returns

The time-series analysis so far confirms that the average factor premium is higher when the flow-driven noise trader risk of the aggregate factor portfolio is expected to be higher. Cross-sectionally, when a factor's flow-induced trading is expected to be more correlated with the flow-induced trading of the aggregate factor portfolio, that is, when a factor's "noise trading beta" is higher, the expected return of this factor should also be higher. We formally test this cross-sectional prediction in this section.

To measure the expected covariation of flow-induced trading between a factor and the aggregate factor portfolio, we compute the co-fragility between the factor and the aggregate factor portfolio by the following equation

$$G_t^{\pi_i,\bar{\pi}} \equiv \text{Co-Fragility}_t\left(\pi_i, \frac{1}{71}\sum_{j=1}^{71}\pi_j\right). \tag{12}$$

Specifically, one can think $G_t^{\pi_i,\bar{\pi}}$ (after dividing by the aggregate fragility) as a proxy of "noise trading beta."[26] That is, a higher $G_t^{\pi_i,\bar{\pi}}$ implies that a factor is expected to experience more flow-induced trading when the aggregate flow-induced demand is higher. As a primitive, Appendix Table C.8 reports the correlations between the "noise trading beta" and the betas with respect to the standard Fama-French five factors and the momentum

[25] A caveat is that our findings do not necessarily suggest noise trader risk is not priced among small stocks. Our flow-induced noise trader risk measure only captures the noise trader risk arising from mutual fund flows, and such flow-induced noise trader risk is not prevalent among small-cap stocks as these stocks have sparse mutual fund ownership. We acknowledge that there could be other sources of noise trader risk (e.g., retail trading) that might have stronger impact on small stocks.

[26] $G_t^{\pi_i,\bar{\pi}}$ is effectively the simple average of co-fragilities between the given factor π_i and the 71 factors. In our estimation of $G_t^{\pi_i,\bar{\pi}}$, in each quarter t we first estimate co-fragility between every pair of factors and we winsorize the co-fragility at 1% and 99% level in the quarter to mitigate the effect of outliers. Then, we compute $G_t^{\pi_i,\bar{\pi}}$ as $1/71\sum_{j=1}^{71}\text{Co-Fragility}_t\left(\pi_i,\pi_j\right)$.

factor. The correlations are fairly low, suggesting that the "noise trading beta" indeed captures information beyond the Fama-French and momentum factors.

We find that in the cross-section, higher expected covariation with the aggregate noise trader risk indeed predicts higher factor returns. To see it, at each quarter-end, we sort factors into quintiles based on $G_t^{\pi_i,\bar{\pi}}$ in that quarter and hold the quintile portfolios over the next quarter. We then measure performance of these factor portfolios. As shown in Table 10, the CAPM alpha (the Fama-French-Carhart four-factor alpha or the Fama-French five-factor alpha) increases monotonically with $G_t^{\pi_i,\bar{\pi}}$. For example, the average quarterly CAPM alpha increases from -0.25% to 2.55% from the bottom to the top quintile. The spread of quarterly CAPM alpha is 2.80% ($t = 3.42$).

[Table 10 Here]

To control for other potential confounding factors, in Appendix Table C.9, we also run Fama-MacBeth regressions to estimate the cross-sectional relation between $G_t^{\pi_i,\bar{\pi}}$ and expected factor returns. We find consistent evidence that higher co-fragility between a factor and the aggregate factor portfolio predicts higher future factor returns. In Appendix Table C.10, we examine the potential interaction effect between academic publication and noise trader risk on factor premia. We follow the specification in McLean and Pontiff (2016) to test the effects through factor-by-month panel regression. We find post-publication status is associated with lower factor returns and higher $G_t^{\pi_i,\bar{\pi}}$ predicts higher factor returns; however, there isn't a significant interaction effect between the two. The results suggest academic publication and noise trader risk are two independent driving forces of factor premia.

In summary, both the time-series and the cross-sectional analyses in this section show that the flow-driven noise trader risk on factors is an important state variable that is priced by arbitrageurs.

5 Conclusion

Asset pricing factors (anomalies) are one of the building blocks of asset pricing research. In this paper, we provide a new perspective on these factors. That is, we demonstrate that asset pricing factors are heavily exposed to noise trader risk, where the noise trader risk arises from uninformed demand shifts of mutual fund investors. We also show that the flow-driven noise trader risk is an important state variable priced in factor premia.

Specifically, we take a bottom-up approach to measure mutual funds' flow-induced trading of asset pricing factors. We first show that the flow-induced trades have a large temporary price impact on factor returns, which fully reverts afterward. This return pattern justifies the premise that the flow-induced trading of factors is mostly uninformed. Taking advantage of the uninformative nature of flow-induced trades, we quantify the flow-induced noise trader risk by estimating the expected variations (covariations) of flow-induced trading of factors. We show that the expected variations (covariations) of flow-induced trading of factors strongly forecast variations (covariations) of factor returns. These results suggest that asset pricing factors are significantly exposed to noise trader risk. More importantly, in both the time-series and the cross-section, we find that arbitrageurs and other investors require higher premia to trade factors (anomalies) when the flow-driven noise trader risk is expected to be more salient.

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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 mutual funds. # Funds is the number of distinct mutual funds in each period. TNA is the average fund total net assets (in million $). % Coverage of stock (EW) is the number of distinct stocks held by mutual funds in our sample, divided by the total number of CRSP stocks. % Coverage of stock (VW) is the total market capitalization of distinct stocks held by mutual funds in our sample, divided by total market capitalization of CRSP stocks. % Market is the percentage of the US common stocks held by the mutual funds in our sample. Panel B reports the stock and factor characteristics. Size and book-to-market ratio of our sample stocks are shown in NYSE percentiles. Stock-level flow-induced trading (FIT) is defined in equation (1). Flow-induced trading of factor (FITOF) is defined as the value-weighted FIT of a factor's long-leg stocks minus that of the short-leg stocks in equation (2). The definitions of factor-level square root of fragility ($\sqrt{\text{Fragility}}$) and factor pairwise co-fragility are in Section 3.3. The list of factors is in Table D.1.

Panel A: Summary statistics of mutual funds						
Period	# Funds	TNA		% Coverage of stock		% Market
		Median	Mean	EW	VW	
1980-1989	325	283.19	117.12	45.92	94.88	2.99
1990-1999	2,178	472.50	96.70	68.42	98.54	10.42
2000-2009	4,088	775.36	125.48	90.12	99.63	16.49
2010-2021	4,892	1,669.82	222.99	91.74	98.91	23.13

Panel B: Summary statistics of stocks and factors					
Variables	Mean	SD	Q1	Median	Q3
Stock level:					
Size	0.3157	0.2885	0.0658	0.2228	0.5193
Book-to-Market	0.4743	0.3040	0.1966	0.4670	0.7436
FIT	0.0206	0.1368	−0.0164	0.0037	0.0338
Factor level:					
Quarterly Ret	0.0079	0.0660	−0.0275	0.0053	0.0397
FITOF	0.0005	0.0183	−0.0049	0.0004	0.0056
SD of Weekly Ret	0.0144	0.0098	0.0086	0.0118	0.0168
$\sqrt{\text{Fragility}}$	0.0010	0.0010	0.0004	0.0008	0.0014
Factor-pair level:					
Cov of Weekly Ret (10^{-6})	2.0089	34.6478	−3.8969	0.4317	5.3301
Co-Fragility (10^{-6})	0.0139	0.2381	−0.0299	0.0007	0.0410

Table 2: **Return patterns of factor portfolios sorted by FITOF**

This table reports the 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 equation (2)). In each quarter t, we sort factors into terciles based on their FITOF in quarter t. Each factor is given equal weight in the respective portfolio. The portfolios are rebalanced every quarter and held for three years. Quarter 0 is the portfolio formation quarter. We track the quarterly 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 calculate equal-weighted returns of portfolios formed in different quarters. Panels A to D report average quarterly raw returns, quarterly CAPM alpha, quarterly Fama-French-Carhart four-factor (FFC4) alpha, and quarterly Fama-French five-factor (FF5) alpha during 1980-2021, respectively. The returns and alphas are reported in percent. The t-statistics in parentheses are computed based on standard errors with Newey-West correction for four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

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: Quarterly Raw Return (%)					**Panel B: Quarterly CAPM Alpha (%)**				
Low	−0.74**	1.18***	1.22***	0.65**	Low	−0.43	1.62***	1.67***	1.14***
	(−2.43)	(3.48)	(3.77)	(2.45)		(−1.52)	(4.26)	(4.55)	(4.39)
Mid	0.77***	0.75***	0.74***	0.76***	Mid	1.07***	1.06***	1.06***	1.07***
	(4.09)	(4.19)	(3.85)	(4.64)		(5.70)	(6.16)	(5.45)	(6.36)
High	2.32***	0.32*	0.38**	0.77***	High	2.70***	0.50***	0.55***	0.99***
	(7.42)	(1.92)	(2.16)	(3.62)		(8.19)	(3.54)	(3.40)	(3.84)
H−L	3.08***	−0.82**	−0.79**	0.13	H−L	3.13***	−1.07***	−1.06***	−0.12
	(6.12)	(−2.29)	(−2.24)	(0.49)		(6.08)	(−2.67)	(−2.59)	(−0.42)
Panel C: Quarterly FFC4 Alpha (%)					**Panel D: Quarterly FF5 Alpha (%)**				
Low	−0.73***	1.15***	1.02***	0.82***	Low	−1.12***	0.69***	0.91***	0.56***
	(−2.81)	(5.07)	(3.81)	(3.27)		(−3.68)	(3.32)	(3.75)	(2.59)
Mid	0.69***	0.70***	0.63***	0.71***	Mid	0.54***	0.54***	0.51***	0.54***
	(3.95)	(5.31)	(4.40)	(5.20)		(3.22)	(4.17)	(3.35)	(3.68)
High	2.20***	0.20	0.42**	0.56***	High	2.33***	0.37*	0.19	0.37**
	(6.48)	(1.23)	(2.54)	(3.70)		(6.70)	(1.85)	(1.15)	(2.13)
H-L	2.93***	−0.93***	−0.56	−0.24	H-L	3.49***	−0.33	−0.70**	−0.17
	(5.04)	(−3.18)	(−1.60)	(−0.83)		(5.54)	(−1.04)	(−2.05)	(−0.53)

Table 3: **Predicting factor return covariance 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 factor co-fragility ($G_t^{\pi_1,\pi_2}$). $\sigma_{t+1}^{\pi_1,\pi_2}$ is estimated as the covariance of weekly returns between factors π_1 and π_2 in quarter t+1. $G_t^{\pi_1,\pi_2}$ is the co-fragility between factors π_1 and π_2 measured at the end of quarter t as defined in equation (4). The control variables include pairwise return covariance in quarter t and pairwise differences in size, book-to-market, and momentum. Panel B reports the Fama-MacBeth regressions of one-quarter-ahead factor return volatility (σ_{t+1}) on the square root of 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 as defined in equation (3). In columns (1) and (2), we report the estimates based on the full sample. In columns (3) and (4), we exclude observations in the crisis periods (from 2000 to 2001 and from 2007 to 2008). For ease of 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*	
$G_t^{\pi_1,\pi_2}$	1.24***	0.60***	1.63***	0.78***
	(3.21)	(4.00)	(3.07)	(3.79)
$\sigma_t^{\pi_1,\pi_2}$		0.48***		0.49***
		(13.62)		(15.96)
Size Diff		−0.02***		−0.02***
		(−4.02)		(−3.81)
BM Diff		−0.00		0.01*
		(−0.06)		(1.70)
MOM Diff		−0.00		−0.01
		(−0.49)		(−1.24)
No. Obs.	397,600	397,600	357,840	357,840
Adj. R^2	0.21	0.39	0.21	0.38

Panel B: Predict factor return volatility

DepVar: σ_{t+1}	(1)	(2)	(3)	(4)
	Full Sample		*Exclude Crisis Period*	
$\sqrt{G_t}$	0.44***	0.21***	0.53***	0.26***
	(8.27)	(7.62)	(7.69)	(7.20)
σ_t		0.58***		0.56***
		(26.52)		(27.83)
No. Obs.	11,360	11,360	10,224	10,224
Adj. R^2	0.17	0.44	0.16	0.42

Table 4: **Correlation between aggregate fragility and other return predictors**

This table reports the pairwise correlations among aggregate fragility and several other predictors of factor returns. Aggregate fragility is the fragility of the equal-weighted portfolio of the 71 factors. Avg Covariance is the average pairwise return covariance of the factors in a given quarter. BW Sentiment is the investor sentiment index of 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. Specifically, the value spread of a factor is computed as the log difference between the portfolio-weighted book-to-market ratio of the long-leg and the short-leg. Avg Factor Ret is the equal-weighted average quarterly return of the factors in a given quarter. Mkt Volatility is the daily return volatility of the CRSP value-weighted market return in a given quarter.

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Aggregate Fragility	1.00					
(2) Avg Covariance	0.54	1.00				
(3) BW Sentiment	0.46	0.34	1.00			
(4) Avg Value Spread	0.47	0.38	0.71	1.00		
(5) Avg Factor Ret	0.25	0.44	0.41	0.32	1.00	
(6) Market Volatility	0.07	0.45	−0.10	−0.07	0.20	1.00

Table 5: **Aggregate fragility and future average factor premia**

This table reports the predictive regressions of average factor premia on aggregate fragility. The dependent variable is the equal-weighted average quarterly return (in percent) of the factors in quarter $t+1$. The independent variables include the fragility of the equal-weighted portfolio of the factors in quarter t (Aggregate Fragility), the average pairwise return covariance of the factors in quarter t (Avg Covariance), the investor sentiment index of 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 (Avg Value Spread), the average quarterly return of the factors in quarter t (Avg Factor Ret), and the market volatility in quarter t (Mkt Volatility). The sample period is from 1982Q1 to 2021Q4. For ease of 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)
Aggregate Fragility	0.78***				0.87***	0.56***	0.56***	0.61***
	(4.50)				(3.79)	(3.19)	(3.91)	(2.74)
Avg Covariance		0.31*			−0.16			−0.19
		(1.72)			(−1.19)			(−0.76)
BW Sentiment			0.75***			0.49**		0.23
			(4.35)			(2.39)		(0.94)
Avg Value Spread				0.74***			0.48***	0.28
				(3.26)			(2.80)	(0.91)
Avg Factor Ret								0.19
								(1.04)
Mkt Volatility								−0.22*
								(−1.81)
No. Obs.	160	160	160	160	160	160	160	160
Adj. R^2	0.15	0.02	0.14	0.13	0.15	0.20	0.19	0.21

Table 6: **Small-sample bias adjustment for the predictive regression in Table 5**

This table reports the analyses of potential small-sample bias in the predictive regression of average factor premia on aggregate fragility. The dependent variable is the equal-weighted average quarterly return (in percent) of the factors in a given quarter $t+1$, and the independent variable is the aggregate fragility of the 71 factors in quarter t (Aggregate Fragility). The sample period is from 1982Q1 to 2021Q4. Panel A reports the OLS estimates from the following two equations: Avg Factor $\text{Ret}_{t+1} = a + b \times$ Aggregate Fragility_t + u_{t+1} and Aggregate $\text{Fragility}_{t+1} = c + d \times$ Aggregate Fragility_t + v_{t+1}. Panel B reports correlations or standard deviations (shown in brackets) of the innovations in the two regressions above. Panel C reports the coefficient estimates and t-statistics (shown in parentheses) of the predictive regression based on the 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
0.41**	0.77***	0.16***	0.68***
(2.53)	(5.25)	(4.98)	(11.45)
Panel B: Correlation [SD]			
	u	v	
u	[1.83]	−0.01	
v		[0.74]	
Panel C: Bias-adjusted estimates			
a^c	b^c		
0.41**	0.77***		
(2.53)	(5.23)		

Table 7: **Robustness checks for predicting average factor premia in Table 5**

This table reports several robustness checks for the predictive regressions of average factor premia (in percent) on aggregate fragility. First, we re-construct factors through forming value-weighted long-short portfolios with the NYSE decile breakpoints of characteristic variables. We re-generate average factor premia and aggregate fragility using NYSE decile long-short portfolios. Other variables are defined following Table 5. The regression results are reported in columns (1) and (2). We also detrend the key independent variable (Aggregate Fragility) in the regressions. Specifically, over the sample period of 1982Q1-2021Q4, we regress Aggregate Fragility on a year-quarter time indicator and use the residuals as linear-detrended Aggregate Fragility. Similarly, we regress Aggregate Fragility on a year-quarter time indicator together with its square term and use the residuals as quadratic-detrended Aggregate Fragility. Regression results with the detrended Aggregate Fragility are reported in columns (3) to (6). For ease of 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)
	NYSE Decile Portfolio		*Detrend-Linear*		*Detrend-Quadratic*	
Aggregate Fragility	0.91***	0.67**	0.83***	0.65***	0.82***	0.62***
	(3.37)	(2.00)	(4.80)	(2.97)	(5.03)	(2.89)
Avg Covariance		−0.24		−0.18		−0.14
		(−0.70)		(−0.78)		(−0.59)
BW Sentiment		0.37		0.21		0.16
		(1.22)		(0.86)		(0.61)
Avg Value Spread		0.35		0.24		0.27
		(0.85)		(0.81)		(0.89)
Avg Factor Ret		0.19		0.18		0.19
		(0.79)		(1.01)		(1.08)
Mkt Volatility		−0.27		−0.22*		−0.24**
		(−1.60)		(−1.83)		(−2.02)
No. Obs.	160	160	160	160	160	160
Adj. R^2	0.13	0.19	0.17	0.21	0.17	0.21

Table 8: **Predicting average factor premia by aggregate fragility: out-of-sample tests**

This table reports the statistics of the out-of-sample forecast errors for average factor premia at a quarterly frequency. We calculate the out-of-sample test statistics, R^2_{OOS} and ΔRMSE, following Welch and Goyal (2008). A star next to the estimates of R^2_{OOS} is based on the critical values of the 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 is the same as in Table 5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Predictor	R^2_{OOS} (%)	ΔRMSE (%)	MSE_F
Aggregate Fragility	7.74***	8.56	13.33
Avg Covariance	−24.92	−25.53	−31.72
BW Sentiment	12.28***	13.76	22.27
Avg Value Spread	9.86***	10.97	17.39
Avg Factor Ret	1.52	1.65	2.45
Mkt Volatility	−0.44	−0.48	−0.70

Table 9: **Predicting average returns of factors formed with subsets of stocks**

This table reports the predictive regressions of average factor returns (in percent) on aggregate fragility as in Tables 5. Here, factors are constructed with subsets of stocks. In Panel A, in each quarter, we sort stocks into two even groups based on their net arbitrage trading (NAT) in this quarter. Then, we re-generate the average factor premia and aggregate fragility using factors in the low-NAT group and high-NAT group separately. In Panel B, in each quarter, we independently double-sort stocks into 2×2 groups based on their market capitalization and liquidity (effective spreads in Corwin and Schultz (2012)) in the previous quarter. For each factor, we re-construct value-weighted long-short portfolios using stocks in each one of the size-liquidity groups, respectively. The average factor premia in columns (1) to (4) are computed separately using factors in each size-liquidity group. Aggregate fragility is generated using factors in the low market-cap group in columns (1)-(2), and it is generated using factors in the high market-cap group in columns (3)-(4). Other variables in this table follow the definitions in Table 5. For ease of 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: NAT

	(1)	(2)	(3)	(4)
	Low NAT		High NAT	
Aggregate Fragility	0.24	0.07	0.66**	0.57***
	(1.00)	(0.40)	(2.27)	(2.75)
Avg Covariance		0.12		0.07
		(0.51)		(0.21)
BW Sentiment		0.41*		0.36
		(1.76)		(0.93)
Avg Value Spread		0.40		0.26
		(1.55)		(0.52)
Avg Factor Ret		−0.11		0.31
		(−0.56)		(1.02)
Mkt Volatility		-0.20		−0.34**
		(−1.37)		(−2.05)
No. Obs.	160	160	160	160
Adj. R^2	0.00	0.09	0.04	0.08

Panel B: Size and Liquidity

	(1)	(2)	(3)	(4)
	Low Mktcap		High Mktcap	
	Less Liquid	More Liquid	Less Liquid	More Liquid
Aggregate Fragility	−0.19	−0.02	0.82**	0.27*
	(−0.49)	(−0.14)	(2.51)	(1.66)
Avg Covariance	0.15	−0.40**	0.04	−0.18
	(0.44)	(−2.04)	(0.16)	(−0.94)
BW Sentiment	0.83*	0.36*	0.69*	0.28
	(1.73)	(1.87)	(1.66)	(1.65)
Avg Value Spread	0.64	0.40	0.15	0.20
	(1.22)	(1.61)	(0.43)	(0.82)
Avg Factor Ret	−0.40	0.29	0.35	0.13
	(−0.90)	(1.48)	(0.86)	(1.07)
Mkt Volatility	−0.50**	−0.35*	−0.30	−0.20**
	(−2.15)	(−1.70)	(−1.51)	(−2.27)
No. Obs.	160	160	160	160
Adj. R^2	0.17	0.23	0.26	0.15

Table 10: **Performance of factor portfolios sorted by $G^{\pi_i,\bar{\pi}}$**

This table reports quarterly returns/alphas of factor portfolios sorted by past $G^{\pi_i,\bar{\pi}}$, which is the co-fragility between a given factor and the aggregate portfolio of the factors. At each quarter-end, we sort factors into quintiles by their $G^{\pi_i,\bar{\pi}}$ in that quarter and hold the portfolios over the next quarter. Each factor is given equal weight in the portfolios. This table reports the average quarterly return, CAPM alpha, Fama-French-Carhart four-factor (FFC4) alpha, and Fama-French five-factor (FF5) alpha for each factor portfolio over the holding period from 1982Q1 to 2021Q4. t-statistics are computed based on standard errors with Newey-West correction for four lags.

Portfolio	RET (%)	CAPM (%)	FFC4 (%)	FF5 (%)
1	−0.03	−0.25	−0.27	−0.02
	(−0.10)	(−0.88)	(−0.83)	(−0.06)
2	0.64***	0.75***	0.51**	0.45**
	(3.93)	(4.56)	(2.45)	(2.26)
3	0.68***	1.03***	0.71***	0.43**
	(2.82)	(3.93)	(3.16)	(2.51)
4	1.07***	1.59***	0.94***	0.81***
	(3.18)	(4.42)	(3.80)	(3.53)
5	1.63***	2.55***	1.75***	1.07***
	(3.05)	(4.44)	(3.83)	(3.37)
5−1	1.66**	2.80***	2.01***	1.08**
	(2.20)	(3.42)	(2.76)	(2.02)

Online Appendix for

"Noise Trading and Asset Pricing Factors"

Authors: Shiyang Huang, Yang Song, and Hong Xiang

A Additional Results on Flow-induced Trading of Factors

This section reports additional results on flow-induced trading of factors.

Table A.1 shows the transition matrix of FITOF quintile portfolios. The time-series variation of FITOF is quite large. For example, the upper left and the lower right cells indicate that the likelihood that factors in the highest (lowest) quintile remain in the highest (lowest) quintile in the next quarter is 41%.

Table A.2 provides robustness checks for return pattern of FITOF. To ensure that the above return dynamics are not driven by the mean reversion of factor returns, we conduct a portfolio-sorting exercise in which we use factor returns as the sorting variable instead of FITOF. We do not find any return patterns (see Panels A and B). Second, we analyze the influence of mutual fund trades of factors that are not driven by fund flows.[27] We find that non-flow-induced trades do not generate return reversals (see Panel C). These placebo tests highlight the uniqueness of the return patterns associated with flow-induced factor trading.

In Table A.3, we isolate fund flows that are driven by fund alphas and re-construct FITOF with the alpha-isolated fund flows. We find that the return patterns are largely unchanged using these "alpha-free" fund flows. Second, to account for time and factor

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

fixed effects that might be correlated with factor returns, we estimate panel regressions of factor returns on flow-induced trading of factors.

In Table A.4, we conduct the regression exercise in the earlier and later sample periods (1982-1999 versus 2000-2021), respectively. We find that the effects of FITOF on factor returns are stronger in the later sample period, which is consistent with the rapid growth of the mutual fund industry over time.

Table A.1: **Transition matrix of FITOF quintile portfolios**

Each quarter we sort the 71 factors into quintiles based on the FITOF in that quarter. This table reports the quarter-to-quarter transition likelihood of the FITOF quintile ranking.

	Rank Qtr $t+1 \rightarrow$				
Rank Qtr $t \downarrow$	1	2	3	4	5
1	0.41	0.22	0.13	0.12	0.12
2	0.22	0.27	0.24	0.16	0.11
3	0.13	0.23	0.29	0.22	0.13
4	0.11	0.15	0.24	0.28	0.21
5	0.12	0.12	0.14	0.21	0.41

Table A.2: **Returns of factor portfolios sorted by factor returns or non-FIT trades.** This table reports the performance of factor portfolios sorted by factor returns or by non-FIT trades. We conduct the following portfolio analysis with different sorting variables in Panels A to C: At the end of each quarter t, we sort the factors into terciles based on a given sorting variable. Each factor is given equal weight in the respective 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 Qtr 12. We deal with overlapping portfolios in each holding month following Jegadeesh and Titman (1993). Monthly FF5 alphas (%) 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 the factor return in Qtr 0. In Panel B, the sorting variable is the cumulative factor return from Qtr −3 to Qtr 0. In Panel C, the sorting variable is mutual funds' non-FIT trade of factors. Specifically, we calculate mutual funds' non-FIT trade of a stock as mutual funds' aggregate realized trade scaled by the total number of shares held by mutual funds minus flow-induced trading (similar with equation (1)). Then we compute mutual funds' non-FIT trade of a factor as the portfolio-weighted average non-FIT trades of stocks that constitute the factor.

Portfolio	**Qtr 1-4**	**Qtr 5-8**	**Qtr 9-12**
Panel A: Sort by current-quarter ret			
Low	0.09^{**}	0.18^{***}	0.18^{***}
	(2.56)	(3.27)	(2.78)
Mid	0.17^{***}	0.17^{***}	0.16^{***}
	(4.08)	(4.20)	(3.51)
High	0.28^{***}	0.19^{***}	0.16^{***}
	(3.06)	(3.92)	(3.71)
H−L	0.19	0.00	−0.02
	(1.62)	(0.06)	(−0.22)
Panel B: Sort by past four-quarter ret			
Low	0.10^{*}	0.20^{**}	0.19^{**}
	(1.85)	(2.54)	(2.53)
Mid	0.17^{***}	0.18^{***}	0.16^{***}
	(4.95)	(4.32)	(3.18)
High	0.27^{***}	0.16^{**}	0.16^{***}
	(2.58)	(2.54)	(3.21)
H−L	0.17	−0.04	−0.02
	(1.21)	(−0.33)	(−0.21)
Panel C: Sort by mutual funds' non-FIT trades			
Low	0.22^{***}	0.25^{***}	0.18^{***}
	(2.81)	(3.79)	(3.07)
Mid	0.18^{***}	0.16^{***}	0.18^{***}
	(5.11)	(3.65)	(3.79)
High	0.14^{***}	0.14^{***}	0.15^{***}
	(3.82)	(4.13)	(4.98)
H−L	−0.08	−0.11	−0.03
	(−0.96)	(−1.60)	(−0.58)

Table A.3: **Returns of factors sorted by flow-induced trading: exclude fund flow components driven by fund alphas**

To isolate fund flows that are driven by fund alpha components, we estimate a fund-quarter panel regression with time fixed effects: The dependent variable is fund flow in quarter t, and the independent variables include the FFC4 alpha of the fund, estimated using observations in the 24 months prior to quarter t, and four lags of fund flow from quarter $t-4$ to quarter $t-1$. We re-construct FITOF using the alpha-isolated flows and use it as sorting variable to re-conduct the portfolio sorting exercise in Table 2. Panel A to Panel D reports monthly raw returns, monthly CAPM alpha, monthly FFC4 alpha, and monthly FF5 alpha, respectively. The returns and alphas are reported in percent. 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	−0.31***	0.38***	0.43***	0.24***	Low	−0.24**	0.49***	0.54***	0.36***
	(−3.19)	(3.92)	(4.35)	(2.89)		(−2.55)	(4.84)	(5.04)	(4.62)
Mid	0.24***	0.25***	0.24***	0.22***	Mid	0.33***	0.33***	0.33***	0.32***
	(3.64)	(4.36)	(4.58)	(3.99)		(5.23)	(5.93)	(6.46)	(5.60)
High	0.85***	0.12**	0.09	0.25***	High	0.95***	0.19***	0.18***	0.34***
	(7.36)	(1.99)	(1.34)	(3.80)		(8.05)	(3.69)	(2.59)	(4.46)
H−L	1.16***	−0.26***	−0.34***	0.02	H−L	1.19***	−0.30***	−0.37***	−0.02
	(6.51)	(−2.57)	(−2.91)	(0.18)		(6.50)	(−2.76)	(−2.86)	(−0.26)
Panel C: Monthly FFC4 Alpha					**Panel D: Monthly FF5 Alpha**				
Low	−0.26***	0.39***	0.37***	0.24***	Low	−0.41***	0.28***	0.34***	0.18***
	(−2.82)	(5.42)	(5.11)	(3.26)		(−3.75)	(4.93)	(4.87)	(2.93)
Mid	0.18***	0.21***	0.21***	0.21***	Mid	0.18***	0.18***	0.18***	0.16***
	(4.88)	(5.40)	(5.69)	(5.06)		(2.98)	(3.74)	(4.05)	(3.35)
High	0.74***	0.06	0.08	0.21***	High	0.80***	0.09	0.04	0.17***
	(7.32)	(1.07)	(1.28)	(4.78)		(6.38)	(1.53)	(0.55)	(2.90)
H−L	1.00***	−0.33***	−0.29***	−0.03	H−L	1.21***	−0.18**	−0.30***	−0.01
	(5.80)	(−3.22)	(−2.57)	(−0.31)		(5.41)	(−2.02)	(−2.70)	(−0.06)

Table A.4: **Regression analysis of factor return on FITOF**

This table reports the panel regressions of factor return on contemporaneous and past FITOF. The dependent variable in both panels is the monthly factor return (in percent) in a given month. Panel A reports the regressions of monthly factor returns on the FITOF in the same quarter. 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 $t-1$ to qtr $t-8$. Columns (1)-(2) report the regression results based on the full sample period from Apr 1982 to Dec 2021. Columns (3)-(6) report the regression results over two sub-periods: 1982-1999 (first-half) and 2000-2021 (second-half), respectively. Year-month fixed effects and factor fixed effects are included. t-statistics are computed based on standard errors clustered by year-month. *, **, *** 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		1981-1999		2000-2021	
Contemporaneous FITOF	0.22***	0.24***	0.13**	0.14**	0.56**	0.60**
	(2.90)	(3.01)	(2.13)	(2.23)	(2.38)	(2.45)
Factor FE	No	Yes	No	Yes	No	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	34,932	34,932	16,188	16,188	18,744	18,744
Adj. R^2	0.08	0.08	0.05	0.06	0.10	0.11

Panel B: Factor return and past FITOF

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		1981-1999		2000-2021	
Past FITOF	−0.21***	−0.23***	−0.12**	−0.14*	−0.44**	−0.48**
	(−2.84)	(−2.79)	(−1.98)	(−1.67)	(−2.13)	(−2.15)
Factor FE	No	Yes	No	Yes	No	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	34,932	34,932	16,188	16,188	18,744	18,744
Adj. R^2	0.07	0.07	0.05	0.05	0.08	0.08

B Additional Analysis on Factor Fragility and Co-Fragility

B.1 Derivation of Factor Fragility and Co-Fragility

In this section, we describe how we derive the measures of factor fragility (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:

$$r_{j,t} = \alpha_j + \lambda_j \frac{\sum_k \text{Shares}_{k,j,t-1} f_{k,t} \text{PSF}_{k,t}}{\sum_k \text{Shares}_{k,j,t-1}} + \varepsilon_{j,t}. \tag{13}$$

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 follow Greenwood and Thesmar (2011) and 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 $t-1$. As explained in Lou (2012), $\sum_k \text{Shares}_{k,j,t-1} f_{k,t} \text{PSF}_{k,t} / \sum_k \text{Shares}_{k,j,t-1}$ is the amount of mutual fund trading in stock j mechanically caused by fund flows and thus does not contain information given mutual fund flows are mostly non-fundamental. 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).

Factors are value-weighted portfolios of stocks and thus the return of factor π can be expressed as:

$$r_{\pi,t} = \sum_j \mu^{\pi}_{j,t-1} r_{j,t}, \tag{14}$$

where $\mu^{\pi}_{j,t-1}$ is the weight of stock j in factor π in quarter t.[28] Combining (13) and (14),

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

we get

$$r_{\pi,t} = \sum_j \mu^{\pi}_{j,t-1}\alpha_j + \lambda\left(\sum_k w^{\pi}_{k,t-1} f_{k,t}\mathrm{PSF}_{k,t}\right) + \sum_j \mu^{\pi}_{j,t-1}\varepsilon_{j,t}, \tag{15}$$

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

Based on equation (15), the conditional variance and covariance of $r_{\pi,t+1}$ at the end of quarter t are

$$\mathrm{Var}_t(r_{\pi,t+1}) = \lambda^2 W^{\pi\prime}_t E_t(\Omega_{t+1}) W^{\pi}_t + \mathrm{Var}_t\left(\sum_j \mu^{\pi}_{j,t}\varepsilon_{j,t+1}\right) \tag{16}$$

and

$$\mathrm{Cov}_t(r_{\pi_1,t+1}, r_{\pi_2,t+1}) = \lambda^2 W^{\pi_1\prime}_t E_t(\Omega_{t+1}) W^{\pi_2}_t + \mathrm{Cov}_t\left(\sum_j \mu^{\pi_1}_{j,t}\varepsilon_{j,t+1}, \sum_j \mu^{\pi_2}_{j,t}\varepsilon_{j,t+1}\right), \tag{17}$$

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

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

$$G^{\pi}_t = W^{\pi\prime}_t E_t(\Omega_{t+1}) W^{\pi}_t. \tag{18}$$

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

$$G^{\pi_1,\pi_2}_t = W^{\pi_1\prime}_t E_t(\Omega_{t+1}) W^{\pi_2}_t. \tag{19}$$

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.

original weight in the short leg multiplied by negative one.

B.2 Determinants of Factor Fragility and Co-Fragility

We discuss the economic determinants of factor fragility and co-fragility in this section. Take factor fragility as an example. We can write factor fragility as (time subscripts are removed for simplicity)

$$G^{\pi} = W^{\pi'} E(\Omega) W^{\pi} = \sum_{k \in K} \sum_{l \in K} w_k w_l E(Cov(f_k, f_l)), \tag{20}$$

where w_k (w_l) is the weight of fund k (fund l) on factor π, and $E[Cov(f_k, f_l)]$ is the expected flow covariance between funds k and l. Here, a mutual fund's weight on a long-short factor portfolio is defined as the value-weighed average ownership of long-leg stocks minus the value-weighed average ownership of short-leg stocks.

We argue that investors' uninformed demand drives factor fragility. To see the point, imagine that funds k and l both have large positive weights on factor π. An increase (decrease) in investors' uninformed demand on factor π leads to correlated inflows (outflows) on the two funds, which in turn generates a positive flow covariance and adds to the fragility of factor π. Similarly, if fund k has a positive weight on factor π but fund l has a negative weight on factor π. An increase in investors' uninformed demand on factor π leads to inflows into fund k but outflows from fund l, leading to negative flow covariance. Multiplying the negative flow covariance by a negative $w_k w_l$ also yields a positive term, which adds to the fragility of factor π.

To further provide causal evidence of our argument, we exploit the Morningstar rating reform event in June 2002 (dubbed by the MS event hereafter). Until mid-2002, Morningstar equity fund ratings were based on an universal return ranking. As a result, Morningstar ratings of mutual funds in the out-performing (under-performing) style go up (down) together. Investors chasing Morningstar rating thus direct flows into (out of) funds in the out-performing (under-performing) style, leading to a style-level "flow co-movement." In June 2002, Morningstar revised its methodology and began ranking funds within the size-value style box, which effectively neutralized the fund rating with respect to style performance and caused a structural break of style-level demand and style-level positive feedback trading (Ben-David et al., 2022a, 2023). In other words, investors' rating chasing behavior should no longer drive style-level flow comovement. Thus, we argue that the MS event should result in a reduction in style-level flow comovement, which would further lead to lower fragility of the affected factors (as illustrated in equation (20)).

To test this argument, we first examine the impact of the MS event on style-level flow comovement through a diff-in-diff analysis. Take value or growth funds as an example. We follow Ben-David et al. (2023) to measure each mutual fund's ex-ante exposure to the MS event and sort mutual funds into terciles by their ex-ante exposure as of December 2001. We assign the top tercile of funds into treatment group and the bottom tercile of funds into control group. In order to examine the MS event's impact on style-level flow comovement, we further assign mutual funds in the treatment group into the treated-value or treated-growth subgroups if a fund has significant positive or negative beta on the Fama-French HML factor. Then, we estimate the pairwise fund flow covariance within the treated-value, treated-growth, and control groups during the pre-event period (2000.Q1-2001.Q4). We also estimate the pairwise fund flow covariance within the treated-value, treated-growth, and control groups during post-event period (2003.Q1-2004.Q4). We pool the pre-event and post-event pairwise flow covariance observations as the final diff-in-diff regression sample.[29]

Column (1) of Panel A in Table B.1 presents the diff-in-diff regression results, where the dependent variable is pairwise fund flow covariance. A significant negative coefficient of Treat$\times$Post confirms that the MS event leads to a reduction in style-level flow comovement for value and growth funds. Similarly, column (2) shows that the MS event leads to a reduction in style-level flow comovement for size-style funds.

The next step is to examine the impact of the MS event on factor fragility. To this end,

[29]We define Treat = 1 for the treated-value and treated-growth groups and Treat = 0 for the control group.

we also follow Ben-David et al. (2023) to construct a measure for each factor's ex-ante exposure to the MS event. A higher absolute value of factor-level exposure indicates a given factor would be more affected by the MS event, which leads to less correlated flows on the factor and ultimately result in lower fragility of the factor. To implement the test, we sort the 71 factors into three groups (bottom 10, top 10, and medium 51) based on the absolute value of factor-level ex-ante exposure to the MS event. Next, we compute factor fragility in the pre-event window of 2000.Q2-2002.Q1 and the post-event window of 2002.Q3-2004.Q2 separately. Then, we compute the change in factor fragility before and after the event. Panel B reports the results of regressing change in factor fragility on the ranking of factor-level exposure to the MS event. We find factors that are more exposed to the MS event indeed experienced a greater reduction in factor fragility.

In short, this event study shows that the MS event led to reductions in factor/style-level flow comovement and factor fragility. These findings further support the idea that investors' uninformed demand significantly determines factor fragility.

B.3 Additional Results about Factor Fragility and Co-Fragility

Table B.2 shows the correlation between aggregate fragility and several other economic variables related to arbitrage activity, such as funding liquidity, the Baker and Wurgler (2006) sentiment, and the VIX index. We find the correlations between aggregate fragility and these variables are fairly low.

Table B.3 reports summary statistics for variables in Table 5.

Table B.4 compares the factor fragility and the co-fragility between a factor and the aggregate factor portfolio between fundamentals-based factors and price-based factors. Fundamentals-based factors are constructed mainly based on accounting variables, while price-based factors are constructed mainly based on stock price and trading friction-related characteristics. We find price-based factors on average have higher factor fragility and co-fragility. This suggests that price-based factors are more subject to uninformative flow-induced trading.

Table B.1: **Impact of Morningstar rating reform on style-fund flows and factor fragility**

This table shows the results about the impact of the Morningstar rating reform event in June 2002 (the MS event) on style-fund flow covariance and factor fragility. Panel A reports the diff-in-diff regression results about the impact of the MS event on pairwise flow covariance among style funds. The unit of observation is at the fund-pair level. The dependent variable is the covariance of fund flows between a given pair of funds. In Dec-2001, we sort mutual funds into tercile by their ex-ante exposure to the MS event. The top tercile of funds enters into the treatment group, and the bottom tercile of funds enters into the control group. In column (1), we construct a regression sample as follows. We first estimate each fund's betas and associated t-values on the Fama-French (1993) three factors in the 24-month window ending in Dec-2001. For funds in the treatment group, we further assign funds to the value (growth) group if they have statistically significant positive (negative) beta on the HML factor. Then, we estimate the fund pairwise flow covariance during 2000.Q1-2001.Q4 within value group, growth group, and control group separately. We define Post = 0 for these fund pair-level observations. Similarly, we estimate the fund pairwise flow covariance during 2003Q1-2004Q4 within the value group, growth group, and control group separately. We define Post = 1 for these fund pair-level observations. Finally, we pool pre-event and post-event observations together to form the final regression sample in column (1). We define Treat = 1 for fund pairs in the value group and the growth group and define Treat = 0 for fund pairs in the control group. In column (2), we take a similar procedure to construct regression sample among size-style funds. We define Treat = 1 for funds which have $t > 1.96$ or $t < -1.96$ on the SMB factor. Panel B presents the regression results on the impact of the MS event on factor-level fragility. We sort factors into three groups (bottom 10, top 10, and medium 51) based on the absolute value of factor-level predicted rating change before the event. We generate a Rank˙Exposure variable which equals one for the bottom group, two for the medium group, and three for the top group. To measure the change in factor fragility, we compute factor fragility in the pre-event window of 2000.Q2-2002.Q1 and the post-event window of 2002.Q3-2004.Q2 separately. Then, we compute the change in factor fragility as the difference between pre-event fragility and post-event fragility. This table reports the results from the regression of change in factor fragility on Rank˙Exposure. t-statistics in parentheses are calculated based on robust standard errors. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Impact on Pairwise Flow Covariance		
DepVar: Pairwise Flow Cov	(1) Treat = 1 for value/growth fund pairs	(2) Treat = 1 for size fund pairs
Treat×Post	−0.01***	−0.00***
	(−19.25)	(−17.11)
Treat	0.01***	0.00***
	(20.03)	(19.46)
Post	−0.00	−0.00
	(−0.08)	−0.08)
Intercept	0.00***	0.00***
	(2.63)	(2.63)
No. Obs.	431,511	452,375
Adj. R^2	0.004	0.001

Panel B: Impact on Factor Fragility	
DepVar: Change in Fragility ($\times 10^5$)	(1)
Rank_Exposure	−0.41**
	(−2.40)
Intercept	0.27
	(2.04)
No. Obs.	71
Adj. R^2	0.064

Table B.2: **Correlations of aggregate factor fragility with other variables**

This table reports the pairwise correlations among aggregate fragility and several other variables. The sample period is from 1982Q1 to 2021Q4. Aggregate Fragility of Factors is the aggregate fragility computed based on the sample factors at each quarter-end, as in Table 5. Aggregate Fragility of Stocks is the equal-weighted average of stock fragility in each quarter. We follow Greenwood and Thesmar (2011) to compute stock fragility in the sample of stocks with market caps greater than the NYSE median each quarter. Funding Liquidity is measured as the TED spread at each quarter-end. VIX is the quarter-end VIX index level. Fraction of Post-Publication Factors is the fraction of sample factors of which the first academic paper has been published each quarter-end. Market IVol is the equal-weighted average idiosyncratic volatility across CRSP stocks. MF Ownership is the percentage mutual fund ownership on the CRSP stocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Aggregate Fragility of Factors	1.00						
(2) Aggregate Fragility of Stocks	0.15	1.00					
(3) Funding Liquidity	−0.12	−0.35	1.00				
(4) VIX	0.14	0.08	0.31	1.00			
(5) Fraction of Post-Publication Factors	0.04	0.88	−0.42	0.03	1.00		
(6) Market IVol	0.22	−0.23	0.47	0.41	−0.38	1.00	
(7) MF Ownership	0.06	0.91	−0.42	0.01	0.99	−0.35	1.00

Table B.3: **Summary statistics of variables in Table 5**

This table reports the summary statistics of the variables in Table 5. The sample period is from 1982Q1 to 2021Q4. The definitions of these variables are in Table 5.

Variable	Mean	SD	P25	P50	P75
Aggregate Fragility ($\times 10^5$)	0.0226	0.0468	0.0027	0.0086	0.0198
Avg Covariance ($\times 10^5$)	0.3963	1.0131	0.0404	0.1065	0.2859
BW Sentiment	0.2231	0.6984	−0.2585	0.0105	0.6325
Avg Value Spread	0.0460	0.0791	0.0085	0.0408	0.0928
Avg Factor Ret	0.0077	0.0197	−0.0023	0.0052	0.0150
Mkt Volatility	0.0001	0.0002	0.0000	0.0001	0.0001

Table B.4: **Factor fragility: price versus fundamentals based factors**

This table compares factor fragility between price-based and fundamentals-based factors. Price-based factors are constructed mainly based on stock price and trading friction-related characteristics. Fundamentals-based factors are constructed mainly based on accounting variables. Column (1) reports average factor fragility among price-based and fundamentals-based factors. Column (2) reports average $G^{\pi_i,\bar{\pi}}$, which is the co-fragility between a given factor and aggregate factor portfolio (see Table 10), among price-based and fundamentals-based factors. The bottom row reports *p*-value of the *t*-test comparing the group average fragility or $G^{\pi_i,\bar{\pi}}$ between the two groups.

Factor Category	(1) Factor Fragility (10^{-6})	(2) $G^{\pi_i,\bar{\pi}}$ (10^{-6})
Fundamentals based	1.238	0.108
Price and trading based	2.101	0.145
p-value of diff (*t*-test)	< 0.0001	0.0265

C Additional Results on Flow-induced Noise Trader Risk

This section presents additional results about flow-induced noise trader risk.

In Table C.1, we examine the predictability of aggregate fragility on factor long-leg and short-leg returns separately. In this test, we use market-adjusted returns of the long-/short-legs to hedge away the market exposures of the long-/short-legs. We find that the aggregate fragility positively predicts factors' long-leg returns and negatively predicts factors' short-leg returns, suggesting that arbitrageurs are reluctant to buy long-leg stocks or sell short-leg stocks in the presence of high noise trader risk.

In Table C.2, we show that our main results are robust under alternative definitions of aggregate factor portfolios. We consider three different ways to construct aggregate factor portfolios: (*i*) equal-weighted combination of 11 factors in Stambaugh et al. (2012); (*ii*) standard mean-variance efficient portfolio of the 71 factors;[30] (*iii*) mean-variance efficient portfolio of factors constructed using the methodology of Kozak et al. (2020).[31] In each specification, we re-construct aggregate fragility based on the corresponding aggregate factor portfolio and use it to forecast one-quarter-ahead returns of the aggregate factor portfolio. We find aggregate fragility positively and significantly predicts future factor premia in all specifications. We also examined the return correlations between the equal-weighted factor portfolio and the three alternative aggregate factor portfolios defined here.

[30]We use daily factor returns to estimate the weights of mean-variance efficient portfolio in an expanding window at every year-end during 1981-2021. We follow Gerakos et al. (2021) to implement the estimation. First, we estimate factor return covariance matrix and set the covariance matrix to be diagonal in order to mitigate the influence of outliers in factor return covariance. Second, we estimate the factor premium and set any negative factor premium to zero. Finally, we compute the weight vector as: $\Omega^{-1}\mu/\mathbf{1}^{\mathbf{T}}\Omega^{-1}\mu$, where Ω is the covariance matrix and μ is the vector of factor premium. We scale the weight such that the sum of factor weights equals 100% in order to make the aggregate factor portfolio comparable with the equal-weighted combination.

[31]We follow the estimation procedure of Kozak et al. (2020) to compute the weight of factors in the mean-variance efficient portfolio as equation (22) of Kozak et al. (2020). Then, we scale the weight such that the sum of factor weights equals 100% in order to make the aggregate factor portfolio comparable with the equal-weighted combination.

We find the correlations are in the range of 0.70-0.92, suggesting that the equal-weighted factor portfolio is indeed representative.

In untabulated results, we find the return predictability of Aggregate Fragility is not sensitive to dropping certain factors from our factor sample. We re-run the regression as in column (8) of Table 5 for 1,000 times. Each time, we randomly drop ten factors from our sample and use the equal-weighted combination of the rest of the factors as the aggregate factor portfolio. Then, we re-perform the regression as in column (8) of Table 5, where the dependent variable is the return of the new aggregate factor portfolio, and the independent variables are the same as those in Table 5. Finally, we obtain the empirical distribution of the coefficient estimates and t-statistics of the Aggregate Fragility variable. For the coefficient estimates of Aggregate Fragility, the 5^{th} and the 95^{th} percentile values are 0.526 and 0.698, respectively. For the t-statistics, the 5^{th} and the 95^{th} percentile values are 2.54 and 3.09, respectively.

Table C.3 examines the predictability of aggregate fragility of stocks on future factor returns. We follow Greenwood and Thesmar (2011) to compute stock fragility in the sample of stocks with market capitalization greater than the NYSE median each quarter. Then, we compute the aggregate fragility of stocks as the equal-weighted average of the stock fragility in each quarter. Through time-series regressions, we find aggregate fragility of stocks does not significantly forecast future factor returns.

Table C.4 examines the predictability of aggregate fragility after controlling for aggregate mutual fund ownership and funding liquidity. Columns (1)-(2) show that funding liquidity is positively associated with average factor premia, but controlling for funding liquidity does not reduce the effect of aggregate fragility. In column (3), we control for aggregate mutual fund ownership on the stock market. We find aggregate fragility still positively and significantly predicts average factor premia, while aggregate mutual fund ownership cannot predict future average factor premia. Column (4) shows that the return predictability of aggregate fragility remains after removing the early sample period of 1982-1989 and controlling for aggregate mutual fund ownership.

Table C.5 considers alternative evaluation periods for the out-of-sample test and finds that the OOS performance is robust. It is also worth noting that the OOS performance of aggregate fragility is stronger in the later periods as the mutual fund sector manages a larger portion of the aggregate market.

Table C.6 conducts placebo tests of predicting non-factor returns by aggregate fragility of factors. Specifically, we tested the return predictability of aggregate fragility on stock market returns and government/corporate bond returns. We do not find significant results in the placebo tests.

In Table C.7, we compare the effect of noise trader risk on factor premia between price-based and fundamentals-based factors through time-series regressions as in Table 5. We find the coefficient estimates and statistical significance associated with aggregate fragility are stronger among price-based factors, indicating that noise trader risk generates a larger price effect on these factors.

Table C.8 reports the correlations between the noise trading beta ($G^{\pi_i,\bar{\pi}}$) and the betas with respect to the standard Fama-French five factors and the momentum factor. The correlations are fairly low, suggesting that the noise trading beta indeed captures information beyond the Fama-French and momentum factors.

In Table C.9, we conduct a robustness check for Table 10 by testing the cross-sectional relationship between $G^{\pi_i,\bar{\pi}}$ and future factor return through Fama-MacBeth regressions. We also control for the average return covariance between factor π_i and the aggregate factor portfolio in the prior quarter, the past-one-quarter factor returns, the factor value spread at the previous quarter-end, and the average FITOF over the past eight quarters. Across all specifications, higher co-fragility between a factor and the aggregate factor portfolio predicts higher future returns of the factor.

In Table C.10, we examine the potential interaction effect of academic publication and noise trader risk on factor premia. We follow the specification in McLean and Pontiff

(2016) to test the effects through factor-by-month panel regression. Column (1) confirms that "noise trading beta" ($G^{\pi_i,\bar{\pi}}$) positively forecasts future factor returns. Column (2) shows that a post-publication dummy variable, which equals one if the first academic paper on a factor has been published in the month and zero elsewhere, is negatively associated with factor returns, consistent with McLean and Pontiff (2016). In column (3), when both $G^{\pi_i,\bar{\pi}}$ and the post-publication dummy variable are included, their respective coefficients do not change compared with those in univariate regressions. Finally, column (4) shows that the interaction effect between $G^{\pi_i,\bar{\pi}}$ and post-publication dummy on factor returns is close to zero. In sum, the results suggest academic publication and noise trader risk only work independently on factor premia.

In Table C.11, we exploit the Morningstar rating reform event in June 2002 (dubbed as MS event, see Appendix Section B.2) as an exogenous shock to factor-level "noise trading beta" ($G^{\pi_i,\bar{\pi}}$) and investigate its impact on factor premia. We hypothesize that factors more exposed to the MS event would experience larger post-event reductions in noise trading beta. The plausibly exogenous reduction in noise trading beta would further lead to reductions in factor premia. To test the hypothesis, we conduct a two-stage least square regression. To begin with, for each factor, we compute the pre-event to post-event difference in noise trading beta ($\Delta G^{\pi_i,\bar{\pi}}$) and the difference in quarterly factor premium ($\Delta Premium$). We also calculate each factor's exposure to the MS event ($Exposure$). In the first stage regression, we regress $\Delta G^{\pi_i,\bar{\pi}}$ on $Exposure$ and find that factors more exposed to the event experienced a larger decline in noise trading beta. In the second stage, we regress $\Delta Premium$ on the fitted value of $\Delta G^{\pi_i,\bar{\pi}}$ from the first-stage regression. We indeed find a larger decline in noise trading beta (instrumented by $Exposure$) is associated with a stronger decline in factor premium. The results provide support for a causal relationship between flow-driven noise trader risk and factor premia.

Table C.1: **Aggregate fragility and future returns: based on factor long or short legs**

This table reports the predictive regressions of the average market-adjusted factor long-leg (short-leg) returns on aggregate fragility. In columns (1) and (2), the dependent variable is the average quarterly long-leg return (in percent) of the factors in excess of the CRSP value-weighted market return in quarter $t+1$ (Avg Mkt-Adj Ret, Long). In columns (3) and (4), the dependent variable is the average quarterly short-leg return (in percent) of the factors in excess of the CRSP value-weighted market return in quarter $t+1$ (Avg Mkt-Adj Ret, Short). The key independent variable in all columns is aggregate fragility computed based on the equal-weighted factor portfolio (see Table 5). Control variables follow the definitions in Table 5. t-statistics in parentheses are calculated 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)
DepVar:	Avg Mkt-Adj Ret, Long		Avg Mkt-Adj Ret, Short	
Aggregate Fragility	0.29***	0.23**	−0.43***	−0.29
	(2.92)	(2.59)	(−3.66)	(−1.62)
Avg Covariance		−0.08		0.07
		(−1.20)		(0.32)
BW Sentiment		0.01		−0.25
		(0.08)		(−0.97)
Avg Value Spread		0.19		−0.07
		(1.58)		(−0.26)
Avg Factor Ret		0.01		−0.20
		(0.10)		(−0.98)
Mkt Volatility		0.19		0.44**
		(1.61)		(2.13)
No. Obs.	160	160	160	160
Adj. R^2	0.09	0.12	0.05	0.14

Table C.2: **Alternative methods of constructing aggregate factor portfolio**

This table reports the time-series return predictability results using alternative methods to construct the aggregate factor portfolio. In columns (1)-(2), we follow Stambaugh et al. (2012) and use the equal-weighted combination of the 11 factors as the aggregate factor portfolio. The dependent variable is the equal-weighted average returns across the 11 factors in each quarter. The key independent variable, Aggregate Fragility, is fragility of the aggregate factor portfolio at each quarter-end. In columns (3)-(4), we construct the aggregate factor portfolio as the standard mean-variance optimal combination of the 71 factors in our sample. The dependent variable is the return of the mean-variance optimal factor portfolio in each quarter, and Aggregate Fragility is fragility of the mean-variance optimal factor portfolio at each quarter-end. In columns (5)-(6), we follow the methodology of Kozak et al. (2020) to estimate the SDF coefficient and construct the implied mean-variance efficient factor portfolio. The dependent variable is the return of the mean-variance efficient factor portfolio in each quarter, and Aggregate Fragility is fragility of the mean-variance efficient factor portfolio at each quarter-end. t-statistics in parentheses are calculated 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)
	SYY(2012) 11 Anomalies		*Standard Mean-Variance Portfolio*		*KNS (2020) Mean-Variance Portfolio*	
Aggregate Fragility	0.74***	0.76**	0.64***	0.48**	0.51***	0.33***
	(2.63)	(2.47)	(4.06)	(2.60)	(5.26)	(3.03)
Avg Covariance		−0.50		−0.06		−0.01
		(−1.41)		(−0.35)		(−0.14)
BW Sentiment		0.52		0.21		0.08
		(1.35)		(0.95)		(0.48)
Avg Value Spread		0.18		0.33		0.41**
		(0.38)		(1.23)		(2.23)
Avg Factor Ret		0.53		0.02		−0.03
		(1.62)		(0.09)		(−0.28)
Mkt Volatility		−0.46**		−0.18*		−0.01
		(−2.15)		(−1.87)		(−0.12)
No. Obs.	160	160	160	160	160	160
Adj. R^2	0.05	0.13	0.12	0.18	0.13	0.21

Table C.3: **Aggregate fragility of factors/stocks and future average factor premia**

This table reports the predictive regressions of average factor premia on aggregate factor fragility and aggregate stock fragility. The sample period is from 1982Q1 to 2021Q4. The dependent variable is the average factor returns in each quarter. Aggregate Fragility of Factors is the aggregate fragility computed based on the sample factors at each quarter-end as in Table 5. Aggregate Fragility of Stocks is the equal-weighted average of stock fragility in each quarter. We follow Greenwood and Thesmar (2011) to compute stock fragility in the sample of stocks with market caps greater than the NYSE median each quarter. Control variables follow Table 5. 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)
Aggregate Fragility of Factors	0.61***		0.60***
	(2.74)		(2.69)
Aggregate Fragility of Stocks		0.25	0.03
		(1.08)	(0.15)
Avg Covariance	−0.19	−0.00	−0.20
	(−0.76)	(−0.00)	(−0.74)
BW Sentiment	0.23	0.42*	0.24
	(0.94)	(1.85)	(0.92)
Avg Value Spread	0.28	0.48	0.29
	(0.91)	(1.18)	(0.93)
Avg Factor Ret	0.19	0.17	0.19
	(1.04)	(0.80)	(1.01)
Mkt Volatility	−0.22*	−0.28**	−0.22*
	(−1.81)	(−2.15)	(−1.82)
No. Obs.	160	160	160
Adj. R^2	0.209	0.161	0.204

Table C.4: **Robustness check for Table 5: additional controls.** This table reports the predictive regressions of average factor premia on aggregate fragility. The dependent variable is the equal-weighted average quarterly return (in percent) of the factors in quarter $t + 1$. The key independent variables include the fragility of the equal-weighted portfolio of the factors in quarter t (Aggregate Fragility). In column (1), we additional control for funding liquidity, which is measured by the average daily TED spread during quarter t. The sample period is 1986Q1-2021Q4 due to the limitation of TED spread data. Other variables follow the definition of Table 5. The regression sample period is from 1982Q1 to 2021Q4. In column (2), we re-run the regressions of columns (1) in the sample period of 1990Q1-2021Q4. In column (3), we additionally control for mutual fund ownership on the stock market (MF Ownership) at the end of quarter t. In column (4), we re-run the regressions of columns (1) in the sample period of 1990Q1-2021Q4. For ease of 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)
Aggregate Fragility	0.90***	0.95***	0.66***	0.76***
	(5.04)	(5.62)	(2.95)	(3.97)
TED Spread	0.61***	0.79***		
	(2.82)	(3.06)		
MF Ownership			−0.14	−0.15
			(−1.12)	(−1.02)
Avg Covariance	−0.14	−0.21	−0.16	−0.19
	(−0.64)	(−0.90)	(−0.66)	(−0.71)
BW Sentiment	0.04	0.02	0.21	0.20
	(0.13)	(0.06)	(0.83)	(0.48)
Avg Value Spread	0.15	0.19	0.20	0.11
	(0.53)	(0.63)	(0.65)	(0.31)
Avg Factor Ret	0.14	0.14	0.17	0.18
	(0.85)	(0.83)	(0.93)	(0.98)
Mkt Volatility	−0.45***	−0.48***	−0.22*	−0.21
	(−3.67)	(−2.93)	(−1.82)	(−1.30)
No. Obs.	143	127	160	127
Adj. R^2	0.273	0.289	0.207	0.205

Table C.5: **OOS tests of aggregate fragility with different evaluation periods**

This table reports the OOS performance of aggregate fragility in predicting one-quarter-ahead average factor premia. We report the OOS performance with three different evaluation periods. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

OOS Period	R^2_{OOS} (%)	ΔRMSE (%)	MSE_F
1987Q1-2021Q4	6.84***	7.20	11.67
1997Q1-2021Q4	7.98***	9.56	13.78
2000Q1-2021Q4	8.56***	10.71	14.88

Table C.6: **Placebo tests: predicting other returns**

This table reports the predictive regressions of one-quarter-ahead quarterly S&P500 excess return (SPR), long-term government bond returns (LTR), and long-term corporate bond returns (CORPR). Definitions of the dependent variables follow Welch and Goyal (2008). *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

DepVar:	(1) SPR	(2) LTR	(3) CORPR
Aggregate Fragility	−0.48	−0.52	−0.44
	(−0.52)	(−1.34)	(−1.22)
Avg Covariance	−0.85	−0.52	−0.08
	(−0.76)	(−1.15)	(−0.13)
BW Sentiment	1.19	−0.30	−0.14
	(1.19)	(−0.51)	(−0.29)
Avg Value Spread	−1.05	1.15*	0.83*
	(-1.06)	(1.91)	(1.74)
Avg Factor Ret	−1.66**	0.89*	0.44
	(−2.17)	(1.84)	(0.93)
Mkt Volatility	1.26	−0.60*	−0.25
	(1.24)	(−1.87)	(−0.42)
No. Obs.	160	160	160
Adj. R^2	0.09	0.06	0.03

Table C.7: **Aggregate fragility and future average factor premia: price-based versus fundamentals-based factors**

This table reports the predictive regressions of average factor premia on aggregate fragility within subsets of factors. The sample period is from 1982Q1 to 2021Q4. The regression specification follows Table 5, but average factor returns and aggregate fragility are re-constructed only using price-based or fundamentals-based factors. In columns (1)-(2), the dependent variable is the average factor returns across fundamentals-based factors in quarter $t+1$. The key independent variable, Aggregate Fragility, is fragility of an equal-weighted combination of fundamentals-based factors at quarter t end. In column (3)-(4), the dependent variable is the average factor returns across price-based factors in quarter $t+1$. The key independent variable, Aggregate Fragility, is fragility of an equal-weighted combination of price-based factors at quarter t end. Control variables follow Table 5. t-statistics in parentheses are calculated 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)
	Fundamentals-based		Price-based	
Aggregate Fragility	0.64***	0.41*	0.90***	0.66***
	(2.94)	(1.73)	(5.64)	(3.01)
Avg Covariance		−0.02		−0.28
		(−0.08)		(−0.76)
BW Sentiment		0.40**		−0.04
		(2.14)		(−0.08)
Avg Value Spread		0.13		0.73
		(0.60)		(1.18)
Avg Factor Ret		0.09		0.41
		(0.56)		(1.12)
Mkt Volatility		−0.15		−0.55*
		(−1.46)		(−1.85)
No. Obs.	160	160	160	160
Adj. R^2	0.133	0.201	0.06	0.115

Table C.8: **Correlation betwen $G^{\pi_i,\bar{\pi}}$ and betas on the Fama-French five factors and the momentum factor**

This table reports the correlation between $G^{\pi_i,\bar{\pi}}$, which is the expected covariation of flow-induced trading between a factor π with the aggregate factor portfolio, and the factor's betas on the Fama-French five factors and the momentum factor. At each quarter-end, we estimate factor betas based on the 24-month rolling window, and we then compute Pearson correlations between these variables. This table reports the average correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $G^{\pi_i,\bar{\pi}}$	1.00						
(2) β_{MktRf}	−0.10	1.00					
(3) β_{SMB}	−0.01	0.23	1.00				
(4) β_{HML}	0.07	0.12	0.09	1.00			
(5) β_{CMA}	0.08	0.03	0.02	−0.26	1.00		
(6) β_{RMW}	0.06	0.03	−0.12	−0.01	0.02	1.00	
(7) β_{UMD}	−0.03	−0.07	−0.15	−0.06	−0.05	−0.03	1.00

Table C.9: **Relationship between factor return and $G^{\pi_i,\bar{\pi}}$: regression evidence**

This table examines the relationship between factor return and covariation with the aggregate noise trading ($G^{\pi_i,\bar{\pi}}$) through Fama-MacBeth regressions. The dependent variable is the return (in percent) of a factor in quarter $t+1$. The key independent variable, $G^{\pi_i,\bar{\pi}}$, is the co-fragility between a factor and the aggregate factor portfolio in quarter t (see Table 10). Rank of $G^{\pi_i,\bar{\pi}}$ is the quintile ranking of $G^{\pi_i,\bar{\pi}}$ in quarter t. Dummy_Rank5 is a dummy that equals one for factors in the highest $G^{\pi_i,\bar{\pi}}$ quintile and zero otherwise. The control variable $\overline{\text{Covariance}}$ is the daily return covariance between a given factor and the equal-weighted portfolio of the factors. Other controls include factor returns in quarter t, the value spread of a given factor at the end of quarter t, and the average FITOF over the past eight quarters. For ease of interpretation, all the control variables are standardized to have unit variance. 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)
$G^{\pi_i,\bar{\pi}}$	0.53**	0.46**		
	(2.07)	(2.11)		
Rank of $G^{\pi_i,\bar{\pi}}$			0.38**	0.29**
			(2.13)	(2.16)
$\overline{\text{Covariance}}$		0.22		0.27
		(0.97)		(1.16)
Past one-quarter return		0.34*		0.34**
		(1.97)		(1.99)
Value Spread		0.07		0.04
		(0.35)		(0.19)
Past eight-quarter FITOF		−0.21*		−0.29**
		(−1.75)		(−2.48)
Adj. R^2	0.17	0.49	0.17	0.48

Table C.10: **Effects of publication and noise trader risk on factor returns**

This table shows the effects of publication and noise trader risk on factor returns through panel regressions. The regression sample consists of factor-by-month level observations from 1982 to 2021. The dependent variable is factor return (in percent). Rank of $G^{\pi_i,\bar{\pi}}$ is the quintile ranking of $G^{\pi_i,\bar{\pi}}$, which is co-fragility between a given factor and aggregate factor portfolio (see Table 10). Dummy_Post_Pub is a dummy variable indicating whether the first academic paper on a factor has been published in the month. We also include the interaction term between Rank of $G^{\pi_i,\bar{\pi}}$ and Dummy_Post_Pub in column (3). Factor fixed effects are included. t-statistics in parentheses are calculated based on standard errors double clustered by factor and time. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

DepVar: Ret(%)	(1)	(2)	(3)	(4)
Rank of $G^{\pi_i,\bar{\pi}}$	0.13***		0.13***	0.16***
	(2.71)		(2.71)	(2.69)
Dummy_Post_Pub		−0.23***	−0.23***	−0.05
		(−2.95)	(−2.97)	(−0.24)
Rank of $G^{\pi_i,\bar{\pi}}$ × Dummy_Post_Pub				−0.06
				(−0.90)
Factor FE	Y	Y	Y	Y
No. Obs.	34,080	34,080	34,080	34,080
Adj. R^2	0.002	0.001	0.003	0.003

Table C.11: **Noise trading beta and factor returns: an instrumental variable regression**

We utilize the Morningstar rating reform event in June 2002 (see Appendix Section B.2) as exogenous shocks to factor-level noise trading beta and investigate the impact of exogenous variation in noise trading beta on factor premia. To this end, we perform a two-stage least square regression. To begin with, for each factor, we compute the pre-event to post-event difference in noise trading beta ($\Delta G^{\pi_i,\bar{\pi}}$) and the difference in quarterly factor premium ($\Delta Premium$), where the pre-event window is 2000.Q2-2002.Q1 and the post-event window is 2002.Q3-2004.Q2. We also calculate each factor's exposure to the MS event ($Exposure$) following Ben-David et al. (2023). In the first-stage regression, we regress $\Delta G^{\pi_i,\bar{\pi}}$ on $Exposure$ and obtain the fitted value of the dependent ($\widehat{\Delta G^{\pi_i,\bar{\pi}}}$). In the second stage, we regress $\Delta Premium$ on $\widehat{\Delta G^{\pi_i,\bar{\pi}}}$ from the first-stage regression. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

First-stage		*Second-stage*	
DepVar:	$\Delta G^{\pi_i,\bar{\pi}}$ (in 10^{-5})		$\Delta Premium$
Exposure	-0.090^{*}	$\widehat{\Delta G^{\pi_i,\bar{\pi}}}$ (in 10^{-5})	0.651^{*}
	(-1.90)		(1.85)
Intercept	-0.005	Intercept	0.002
	(-0.45)		(0.19)
No. Obs.	71		71
Adj. R^2	0.036		0.034

D List of Factors

Table D.1 lists the 71 factors studied in our paper and reports their average monthly raw returns, CAPM alphas, and Fama-French five-factor alphas during January 1980-December 2021. We compute the sorting variables for the 71 factors (anomalies) following Hou, Xue, and Zhang (2020), 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 the 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, and 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.

Figure D.1 plots the time series of average factor premia (defined as the average return across the factors in each quarter), where the shaded area indicates the NBER-defined recession period. One can observe large fluctuations of factor premia over time/business cycle. The average factor premia during the recession and non-recession periods are 1.14% and 0.74% per quarter, respectively. In addition, we examine the time trend of average factor premia and find that the average factor premia is 1.17% per quarter in the first half sample period (1982-2001), and it drops to 0.41% per quarter in the second half sample period (2002-2021).

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

Factor	Raw Ret	CAPM	FF5	Factor	Raw Ret	CAPM	FF5
52-week high	0.56	1.07	0.62	Intermediate momentum	0.36	0.34	0.43
Abnormal capital investment	0.21	0.15	0.23	Investment growth	0.17	0.27	−0.02
Accruals	0.21	0.32	0.07	Investment-to-assets	0.03	0.01	−0.19
Advertising expense	0.28	0.33	−0.03	Investment-to-capital	−0.02	0.28	−0.29
Altman’s Z-score	0.14	−0.01	0.23	Long-term reversals	0.07	0.07	−0.05
Amihud illiquidity	0.07	0.01	0.07	M/B and accruals	0.13	0.22	−0.14
Analyst earnings forecast Revision	0.33	0.41	0.31	Maximum daily return	0.31	0.94	0.14
Asset Growth	0.19	0.33	-0.16	Momentum	0.27	0.38	0.35
Book-to-june-end-market	0.12	0.17	−0.06	Net operating assets	0.37	0.36	0.37
Book-to-market	0.09	0.16	-0.07	Net payout yield	0.29	0.60	0.02
Capital turnover	0.25	0.21	0.20	Number of earnings increase	0.22	0.25	0.26
Cash-based profitability	0.30	0.41	0.47	Ohlson’s O-score	0.27	0.45	0.37
Cashflow-to-price	0.17	0.35	−0.08	One-year share issuance	0.36	0.55	0.05
Change in asset turnover	0.15	0.17	0.01	Operating cash flow-to-price	0.24	0.37	−0.05
Change in long-term NOA	0.20	0.26	−0.02	Operating leverage	0.37	0.45	0.22
Customer momentum	0.38	0.49	0.43	Operating profitability	0.45	0.69	0.22
Debt issuance	0.21	0.14	0.35	Organizational capital-to-book	0.28	0.43	0.17
Discretionary accruals	0.23	0.17	0.36	Percent accruals	0.23	0.28	0.06
Distress risk	0.66	0.95	0.69	Piotroski’s F-score	0.05	0.08	0.00
Earnings forecast to Price	0.27	0.46	0.00	Profit margin	−0.03	0.19	−0.06
Earnings predicatbility	0.55	0.71	0.60	QMJ profitability	0.47	0.56	0.34
Earnings timeliness	0.08	−0.06	0.02	R&D expense	0.48	0.32	0.46
Earnings-to-price	0.28	0.54	0.09	Real estate ratio	0.28	0.22	0.39
Enterprise multiple	0.17	0.14	0.32	Residual momentum	0.49	0.58	0.40
Firm age	−0.01	−0.32	0.27	Return on assets	0.41	0.65	0.26
Five-year share issuance	0.41	0.53	0.19	Return on equity	0.41	0.62	0.20
Frazzini-Pedersen beta	0.19	0.86	0.39	Sales growth	−0.04	−0.25	0.21
Geographic momentum	0.21	0.25	0.18	Sales-minus-inventory growth	0.21	0.20	0.14
Gross profitability	0.27	0.34	0.29	Sales-to-price	0.28	0.24	−0.17
Growth in Inventory	0.35	0.45	0.21	Segment momentum	0.23	0.27	0.26
Growth score	0.18	0.34	0.28	Short-term reversal	0.22	0.02	0.09
Idiosyncratic volatility	0.42	0.93	0.31	Size	0.00	−0.11	−0.02
Industry adjusted CAPX growth	0.17	0.26	0.02	Sustainable growth	0.27	0.41	0.05
Industry concentration	0.31	0.22	0.58	Tax expense change	0.22	0.16	0.20
Industry lead-lag	0.37	0.47	0.31	Total external financing	0.23	0.51	0.03
Industry momentum	0.41	0.51	0.33	Average	0.25	0.34	0.18

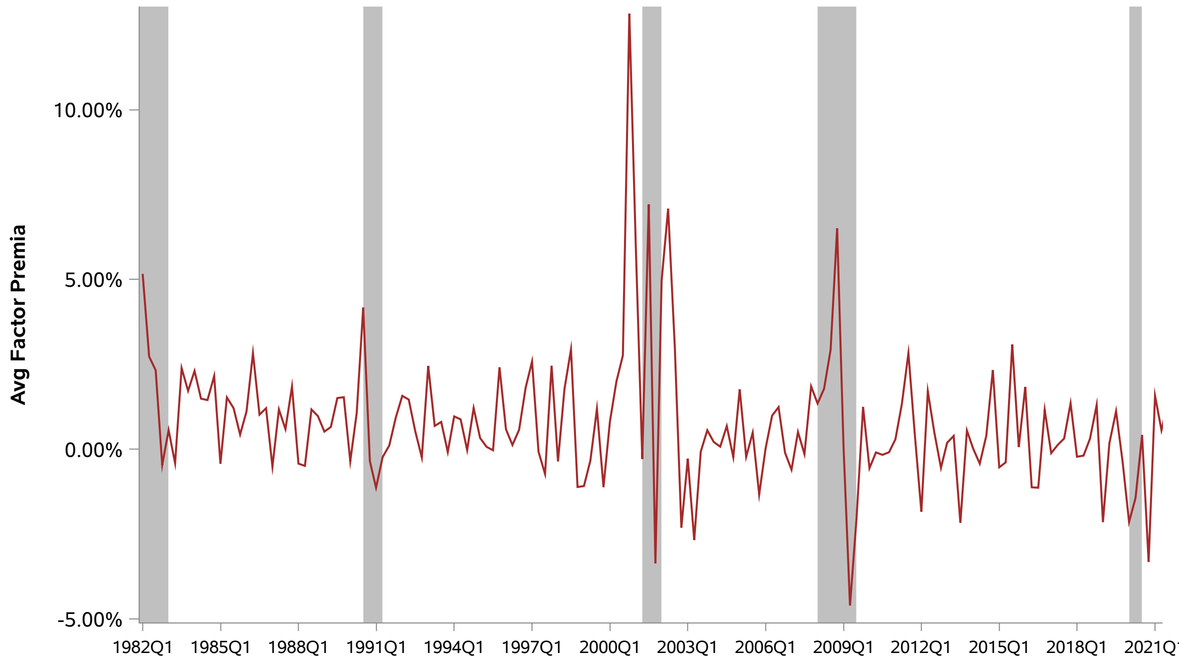

Figure D.1: **Average factor premia.** This figure plots times-series of average factor premia from 1982Q1 to 2021Q4. Average factor premia is defined as the average return across the 71 sample factors in each quarter. Shaded area indicates the NBER-defined recession period.