Fragile Factor Premia *

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(Very Preliminary, Comments are very welcome)

Abstract

We demonstrate that returns and volatilities of the Fama-French size and value factors are significantly determined by non-fundamental flow-induced trading from actively managed equity mutual funds. Mutual fund flows are largely ignorant about systematic risks. These non-fundamental shifts in demand induce large return heterogeneity within and across the Fama-French size and book-to-market portfolios. We show that aggregate mutual fund flow-induced trades across the size and book-to-market spectrum significantly influence the size and value premia, followed by large subsequent reversals. We also find that the expected volatilities of mutual funds' flow-induced trades strongly predict future factor volatilities. Our results highlight the importance of non-fundamental demand shocks in determining factor premia and factor volatilities.

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1 Introduction

Mutual fund trading has a considerable price impact on individual stocks (Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012). However, some more recent work suggests that mutual fund investors are largely ignorant about systematic risks, when allocating capitals among mutual funds (Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016; Ben-David, Li, Rossi, and Song, 2018). Empirically, it remains unclear how trades induced by the non-fundamental mutual fund flows impact returns and volatilities of size and value, the two prominent factors (Fama and French (1993)). This paper aims to fill this gap.

Over the sample period from 1980 to 2017, we show that the *non-fundamental* mutual fund flow-induced trades induce large heterogeneity in stock returns within and across the six Fama-French (FF) size and book-to-market portfolios.[1] We also find that aggregate flow-driven demand shifts across the size spectrum and across the book-to-market ratio spectrum significantly affect returns of the size and value factors, respectively. For example, a one-standard-deviation change of the aggregate factor-level flow-induced trades is associated with a 6.61% change in the SMB return and with a 6.48% change in the HML return per year, respectively. Moreover, we find that the expected volatilities of mutual funds' flow-driven trades strongly predict future volatilities of the FF size and value factors, as measured by standard deviations of daily factor returns. Our results highlight the importance of the non-fundamental demand shifts from mutual fund investors in determining the size and value premia.

A large fraction of the US equities market is held by actively-managed equity mutual funds.[2] Despite the important role of mutual funds in the equities market, recent research finds that mutual fund investors are largely ignorant about systematic risks when allocating capitals among

[1]The six FF portfolios are the intersections of the two portfolios formed on size and the three portfolios formed on the book-to-market ratio (Fama and French, 1992), and are used to construct the size and value factors.

[2]Based on our calculation, the fraction of the US equities held by actively-managed equity mutual funds increased from about 5% in the 1980s to 20% by the end of 2017.

active mutual funds. For example, Ben-David, Li, Rossi, and Song (2018) show that mutual fund investors don't account for funds' exposures to systematic risks.[3] This is likely due to that the majority of mutual fund investors are unsophisticated retails in the US (Investment Company Institute, 2017). Building on this observation, we investigate how the non-fundamental flow-induced trades of mutual funds influence returns of the Fama-French size and book-to-market portfolios and, further, premia and volatilities of the Fama-French size and value factors.[4]

In our study, we use a bottom-up approach and estimate mutual fund flow-induced trading (FIT) for each stock-quarter from 1980 to 2017 following Lou (2012). In a nutshell, FIT measures the magnitude of flow-driven trading by the aggregate equity mutual fund industry on a particular stock in a given quarter. 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 ignorant about fundamentals (Ben-David, Li, Rossi, and Song, 2018). Our final sample consists of 208,419 fund-quarter observations with 4,999 unique domestic active equity mutual funds in the US.

Our main findings are as follows. First, we find that returns of the six FF size and book-to-market portfolios are largely determined by the uninformed mutual fund flow-induced trades. Within each of the six FF portfolios, stocks with higher FIT have higher return performance. For example, stocks with a top-quartile FIT, on average, outperform the bottom-quartile-FIT stocks in the same portfolio by about 1% per month, although they have similar firm size and book-to-market ratio. This finding is consistent with Lou (2012) that FIT causes positive contemporaneous stock returns. Take the FF big-growth portfolio, the one with the lowest average returns, as an example. The top-quartile-FIT stocks in this portfolio actually have a

[3]Song (2018) shows that this investor behavior leads to a significant mismatch between scale and skill among actively managed equity mutual funds.

[4]Responding to flows in and out of mutual funds, mutual fund managers, to a large extent, scale up or liquidate existing positions mechanically. For example, Lou (2012) estimates that mutual fund managers sell their holdings dollar-for-dollar to meet redemptions, and invest around eighty cents for every dollar of inflow in their existing positions.

significantly positive CAPM alpha of 0.71% per month ($t = 3.99$), while the bottom-quartile-FIT stocks in this same portfolio, on average, have a significant negative CAPM alpha of -0.44% per month ($t = -3.26$). The difference in CAPM alpha between the high and low FIT groups within this big-growth portfolio is 13.8% on an annual basis ($t = 5.21$).

More interestingly, across the FF size and book-to-market portfolios, we find that growth stocks with a positive FIT significantly outperform value stocks with a negative FIT, controlling for firm size. Controlling for book-to-market ratio, large-cap stocks with a positive FIT significantly outperform the negative-FIT small-cap stocks.[5] This implies that the well-known size (SMB) premium is due to the component of small-cap-inflow stocks minus large-cap-outflow stocks, while the value (HML) premium is due to the component of value-inflow stocks minus growth-outflow stocks. The other components of the size and value factors actually have significantly negative average premia. Besides, we find that this flow-induced heterogeneity in performance is more pronounced in the more recent sample period, consistent with the rise in the size of mutual fund industry over time.

Having shown that the uninformed flow-driven trades generate large return heterogeneity of stocks within and across the FF portfolios, we proceed to study how aggregate flow movements influence time-variation of the size and value returns. Intuitively, the SMB (HML) returns should be high in the periods when there are more flow-driven trades into small-cap (value) stocks relative to large-cap (growth) stocks, and vice versa.

Indeed, we find that the aggregate flow-driven demand shifts across the small-cap and large-cap portfolios and demand shifts across the value and growth portfolios are statistically and economically significant drivers of the size and value returns, respectively. For example, in the univariate time-series regression of quarterly frequency, the difference of flow-induced trades into

[5] In Appendix B, we also extend our analysis to another 11 asset pricing anomalies studied in Stambaugh, Yu, and Yuan (2012). We find similar patterns as in the case of size and value factors. For example, we observe that stocks in the short-leg of each anomaly with positive FIT significantly outperform stocks in the corresponding long-leg with negative FIT.

small-cap stocks and flow-induced trades of large-cap stocks explains 13% of the variation in quarterly SMB returns. The economic magnitude is also significant: a one-standard-deviation change of the aggregate FIT across the size spectrum is positively associated with a 1.65% change in quarterly SMB returns (6.61% on an annual basis). The results are similar after controlling for past factor returns and the standard predictors of stock market returns in Welch and Goyal (2007), for example, market volatility and dividend- and earnings-price ratios.

To further verify that mutual fund flow-induced trades are non-fundamental, we show that the flow-induced effects on factor returns significantly revert over longer horizons. To examine the long-term reversals, we extend the estimation window and regress factor returns in a given year on the average factor-level FIT over the prior four years or five years. We find that, for example, a one-standard-deviation increase in the difference of flow-induced trades into value stocks and flow-induced trades into growth stocks over the prior five years, on average, predicts a 4.19% decrease in the HML returns over the next year.

Greenwood and Thesmar (2011) (GT) argue that if investor demand unrelated to fundamental does influence asset prices, expected volatility of these non-fundamental demand shifts should be useful for forecasting future asset volatility. In our third exercise, we link volatility of mutual funds' flow-driven demand and factor return volatility. To this end, we derive the so-called fragility measures for the size and value factors, respectively, following the approach in GT.[6] Similar to the stock-level fragility in GT, our factor-level fragility measures expected variance of the non-fundamental flow-driven trades of the size and value factors. As expected, we find that expected volatilities of mutual funds' flow-driven trades strongly predict volatilities of the Fama-French size and value factors, even after controlling for the CBOE VXO index and the past factor volatilities. For example, in the univariate regressions, a one-standard-deviation

[6]The fragility depends on ownership concentration and the volatilities and correlations of mutual funds' expected flow-driven trades. See Section 5 for details.

increase in the square root of size (value) fragility predicts an increase of 35% (44%) of a standard deviation in future volatility of the size (value) factor, calculated based on daily factor returns over the next quarter.

This paper contributes to the literature in several aspects. A vast empirical literature shows that investor demand is unrelated to fundamentals and can impact asset prices. Shleifer (1986) and Harris and Gurel (1986) show that stock prices rise when stocks are added to an index. More recent work includes Mitchell, Pedersen, and Pulvino (2007), Gârleanu, Pedersen, and Poteshman (2009), Barber, Odean, and Zhu (2009), Greenwood and Vayanos (2010), and Foucault, Sraer, and Thesmar (2011), among several others. Coval and Stafford (2007), Frazzini and Lamont (2008), Lou (2012), and Greenwood, Hanson, and Liao (2018) show that mutual fund flow-induced demand shocks have considerable price impacts on individual stock prices. We complement this literature by empirically showing that uninformed mutual fund flow-driven demand induces large return heterogeneity within and across the Fama-French portfolios and significantly influences returns and volatilities of the size and value factors.

This paper also fits into the literature that tries to understand the positive average premia of the size and value factors. Examples in the literature include Lakonishok, Shleifer, and Vishny (1994), Fama and French (1995), Berk, Green, and Naik (1999), Gompers and Metrick (2001), Gomes, Kogan, and Zhang (2003), Schwert (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Asness, Ilmanen, Israel, and Moskowitz (2015), and McQuade (2018), among many others.[7] We provide a new perspective by highlighting the importance of non-fundamental demand shocks from mutual fund investors on factor premia.

Our paper is also related to Li (2018). Li (2018) sorts mutual funds into portfolios based on the estimated fund loadings to the size and value factors over the previous one year, and

[7]See Asness, Ilmanen, Israel, and Moskowitz (2015) and McQuade (2018) for a more comprehensive review of the literature on the size and value premia.

shows that flow movements across the mutual fund portfolios over the subsequent year covary with returns of the size and value factors.[8] The author attributes fund flow movements to the changes in investor preferences and beliefs about the investment prospects of stock styles.

Our motivation, approach, and results are distinct from those of Li (2018). We are motivated by the recent findings that mutual fund investors don't account for systematic factors when allocating capital among mutual funds. We use a bottom-up approach and measure mutual fund flow-induced trading for each individual stock. We show that non-fundamental flow-induced trades cause large heterogeneity in returns of stocks within and across the FF size and book-to-market portfolios. We also show that aggregate flow-induced demand shifts across size and book-to-market spectrum significantly explain the time-series variation in factor returns. Moreover, our bottom-up approach has advantages in estimating the expected volatilities of mutual funds' flow-driven trades, which are further linked to volatilities of the size and value factors.

The rest of the paper is organized as follows. Section 2 introduces the dataset and the measure of flow-induced trading. Section 3 analyzes how trades induced by the uninformative fund flows influence stock returns within and across the Fama-French size and book-to-market portfolios. Section 4 studies time-series variation of aggregate flow-induced trades across the size and book-to-market spectrum and how these demand shifts affect the time-variation of factor returns. Section 5 links factor volatility and volatility of mutual funds' flow-driven trades of factors. Section 6 provides a concluding remark. Robustness checks and supplementary results are in the appendices.

2 Data and Mutual Fund Flow-induced Trading

In this section, we describe our dataset and the methodology on how we estimate mutual fund flow-induced trading (FIT).

[8] Estimating fund loadings to factors using monthly returns over a short period renders non-trivial noises.

2.1 Data

Our study combines several data sources. First, we obtain the stock data from CRSP and COMPUSTAT to form the six Fama-French portfolios. As in the literature, we define book equity as the book value of stockholders' equity, plus deferred taxes and investment tax credit (zero for missing value), minus the book value of preferred stock. Depending on data availability, we use redemption, liquidation, par value, or zero in that order as the book value of preferred stock. After that, we compute book-to-market ratio as the ratio of book-equity to market value of equity.

Second, we merge the Thomson Reuters CDA/Spectrum database with the CRSP Survivorship-bias-free mutual fund database to construct the mutual fund flow-induced trading (FIT) for each individual stock. Mutual funds' holding data is from the CDA/Spectrum database. Mutual funds' total net assets (TNA), net monthly returns, expense ratios, and other fund characteristics are obtained from the CRSP database. We compute monthly gross returns as monthly net returns plus 1/12 of the annual expense ratio. For funds with multiple share classes, we derive fund TNA as the sum of share-class TNA, and we compute fund gross returns as TNA-weighted average gross returns across share classes.

We focus on US domestic actively-managed equity mutual funds. Specifically, we exclude non-equity funds based on investment objectives reported in Thomson and Reuters CDA/Spectrum database and CRSP mutual fund database.[9] In addition, for the investment objective filter, we

[9]We follow Kacperczyk, Sialm, and Zheng (2008) and Lou (2012) to screen funds in the following steps. First, we screen funds by investment objectives reported by CDA/Spectrum database. We exclude funds with Investment Objective Codes in 1, 5, 6, or 7 in the CDA/Spectrum database. Then, we screen funds by investment objectives reported by CRSP mutual funds database. For funds with non-missing "Type of Securities Mainly Held by Fund" variable (policy variable), we remove those with policy in C&I, Bal, Bonds, Pfd, B&P, GS, MM, or TFM. We then require remaining funds to have Lipper Classification Code in EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, or Missing. For funds with missing Lipper Classification Code, we require them to have Strategic Objective Insight Code in AGG, GMC, GRI, GRO, ING, SCG, or missing. If a fund has both missing Lipper Classification Code and Strategic Objective Insight Code, we screen them through Wiesenberger Fund Type Code and retain funds with objective codes in G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, SCG, or Missing.

require the ratio of common stock holdings to TNA to be between 80% and 105% on average during our sample period. We further exclude fund-quarter observations with less than \$1 million TNA.

Our final sample includes 4,999 distinct funds and 208,419 fund-quarter observations from 1980 to the end of 2017. Table 1 reports the summary statistics of our domestic equity fund sample in the sub-periods from 1980 to 2017. Table 1 shows that the number of mutual funds in our sample increases from 370 in the early 1980s to 2216 in the period of 2014-2017. Meanwhile, the fraction of the US equities market held by mutual funds in our sample steadily increases from 2.62% to 20.07% during 1980-2017.

Table 1: **Summary Statistics.** This table reports summary statistics of the US equity mutual funds in our sample from 1980 to 2017. No.Funds is the number of distinct mutual funds in each period. TNA is the average fund total net assets (in million \$). Total Equity Holdings (in million \$) is the total market capitalization of the common stock holdings of an average fund. % Market Held is the average percentage of the US common stocks held by the mutual funds in our sample.

Period	No.Funds	TNA		Total Equity Holdings		% Market Held
		Median	Mean	Median	Mean	
1980-1984	370	64.43	159.62	39.00	111.31	2.62
1985-1989	610	79.18	264.52	57.13	198.09	4.33
1990-1994	1,453	71.81	299.02	47.60	215.16	7.51
1995-1999	2,699	110.79	698.13	69.79	537.19	13.19
2000-2004	3,461	120.31	837.97	71.42	655.13	15.35
2005-2009	3,636	172.73	1,097.92	104.06	799.67	18.52
2010-2014	2,875	297.49	1,664.22	157.97	1,172.03	18.61
2014-2017	2,216	479.88	2,757.40	287.47	2,210.29	20.07

2.2 Construction of flow-induced trading

We take two steps to calculate the stock-level flow-induced trading (FIT). First, we calculate quarterly fund flows for each mutual fund following Sirri and Tufano (1998). Specifically, we define fund flow as the percentage change of total net assets after adjusting for appreciation of fund holdings:

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

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

Second, we gauge quarterly aggregate mutual fund trading on each individual stock in response to fund flows. We calculate the flow-induced-trading measure following Lou (2012):

$$\text{FIT}_{j,t} = \frac{\sum_i \text{Share}_{i,j,t-1} \times \text{Flow}_{i,t} \times \text{PSF}}{\sum_i \text{Share}_{i,j,t-1}}, \tag{1}$$

where $\text{Share}_{i,t-1}$ is the number of shares of stocks j held by fund i at the end of quarter $t-1$, $\text{Flow}_{i,t}$ is the percentage flow of fund i in quarter t, and PSF is the partial scaling factor. In particular, the scaling factor reflects how fund managers, on average, increase/liquid their holdings dollar-for-dollar in response to capital inflows/outflows. Lou (2012) estimates that the average PSF is 0.970 for outflows and is 0.858 for inflows, and we use the estimations of Lou (2012) in our empirical analysis. As robustness checks in Appendix A, we consider some alternative scaling factors.[10]

In a nutshell, FIT captures the magnitude of flow-induced trading by the aggregate equity mutual fund industry on a particular stock in a given quarter. We use the FIT measure rather than the entire realized trading of mutual funds because FIT only captures those trades that are driven by the uninformed demand from retail mutual fund investors, which are largely unrelated to fundamentals (Ben-David, Li, Rossi, and Song, 2018).

Figure 1 shows the market-cap-weighted FIT of all stocks and the fraction of stocks with positive FIT each quarter from 1980 to 2017. The average FIT ranges between -0.04 and 0.15, suggesting that, on average, mutual funds adjust their stock holdings relative to their exiting

[10]In Appendix Table A.1, we show that the scaling factors estimated in our sample are comparable to those of Lou (2012).

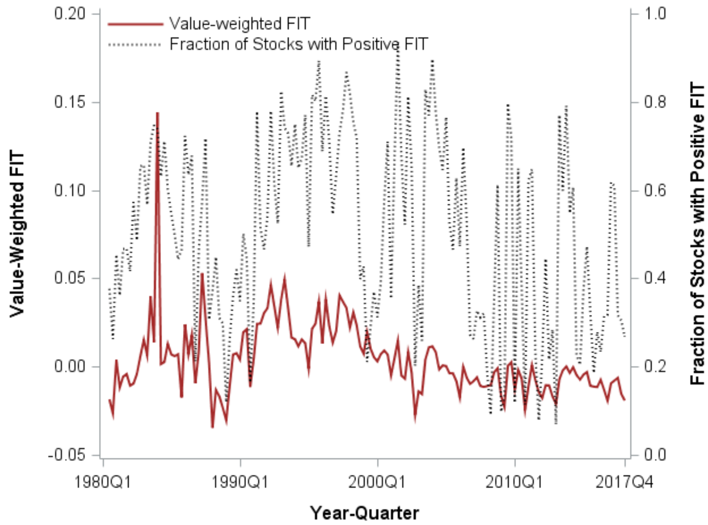

Figure 1: Mutual fund flow-induced trading from 1980 to 2017 (Quarterly).

holdings at a scale of between -4% and 15% in a given quarter.

3 Flow-Induced Trading and the Fama-French Portfolios

In this section, we study how trading induced by the uninformed mutual fund flows affects stock returns within and across the six Fama-French size and book-to-market portfolios. We find that (i) within each of the six FF portfolios, stocks with higher FIT have higher returns despite similar firm size and book-to-market ratio, and (ii) across the FF portfolios, growth (large-cap) stocks with above-median FIT outperform value (small-cap) stocks with below-median FIT. We further decompose the Fama-French SMB and HML factors based on the directions of flow-induced trading. We show that the positive size premium is due to the component of small-inflow stocks minus big-outflow stocks, while the positive value premium is due to the component of value-inflow stocks minus growth-outflow stocks.

3.1 Return Heterogeneity within and across the FF Portfolios

We first examine the extent to which the uninformed trading driven by mutual fund investors' demand can generate cross-sectional return variation within each of the FF size and book-to-market portfolios.

To this end, we form the six FF portfolios based on size and book-to-market ratio following Fama and French (1992). That is, at the end of June each year, we sort NYSE, AMEX, and NASDAQ stocks into two groups (small (S) and big (B)) based on the NYSE median size at the June-end. We also divide stocks into three groups (growth (G), neutral (N), and value (V)) based on the NYSE 30% and 70% book-to-market breakpoints.[11] The six FF size and book-to-market portfolios are the intersections of the two size portfolios and the three book-to-market portfolios.

We then sort all NYSE, AMEX, and NASDAQ stocks into quartiles based on the FIT at the end of each quarter. We take intersections of the six FF portfolios and the quartile portfolios sorted on FIT, which generate 24 portfolios ($2 \times 3 \times 4$) formed on size, book-to-market (BM), and FIT. We then calculate the monthly value-weighted returns for each portfolio in the formation quarter.[12] Table 2 shows the detailed firm characteristics for these 24 size-BM-FIT portfolios.

Table 2 shows that there are no association between FIT and firm size or book-to-market ratio. For example, among the small-value stocks, the average market capitalization (Panel A) for stocks in the top-FIT quartile is comparable to that in the bottom-FIT quartile ($178 million versus $187 million). The average book-to-market ratio (Panel B) for these top-quartile-FIT stocks is also comparable to that of the bottom-FIT-quartile stocks in the same portfolio (1.54 versus 1.57).

Panel D shows that there is large heterogeneity in FIT within each FF portfolio. For example, there are, on average, 207 firms in the small-value portfolio that have bottom-quartile FIT, and 224 firms that have top-quartile FIT. The average difference in FIT between the two groups is 15% per quarter, suggesting that mutual funds, on average, increase holdings of the top-quartile

[11] The book-to-market ratio in year t is calculated as book equity for the fiscal year ending in the calendar year $t-1$ divided by the market value of equity at the end of the calendar year $t-1$.

[12] In the Appendix, we also look at the equal-weighted portfolios and we get similar results.

Table 2: **Descriptive statistics for portfolios formed on size, book-to-market ratio, and flow-induced trading, 1980-2017.** This table reports characteristics of portfolios formed on size, book-to-market, and FIT. The portfolios are formed as follows. We first follow Fama and French (1992) to form the six portfolios based on size and book-to-market. In each quarter, we also group stocks into quartiles based on FIT in the quarter. We take intersections of the six Fama-French portfolios and the quartile portfolios sorted on FIT, which generates the 24 portfolios formed on size, book-to-market, and FIT. In addition, we show the characteristics of stocks with missing FIT in each Fama-French portfolio. Panel A, Panel B, Panel C, and Panel D report average market capitalization, book-to-market ratio, FIT, and the number of firms of each portfolio as of portfolio formation. The descriptive statistics are computed when the portfolios are formed during 1980 Q2-2017 Q4, then averaged across the 151 quarters.

Panel A: Average Market Capitalization ($ million)

	Growth					Neutral					Value				
FIT	1 (low FIT)	2	3	4	FIT NA	1	2	3	4	FIT NA	1	2	3	4	FIT NA
Small	353.87	450.16	414.93	281.18	73.33	295.41	392.01	384.71	277.82	88.78	187.23	262.14	248.66	178.49	48.93
Big	10295.07	11111.53	9449.37	5985.01	4147.12	7705.89	9143.05	7579.86	4583.30	4202.68	8095.77	7910.88	6498.50	4064.33	6625.54

Panel B: Average Book-to-Market

	Growth					Neutral					Value				
FIT	1 (low FIT)	2	3	4	FIT NA	1	2	3	4	FIT NA	1	2	3	4	FIT NA
Small	0.27	0.28	0.28	0.27	0.24	0.68	0.68	0.68	0.68	0.69	1.57	1.51	1.51	1.54	1.84
Big	0.28	0.29	0.28	0.28	0.28	0.66	0.66	0.67	0.67	0.72	1.26	1.26	1.25	1.26	1.36

Panel C: Average Flow-Induced Trading

	Growth					Neutral					Value				
FIT	1 (low FIT)	2	3	4	FIT NA	1	2	3	4	FIT NA	1	2	3	4	FIT NA
Small	−0.05	−0.01	0.02	0.09	-	−0.05	−0.01	0.02	0.10	-	−0.05	−0.01	0.02	0.10	-
Big	−0.03	−0.01	0.01	0.06	-	−0.03	−0.01	0.01	0.07	-	−0.04	−0.01	0.01	0.07	-

Panel D: Number of Firms

	Growth					Neutral					Value				
FIT	1 (low FIT)	2	3	4	FIT NA	1	2	3	4	FIT NA	1	2	3	4	FIT NA
Small	187	153	162	198	267	209	193	206	235	242	207	171	183	224	337
Big	91	121	105	57	4	65	101	89	47	3	31	47	41	28	3

stocks by 15% more than the bottom-quartile stocks in a given quarter. Among all stocks within the Fama-French portfolios, around 20% of the stocks are not reported to be held by the actively managed equity funds included in our data. As one can see, these stocks tend to be small-cap stocks (Panel D). Since our later analysis, including the portfolio construction, is based on a value-weighting scheme, these stocks have little influence on our analysis.[13]

We now examine the return performance of the 24 size-BM-FIT portfolios. Table 3 reports the average monthly excess returns and alphas of these portfolios from 1980 to 2017. As one can see, fund flow-induced trading indeed generates large return heterogeneity. First, within each of the six FF portfolios, excess returns and alphas are strictly increasing with the FIT. On average, stocks in the top-FIT quartile outperform those in the bottom-FIT quartile by 0.75% to 1.17% per month (Panel A). Once we adjust for the market return, the differences in CAPM alphas range from 0.82% to 1.16% per month (Panel B). The return heterogeneity cannot be explained by exposures to the momentum factor (Panel D).

Take the big-growth portfolio, the one with the lowest average returns, as an example. The value-weighted CAPM alpha of the big-growth stocks in the top-FIT quartile is positive (0.71% per month with $t = 3.99$). By contrast, the value-weighted CAPM alpha is -0.44% per month ($t = -3.26$) for the big-growth stocks in the bottom-FIT quartile. Their difference in CAPM alpha is 1.16% per month (14% per year), which is highly statistically significant ($t = 5.21$).

More strikingly, we find that mutual funds' flow-driven trades even revert the positive size and value premia (Fama and French (1993)). That is, within the same book-to-market portfolios, we find large-cap stocks with above-median FIT outperform small-cap stocks with below-median FIT. Within the same size portfolios, growth stocks with above-median FIT outperform value stocks with below-median FIT. For example, among value stocks, large-cap stocks in the top-FIT

[13] For example, the factors based on the sample with non-missing FIT are almost the same as the original factors from Kenneth French's data library.

Table 3: **Average monthly value-weighted returns of portfolios formed on size, book-to-market ratio, and flow-induced trading: 1980-2017.** This table reports monthly returns and alphas of portfolios formed on size, book-to-market, and FIT in the formation quarter. The portfolios are formed as follows. We first follow Fama and French (1992) to form the six portfolios based on size and book-to-market. In each quarter, we also group stocks into quartiles based on FIT in the quarter. We take intersections of the six Fama-French portfolios and the quartile portfolios sorted on FIT, which generates the 24 portfolios examined in this table. The portfolios are rebalanced every quarter and held in the formation quarter. The holding period is from April 1980 to December 2017. In Panel A, we report monthly value-weighted excess returns of the portfolios in the formation quarter. Panel B and Panel C report the monthly CAPM alpha and the Fama-French-Carhart four-factor alpha of the 24 portfolios in the formation quarter. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags.

	Growth					Neutral					Value				
	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1
Panel A: Excess Returns															
Small	0.14	0.54	0.69	1.16	1.02	0.52	0.76	1.13	1.46	0.94	0.55	0.89	1.10	1.62	1.07
	(0.45)	(1.94)	(2.45)	(3.94)	(5.86)	(1.95)	(3.07)	(4.85)	(5.97)	(5.60)	(2.00)	(3.21)	(4.27)	(6.50)	(7.40)
Big	0.32	0.52	0.91	1.48	1.17	0.27	0.56	0.99	1.29	0.99	0.35	0.54	0.86	1.09	0.75
	(1.31)	(2.28)	(3.78)	(5.62)	(5.41)	(1.04)	(2.34)	(4.19)	(5.84)	(5.85)	(1.13)	(2.28)	(3.35)	(4.60)	(3.39)
Panel B: CAPM Alpha															
Small	−0.78	−0.32	−0.16	0.29	1.06	−0.22	0.04	0.42	0.77	0.99	−0.15	0.19	0.42	0.97	1.12
	(−5.23)	(−2.45)	(−1.02)	(1.56)	(6.38)	(−1.39)	(0.26)	(2.60)	(3.78)	(6.05)	(-0.77)	(0.90)	(2.28)	(4.77)	(7.53)
Big	−0.44	−0.16	0.18	0.71	1.16	−0.38	−0.08	0.35	0.62	1.00	−0.30	−0.04	0.24	0.50	0.82
	(−3.26)	(−1.47)	(1.75)	(3.99)	(5.21)	(−2.34)	(−0.64)	(2.44)	(4.27)	(5.98)	(−1.28)	(−0.26)	(1.14)	(3.06)	(3.63)
Panel C: Fama-French-Carhart 4-Factor Alpha															
Small	−0.56	−0.24	−0.09	0.33	0.89	−0.24	−0.10	0.24	0.54	0.78	−0.40	−0.07	0.13	0.62	1.02
	(−6.49)	(−3.02)	(−1.01)	(3.38)	(5.94)	(−2.59)	(−1.70)	(3.81)	(6.61)	(5.97)	(−4.72)	(−0.96)	(1.82)	(7.00)	(7.07)
Big	−0.24	−0.07	0.28	0.79	1.02	−0.48	−0.18	0.21	0.49	0.98	−0.61	−0.31	−0.07	0.24	0.85
	(−1.59)	(−0.77)	(2.60)	(4.94)	(4.85)	(−3.21)	(−2.19)	(2.29)	(4.56)	(5.16)	(−3.84)	(−2.95)	(−0.62)	(1.61)	(3.81)

quartile earn an average CAPM alpha of 0.50% ($t = 3.06$) per month, while small stocks in the bottom-FIT quartile earn an average CAPM alpha of −0.15% per month, which is significantly lower than that of the large-cap stocks. In Appendix B, we also observe "reverted" premia for another 11 asset pricing anomalies in Stambaugh, Yu, and Yuan (2012).

We also conduct several robustness checks in Appendix A. For example, we show that the patterns are robust in both the first half (1980 to 1998) and the second half (1999 to 2017) of our sample period (Table A.2). Interestingly, we find that the return heterogeneity is even more pronounced in the second sub-sample, which coincides with the sharp rise in the size of the active mutual fund industry.[14]

3.2 Decomposition of SMB and HML

Section 3.1 demonstrates that uninformed flow-induced trades lead to large return heterogeneity within and across the FF size and book-to-market portfolios. This return heterogeneity motivates us to decompose SMB and HML based on the directions of FIT in their long legs relative to short legs.

Recall that the SMB and HML factors are defined as

$$\mathrm{SMB} = \frac{\mathrm{SV} + \mathrm{SN} + \mathrm{SG}}{3} - \frac{\mathrm{BV} + \mathrm{BN} + \mathrm{BG}}{3} \tag{2}$$

$$\mathrm{HML} = \frac{\mathrm{SV} + \mathrm{BV}}{2} - \frac{\mathrm{SG} + \mathrm{BG}}{2}, \tag{3}$$

where SV, SN, SG, BV, BN, and BG are the FF size and book-to-market portfolios. That is, the SMB and HML factors are essentially long-short strategies constructed by the FF portfolios.

For each quarter, we sort all stocks into two groups based on the sign of FIT in that quarter. The positive-FIT group and the negative-FIT group roughly correspond to the stocks with inflows and outflows, respectively. Then we take the intersections of the six FF portfolios and

[14] In the untabulated exercises, we also consider equal-weighted portfolio returns or exclude two recent financial crisis (2000-2001 and 2007-2008). We find similar patterns.

the two portfolios by signs of FIT.[15] For example, the small-value portfolio (SV) is divided into small-value-inflow, SVI, and small-value-outflow, SVO. That is, SV = SVI + SVO.

With this, we can then write HML as

$$\mathrm{HML} = \underbrace{\left[\frac{\mathrm{SVI}+\mathrm{BVI}}{2} - \frac{\mathrm{SGO}+\mathrm{BGO}}{2}\right]}_{\mathrm{HML_{Inflow}}} + \underbrace{\left[\frac{\mathrm{SVO}+\mathrm{BVO}}{2} - \frac{\mathrm{SGI}+\mathrm{BGI}}{2}\right]}_{\mathrm{HML_{Outflow}}}. \tag{4}$$

That is, we decompose the value minus growth returns (HML) into two components: (*i*) value-inflow minus growth-outflow returns ($\mathrm{HML_{Inflow}}$) and (*ii*) value-outflow minus growth-inflow ($\mathrm{HML_{Outflow}}$). Similarly, we can write SMB as

$$\begin{aligned}\mathrm{SMB} \quad &= \quad \underbrace{\left[\frac{\mathrm{SVI}+\mathrm{SNI}+\mathrm{SGI}}{3} - \frac{\mathrm{BVO}+\mathrm{BNO}+\mathrm{BGO}}{3}\right]}_{\mathrm{SMB_{Inflow}}} \\ &+ \quad \underbrace{\left[\frac{\mathrm{SVO}+\mathrm{SNO}+\mathrm{SGO}}{3} - \frac{\mathrm{BVI}+\mathrm{BNI}+\mathrm{BGI}}{3}\right]}_{\mathrm{SMB_{Outflow}}},\end{aligned} \tag{5}$$

where we decompose the small minus big returns (SMB) into the sum of (*i*) small-inflow minus big-outflow returns ($\mathrm{SMB_{Inflow}}$) and (*ii*) small-inflow minus big-outflow returns ($\mathrm{SMB_{Outflow}}$).

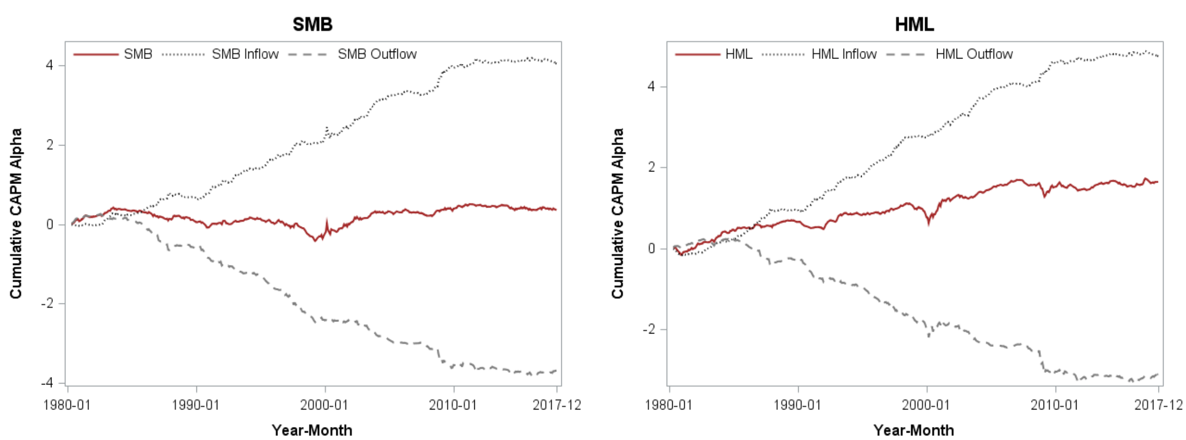

Figure 2: Cumulative CAPM alphas of the inflow-components and outflow-components of SMB and HML in (4) and (5): 1980-2017.

[15]Through taking the intersection, we remove stocks with missing FIT and lose 22% of stock-quarter observations in the six Fama-French portfolios. These stocks are mostly small-cap stocks (see Table 2). Since the whole analysis including the factor construction are based on the value-weighted scheme, these stocks have little influence on our analysis.

Table 4: **Performance of decomposed SMB and HML factors, 1980-2017.** This table reports performance of the inflow and outflow components of the HML and SMB factors in (4) and (5). In particular, SMB is decomposed into (*i*) small-cap-inflow minus big-cap-outflow returns ($\text{SMB}_{\text{Inflow}}$) and (*ii*) small-cap-outflow minus big-cap-inflow ($\text{SMB}_{\text{Outflow}}$). HML is decomposed into (*i*) value-inflow minus growth-outflow returns ($\text{HML}_{\text{Inflow}}$) and (*ii*) value-outflow minus growth-inflow ($\text{HML}_{\text{Outflow}}$). Raw returns and risk-adjusted returns are reported in Panel A to Panel C. Annualized Sharpe ratios are reported in Panel D. *t*-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Panel A: Monthly Returns (%)				
	Full	Inflow	Outflow	Diff
SMB	0.12	0.83***	−0.65***	1.49***
	(0.91)	(4.80)	(−3.78)	(4.63)
HML	0.28*	0.86***	−0.64***	1.50***
	(1.66)	(4.78)	(−3.37)	(4.54)
Panel B: Monthly CAPM Alpha (%)				
	Full	Inflow	Outflow	DIff
SMB	0.02	0.89***	−0.81***	1.71***
	(0.16)	(4.80)	(−4.66)	(5.09)
HML	0.42**	1.05***	−0.68***	1.73***
	(2.17)	(6.52)	(−2.96)	(4.92)
Panel C: Monthly FFC 4-factor Alpha (%)				
	Full	Inflow	Outflow	Diff
SMB	-	0.95***	−0.90***	1.86***
		(5.08)	(−4.83)	(4.96)
HML	-	0.93***	−0.97***	1.90***
		(4.75)	(−4.97)	(4.87)
Panel D: Annualized Sharpe Ratio				
	Full	Inflow	Outflow	Diff
SMB	0.14	0.93	−0.75	0.96
HML	0.33	1.05	−0.65	0.93

Figure 2 and Table 4 report the average monthly returns and alphas of SMB, HML, and their inflow and outflow components. In the sample period from 1980 to 2017, SMB earns an average monthly CAPM alpha of 0.02% ($t = 0.16$). The inflow-component, $\text{SMB}_{\text{Inflow}}$, and the outflow-component, $\text{SMB}_{\text{outflow}}$, generate average monthly CAPM alphas of 0.89% ($t = 4.80$) and −0.81% ($t = -4.66$), respectively. While HML has an average monthly CAPM alpha of 0.42%, the inflow-component, $\text{HML}_{\text{Inflow}}$, and the outflow-component, $\text{HML}_{\text{Outflow}}$, have average monthly CAPM alphas of 1.05% ($t = 6.52$) and −0.68% ($t = -2.96$), respectively. The momentum factor doesn't explain the return differences (Panel C).

In sum, we find that the size premium is due to the component of small-inflow stocks minus big-outflow stocks, while the value premium is due to the component of value-inflow stocks minus growth-outflow stocks. The other components of the size and value factors even have significant negative average premia. In the next section, we explore the effect of aggregate flow-induced trades on the time-variation of factor returns.

4 Aggregate Flow-Induced Trading and Factor Returns

In this section, we study to what extent the aggregate flow-induced demand shifts across the size and across the book-to-market spectrum affect factor returns. Intuitively, the SMB (HML) return should be high in the periods when there are more mutual fund flow-driven trades into small-cap (value) stocks relative to large-cap (growth) stocks, while the SMB (HML) return should be low or negative in the periods when there are more mutual fund flows into large-cap (growth) stocks relative to small-cap (value) stocks.

To this end, we first show that there are large aggregate flow-driven demand shifts across the size and across the book-to-market spectrum over time. To see the flow movements, we plot in Figure 3 the time-series of the value-weighted FIT of the extreme size quintiles and the

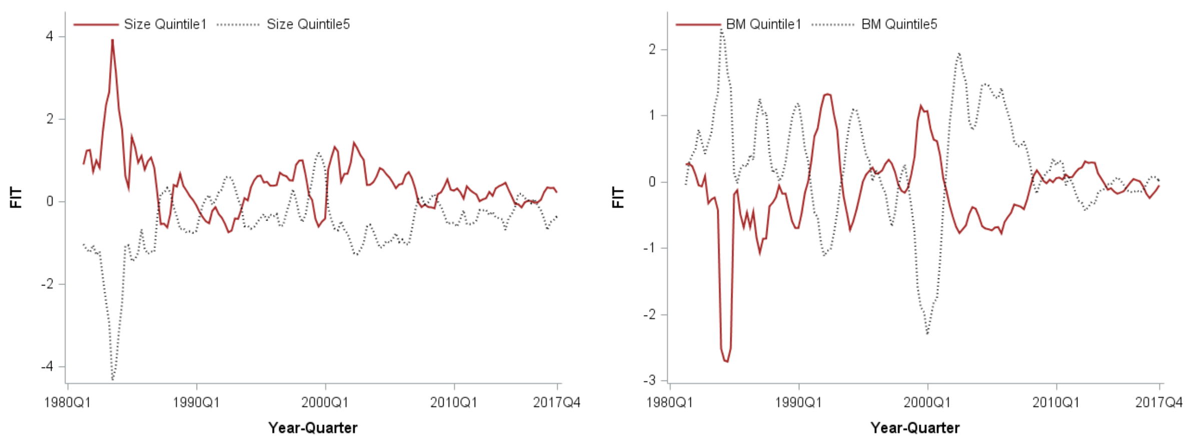

Figure 3: FIT of the extreme size and book-to-market quintiles (quarterly).

value-weighted FIT of the extreme book-to-market quintiles.[16] To make the FIT across different portfolios comparable, we standardize the portfolio-level FIT by their time-series standard deviations.

Figure 3 shows that fund flows into the top-size quintile, as measured by the value-weighted FIT, move in the opposite direction to fund flows into the bottom-size quintile. We also observe similar patterns of flow movements across the book-to-market spectrum. In fact, the correlation between the quarterly FIT of the bottom-size and the top-size quintiles is -0.85, and the correlation between the extreme book-to-market quintiles is -0.78. These negative correlations suggest that there are considerable flow movements across the size and across the book-to-market spectrum. Thus, the aggregate flow movements at the factor level should be an important driver of the time-variation of size and value returns.[17]

To investigate the explanatory power of the flow-driven demand on factor returns, we measure

[16]This figure plots quarterly value-weighted FIT within the bottom versus the top size (book-to-market) quintile during 1980Q1-2017Q4. To form size quintiles and book-to-market quintiles, we sort all NYSE, AMEX, and NASDAQ stocks into size and book-to-market quintiles based on NYSE quintile breakpoints in each June and we rebalance the portfolios on an annual basis following Fama and French (1992). In each quarter, we calculate value-weighted FIT for each quintile portfolio and adjust for the market-level FIT.

[17]In Appendix Table A.3, we provide detailed information about the correlations among quarterly FIT of different size (book-to-market) quintile portfolios. Appendix Table A.3 shows that there are systematic patterns of these correlations. Specifically, when the firm characteristics (e.g., size or book-to-market) of two portfolios are more similar, the correlation between FIT of these two portfolios are higher. For example, the correlation between FIT of the bottom and the top size (book-to-market) quintiles is -0.85 (-0.78), while the correlation between the second quintile and the top quintile is -0.51 (0.76).

factor-level flow-induced trading each quarter by

$$\text{FIT}_{\text{SMB}} = \frac{\text{FIT}_{\text{SG}} + \text{FIT}_{\text{SN}} + \text{FIT}_{\text{SV}}}{3} - \frac{\text{FIT}_{\text{BG}} + \text{FIT}_{\text{BN}} + \text{FIT}_{\text{BV}}}{3} \tag{6}$$

$$\text{FIT}_{\text{HML}} = \frac{\text{FIT}_{\text{SV}} + \text{FIT}_{\text{BV}}}{2} - \frac{\text{FIT}_{\text{SG}} + \text{FIT}_{\text{BG}}}{2}. \tag{7}$$

For example, FIT_{SV} and FIT_{BG} are the value-weighted FIT of the Fama-French small-value and big-growth portfolios in a given quarter, respectively. Intuitively, FlT_{SMB} captures the flow-induced trades of small-cap stocks relative to the flow-induced trades of large-cap stocks. Similarly, the variable, FlT_{HML}, captures the flow-induced trades of value stocks relative to growth stocks.

With these factor-level FIT measures, we estimate the following time-series regressions of quarterly factor returns on the corresponding factor-level FIT:

$$\text{SMB}_t = a + b\ \text{FIT}_{\text{SMB},t} + c \cdot \mathbf{X}_t + \epsilon_t, \tag{8}$$

$$\text{HML}_t = c + d\ \text{FIT}_{\text{HML},t} + e \cdot \mathbf{Y}_t + \xi_t. \tag{9}$$

Here, $\mathbf{X}_t$ and $\mathbf{Y}_t$ are vectors of controls including lagged factor returns in past four quarters and predictors of stock market returns as in Welch and Goyal (2007), which are dividend-price ratio, earnings-price ratio, market volatility, net equity expansion, the 3-month T-bill rate, inflation, and investment-capital ratio.[18]

Table 5 reports the results. As one can see, the factor-level flow-induced trading is a statistically strong and economically significant driver of factor returns. In the univariate regressions,

[18] The definitions of control variables are as follows: Dividend-price ratio is the difference between the log dividends and the log S&P500 price, where dividends are 12-month moving sums of dividends paid on the S&P 500 index. Earnings-price ratio is the log of earnings and log of S&P500 price, where earnings are 12-month moving sums of earnings on S&P 500 index. Market volatility is the standard deviation of daily CRSP value-weighted market returns in a given quarter. Net equity expansion is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total year-end market capitalization of NYSE stocks. Inflation is measured by Consumer Price Index. T-bill rate is the three month T-bill rate. Investment-capital ratio is the ratio of aggregate investment to aggregate capital for the whole economy. Detailed definitions of dividend-price ratio, earnings-price ratio, net equity expansion, investment-capital ratio can be found in Welch and Goyal (2007).

Table 5: **Time-series regression of factor returns on factor-level flow-induced trading.** This table reports the time-series regressions of quarterly factor returns on the contemporaneous factor-level FIT, as defined in (6) and (7). The controls include lagged factor returns in past four quarters and other variables that are not explicitly shown in this table: the dividend-price ratio (DP), earnings-price ratio (EP), market volatility (MktVol), net equity expansion (Ntis), T-Bill rate (Tbl), Inflation (Infl), and the investment-capital ratio (IK) as in Welch and Goyal (2007). t-statistics, shown in parentheses, are computed based on standard errors with the Newey-West corrections of four lags. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
DepVar:	$\mathrm{SMB_t}$		$\mathrm{HML_t}$	
$\mathrm{FIT_{SMB,t}}$	0.60***	0.78***		
	(4.78)	(4.69)		
$\mathrm{FIT_{HML,t}}$			0.82***	0.90***
			(3.50)	(3.29)
$\mathrm{Factor_{t-1}}$		−0.13		0.07
		(−1.58)		(0.69)
$\mathrm{Factor_{t-2}}$		−0.05		−0.06
		(−0.70)		(−0.57)
$\mathrm{Factor_{t-3}}$		−0.05		−0.05
		(−0.62)		(−0.67)
$\mathrm{Factor_{t-4}}$		−0.02		−0.07
		(−0.21)		(−0.66)
Controls	No	Yes	No	Yes
Observations	151	151	151	151
Adjusted R^2	0.13	0.15	0.07	0.04

the quarterly SMB return loads significantly on the factor-level FIT_{SMB} with a coefficient of 0.60 ($t = 4.78$), and the quarterly HML return loads significantly on the quarterly FIT_{HML} with a coefficient of 0.82 ($t = 3.50$). Regarding the economic magnitude, a one-standard-deviation increase in quarterly FIT_{SMB} and a one-standard-deviation increase in FIT_{HML} raise the quarterly SMB and HML returns by 1.65% and 1.62%, respectively. In terms of explanatory power, the factor-level flow-induced trading, FIT_{SMB} and FIT_{HML}, can explain 12.9% and 7.2% of the time-series variation in the quarterly SMB and HML returns, respectively. After controlling for the past factor returns and the list of controls in Welch and Goyal (2007), the positive correlations between factor returns and factor-level FIT still remain highly significant (columns (2) and (4)).

While mutual funds' flow-induced trades drive contemporaneous stock returns, Coval and Stafford (2007) and Lou (2012) also find that the flow-induced effects revert over the subsequent several years. We also expect that, over longer horizons, past aggregate factor-level FIT should negatively predict future factor returns. To test the long-term reversal, we extend the estimation window and regress factor returns in a given year on the average factor-level FIT over the prior four or the prior five years, respectively.

Table 6 shows the results. For both SMB and HML, factor-level FIT over the past four or five years indeed negatively predict future factor returns. For example, a one-standard-deviation increase in the average past-five-year FIT_{HML} leads to a 4.19% decrease in the HML returns over the subsequent year.

In summary, the analysis in this section shows that aggregate flow-driven demand shifts across the size spectrum and across the book-to-market spectrum are important drivers of factor returns. In the next section, we explore the effects of mutual fund flow-driven trades on volatilities of factor returns.

Table 6: **Long-term reversal: regression of factor return on the past factor-level FIT over longer horizons.** This table reports the time-series regressions of factor returns in a given year on the past four-year or past five-year factor-level FIT. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of one lag. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

DepVar:	SMB		HML	
past four-year FIT_{SMB}	−1.85***			
	(−3.17)			
past four-year FIT_{HML}			−3.69*	
			(−1.73)	
past five-year FIT_{SMB}		−2.00***		
		(−3.13)		
past five-year FIT_{HML}				−5.24**
				(−2.11)
Observations	34	33	34	33
Adjusted R^2	0.05	0.04	0.09	0.09

5 Flow-Induced Trading and Factor Volatility

In this section, we link volatilities of mutual funds' flow-driven trades of factors and volatilities of factor returns. Greenwood and Thesmar (2011) (GT) argue that if investor demand unrelated to fundamental does influence asset prices, the expected volatilities of the non-fundamental demand shifts should be useful for forecasting future asset volatilities. Motived by Section 4 that flow-induced trading significantly affects factor returns, there should also be a strong positive correlation between volatilities of factor returns and volatilities of fund-driven trades of factors.

5.1 Derivation of Factor Fragility

To this end, we first derive the expected variance of mutual funds' flow-driven trades of factors, which we call "factor fragility" following GT, who instead focus on individual stocks.

As in GT, we assume that there is a stable relationship between aggregate mutual fund flow-induced trades of stock j and its contemporaneous return:

$$r_{j,t} = \alpha_j + \lambda \frac{\sum_k n_{j,k,t-1} f_{k,t} \mathrm{PSF}}{\mathrm{Shrout}_{j,t-1}} + \varepsilon_{j,t}. \tag{10}$$

Here, $r_{j,t}$ is the return of stock j in quarter t, $n_{j,k,t-1}$ is the number of shares of stock j held by fund k at the end of quarter $t-1$, $f_{k,t}$ is percentage flow of fund k in quarter t, $\mathrm{Shrout}_{j,t-1}$ is total shares outstanding of stock j at the end of quarter $t-1$, and PSF is the partial scaling factor as in equation (1). The parameter λ captures price impact of aggregate mutual fund trading. $\varepsilon_{j,t}$ is the error term with conditional mean of zero, which may be driven by other sources of variation of returns, and can be interpreted as reflecting news about fundamentals.

Recall factor returns are the weighted-average returns of its constituents. For simplicity, we write SMB and HML as

$$\mathrm{SMB}_t = \sum_j \mu_{j,t-1}^{\mathrm{smb}} r_{j,t}, \tag{11}$$

$$\mathrm{HML}_t = \sum_l \mu_{l,t-1}^{\mathrm{hml}} r_{l,t}, \tag{12}$$

where $\mu_{j,t-1}^{\mathrm{smb}}$ is the weight of stock j in SMB in quarter t and $\mu_{l,t-1}^{\mathrm{hml}}$ is the weight of stock l in HML.[19] Plugging equation (10) into (11) and (12), we get

$$\mathrm{SMB}_t = \sum_j \mu_{j,t-1}^{\mathrm{smb}} \alpha_j + \lambda \sum_k w_{k,t-1}^{\mathrm{smb}} f_{k,t} + \sum_j \mu_{j,t-1}^{\mathrm{smb}} \varepsilon_{j,t},$$

$$\mathrm{HML}_t = \sum_l \mu_{l,t-1}^{\mathrm{hml}} \alpha_l + \lambda \sum_k w_{k,t-1}^{\mathrm{hml}} f_{k,t} + \sum_l \mu_{l,t-1}^{\mathrm{hml}} \varepsilon_{l,t},$$

where $w_{k,t-1}^{\mathrm{smb}} = \sum_j \mu_{j,t-1}^{\mathrm{smb}} n_{j,k,t-1} \mathrm{PSF}/\mathrm{shrout}_{j,t-1}$ and $w_{k,t-1}^{\mathrm{hml}} = \sum_l \mu_{l,t}^{\mathrm{hml}} n_{l,k,t-1} \mathrm{PSF}/\mathrm{shrout}_{l,t-1}$ are the weights of fund k in SMB and HML at quarter t.

[19] For example, for stock j in the Fama-French big-value portfolio, its portfolio weight in the SMB factor is the ratio of the market cap of stock j relative to the total market cap of all the stocks in the big-value portfolio multiplied by $-1/3$.

Thus, the conditional variance of SMB_{t+1} at the end of quarter t is

$$\text{Var}_t(\text{SMB}_{t+1}) = \lambda^2 W_t^{\text{smb}'} E_t(\Omega_{t+1}) W_t^{\text{smb}} + \text{Var}_t\left(\sum_j \mu_{j,t}\varepsilon_{j,t+1}\right), \tag{13}$$

and the conditional variance of HML_{t+1} is

$$\text{Var}_t(\text{HML}_{t+1}) = \lambda^2 W_t^{\text{hml}'} E_t(\Omega_{t+1}) W_t^{\text{hml}} + \text{Var}_t\left(\sum_l \mu_{l,t}\varepsilon_{l,t+1}\right). \tag{14}$$

Here, $E_t(\Omega_{t+1})$ is the conditional variance-covariance matrix of mutual fund flows in quarter $t+1$, and $W_t^{\text{smb}} = (w_{1,t}^{\text{smb}}, \ldots, w_{K,t}^{\text{smb}})$ and $W_t^{\text{hml}} = (w_{1,t}^{\text{hml}}, \ldots, w_{K,t}^{\text{hml}})$ are the vectors of mutual fund weights in SMB and HML, respectively.

Similar to the stock-level fragility in GT, we define fragility of SMB in quarter t as

$$G_t^{\text{SMB}} = W_t^{\text{smb}'} E_t(\Omega_{t+1}) W_t^{\text{smb}}. \tag{15}$$

Similarly, we define fragility of HML as

$$G_t^{\text{HML}} = W_t^{\text{hml}'} E_t(\Omega_{t+1}) W_t^{\text{hml}}. \tag{16}$$

As one can see, factor fragility depends on ownership concentration and the variance-covariance matrix of mutual funds' expected liquidity trades. To estimate $E_t(\Omega_{t+1})$, we calculate the variance-covariance matrix of mutual fund percentage flows using observations in the most recent four quarters (including quarter t).

5.2 Factor Volatility and Factor Fragility

Clearly, equations (13) and (14) suggest that flow-induced non-fundamental risk, as measured by factor fragility, should forecast future factor volatility. In particular, we estimate the following regressions:

$$\sigma_{t+1}^{\text{SMB}} = \pi_1 + \beta_1\sqrt{G_t^{\text{SMB}}} + \gamma_1 U_t + \epsilon_{t+1} \tag{17}$$

$$\sigma_{t+1}^{\text{HML}} = \pi_2 + \beta_2 \sqrt{G_t^{\text{HML}}} + \gamma_2 V_t + \eta_{t+1}, \tag{18}$$

where $\sigma_{t+1}^{\text{SMB}}$ and $\sigma_{t+1}^{\text{HML}}$ are the factor volatilities in quarter $t+1$, which we measure as one-quarter-ahead volatility of daily factor returns, and U_t and V_t are vectors of controls.

At a first glance, Figure 4 plots the four-quarter-moving-averages of factor volatility and the lagged square root of factor fragility. There is a clear positive correlation between future factor volatility and volatility of flow-induced trades of factors.

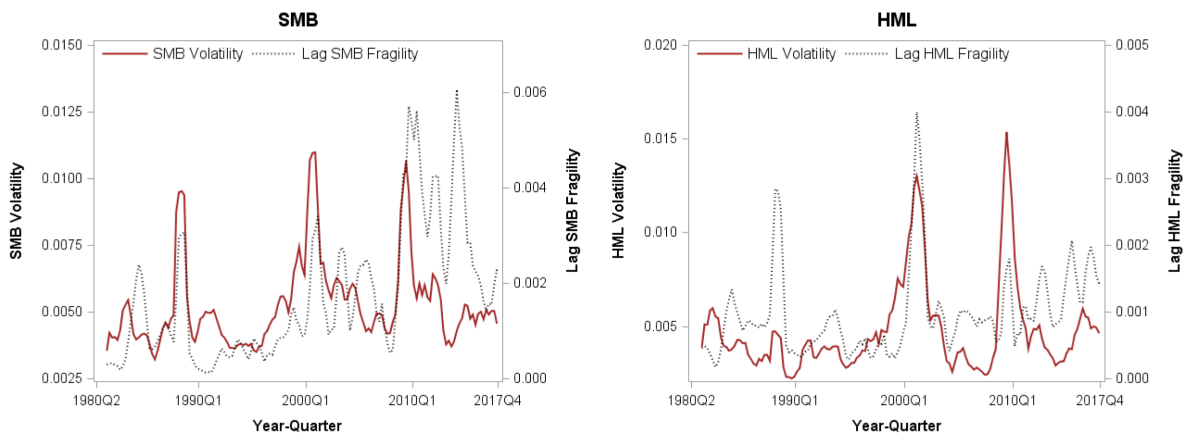

Figure 4: **Factor volatility and lagged square root of factor fragility.** This figure plots the four-quarter moving averages of factor volatility and the lagged square root of factor fragility. Factor volatility is measured as standard deviation of daily factor returns in a quarter and factor fragility is defined in equation (15).

Table 7 presents the results for regressions (17) and (18). Column (1) reports the univariate regression of one-quarter-ahead daily factor volatility, $\sigma_{t+1}^{\text{SMB}}$, on the volatility of flow-driven trades of SMB. It shows that $\sqrt{G_t^{\text{SMB}}}$ significantly predicts the daily SMB return volatility in the next quarter, with a t-statistic of 4.54. The economic magnitude is also meaningful. A one-standard-deviation increase in the square root of SMB fragility is associated with an increase in daily volatility of SMB over the next quarter by 0.081%, which is 35.2% of a standard deviation in daily SMB volatility. Column 4 shows that a one-standard-deviation increase in the square root of HML fragility is associated with an increase in daily volatility of HML by 0.13%, which is 44% of a standard deviation in daily HML volatility.

Table 7: **Time-series regression of factor volatility on the lagged square root of factor fragility.** This table reports predictive regression of factor volatility on square root of lagged factor fragility. The sample period is 1981 Q2-2017 Q4. Factor volatility is measured by the standard deviation of daily factor return in a given quarter t. In columns (2), (3), (5) and (6), we control for lagged factor volatilities in past four quarters and the average VXO index in contemporaneous quarter. The sample period is 1986 Q2-2017 Q4 in these two columns due to inclusion of VXO. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		SMB			HML	
DepVar:	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$
$\sqrt{G_t}$	0.48***	0.27**		1.45***	0.53**	
	(4.54)	(2.34)		(5.93)	(2.43)	
$\triangle\sqrt{G_t}$			0.52***			0.78***
			(3.83)			(3.63)
$\text{VXO}_t/100$		0.01***	0.01***		0.00	0.00
		(3.91)	(4.25)		(1.43)	(1.48)
σ_t		0.16	−0.86***		0.54***	−0.44***
		(1.45)	(−8.63)		(4.79)	(−4.25)
σ_{t-1}		0.05	0.18*		0.13	0.23**
		(0.49)	(1.88)		(1.20)	(2.10)
σ_{t-2}		−0.10	−0.13		0.05	0.04
		(−1.07)	(−1.48)		(0.48)	(0.39)
σ_{t-3}		0.02	0.06		−0.11	−0.14
		(0.28)	(0.70)		(−1.21)	(−1.55)
Observations	147	127	127	147	127	127
Adjusted R^2	0.12	0.30	0.39	0.19	0.60	0.19

We also add lagged factor volatilities in the past four quarters and the average CBOE S&P100 Volatility Index (VXO) as control variables.[20] Although the point estimates of factor fragilities are reduced by half with all these controls, they remain statistically significant with t-statistics of 2.34 and 2.43, respectively. This suggests that factor fragilities indeed forecast factor volatilities beyond past factor volatilities and the expected market volatilities, as reflected by the VXO index. Furthermore, we take first-order differences in both dependent and independent variables to detrend the time-series, and then examine how factor fragility changes forecast factor volatility changes. Column (3) and (6) show that the positive correlations between factor fragilities and future factor volatilities are still highly significant.[21]

In sum, our study shows that the non-fundamental flow-driven demand from mutual fund investors heavily influences both factor returns and factor volatilities.

6 Conclusion

Recent work shows that mutual fund investors are largely ignorant about systematic risks when allocating capitals among actively managed equity mutual funds. In this paper, we empirically investigate how the non-fundamental flow-induced trades of mutual funds influence returns and volatilities of the Fama-French size and value factors. To this end, we take a bottom-up approach by measuring flow-induced trading of active mutual funds on each individual stock.

Over the period from 1980 to 2017, we find that the non-fundamental flow-driven trades induce large return heterogeneity of stocks within and across the Fama-French size and book-to-market portfolios. We then proceed to study the influence of aggregate flow movements on the time-variation of factor returns. We find that the aggregate flow-induced demand shifts across the size spectrum and across the book-to-market spectrum are statistically and economically

[20] We use VXO instead of VIX in the regression because the time-series of VXO provided by CBOE starts from 1986 while VIX is available only after 1990. In fact, VXO and VIX are highly correlated.

[21] In Appendix Table A.9, we show that the results are robust by excluding the 2008-2009 financial crisis.

significant drivers of the size and value premia, respectively. We also find that the expected volatilities of mutual funds' flow-driven trades strongly predict future factor volatilities.

What do our study leave for the study of asset pricing? Clearly, our results highlight the importance of non-fundamental demand shocks in determining factor premia and factor volatilities. These results have important implications for the asset management industry. For example, our study cautions a possible dysfunction of benchmarking asset managers' performance using factor returns, given that factors, like value and size, are heavily influenced by the non-fundamental shifts in demand from retail mutual fund investors.

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Appendix

A Robustness Checks and Additional Results

In this section, we provide additional results to further support our main analysis. We start from the justification of our choice of partial scaling factors in the calculation of FIT. In Table A.1, we replicate Table 2 of Lou (2012), which shows how mutual funds trade on stocks in response to inflows and outflows. We find parameter estimates close to those in Lou (2012).

We next conduct sub-sample analysis on return heterogeneity patterns presented in Table 3. In Table A.2, we split the sample period into two sub-periods. Results show that return heterogeneity within and across Fama-French portfolios is stronger among the second-half sample period, which is consistent with a growing aggregate mutual fund size in our sample period.

We further conduct robustness checks on the effects of flow-induced trading on returns and volatilities of factors. First, we report the correlation of market-adjusted FIT between size and book-to-market quintile portfolios in Table A.3. This table confirms that the aggregate fund flow into the top size (book-to-market) quintile, measured by value-weighted FIT in that portfolio, moves in the opposite direction to the aggregate fund flow into bottom size (book-to-market) quintile. Then, we show that the main results are robust under alternative specifications of partial scaling factor (PSF). In Table A.4, Table A.5, and Table A.6, we show that results on time-variation of factor returns, long-term reversal of factor returns, and factor fragility are robust to alternative specifications of PSF. Furthermore, Table A.7 shows that, after controlling for common stock market return predictors, the negative correlation between past factor-level FIT and subsequent factor return remains significant. Table A.8 shows that factor fragility can still significantly forecast future factor volatility after controlling for time-trend and control variables as in Welch and Goyal (2007). In addition, Table A.9 shows that results on factor fragility are robust to excluding the observations in the recent financial crisis period: year 2008 and 2009.

Finally, we provide results on aggregate mutual fund size and factor volatilities. Panel A of Table A.10 reports that factor volatility loads positively and significantly on the ratio of aggregate equity fund TNA to total market capitalization of common stocks. Considering the growing trend of aggregate fund size, we take the first-order differences to fully detrend the time-series. Panel B of Table A.10 shows that there is a positive significant correlation between annual change of factor volatility and aggregate equity fund TNA. Figure A.1 presents the relationship graphically.

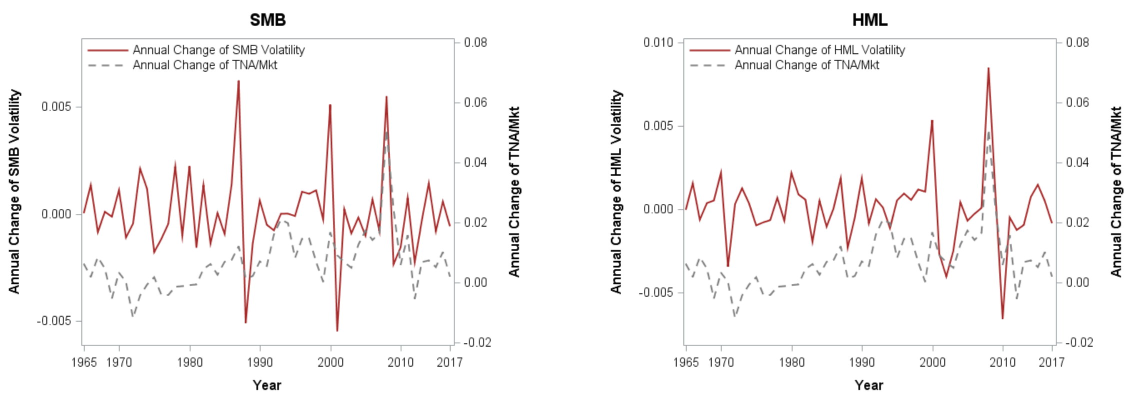

Figure A.1: Annual change of factor volatility and aggreagte equity fund TNA

Table A.1: **Fund response to flow, replicating Lou (2012).** This table replicates fund responses to capital flows, as documented in Lou(2012). The dependent variable is the percentage change in shares of stock j held by fund i in quarter t. The independent variable is the percentage flow of fund i in quarter t. In this regression, We restrict to the sample of NYSE, AMEX, and NASDAQ stocks whose market capitalization is above the bottom NYSE size decile and whose share price is above five dollars during 1980-2006. Year-quarter fixed effects are included. Standard errors are clustered by fund. t-statistics are shown in parentheses.

DepVar: $\mathrm{Trade}_{\mathrm{i,j,t}}$	Inflow Sample	Outflow Sample
Intercept	0.03	0.11***
	(0.87)	(6.63)
$\mathrm{Flow}_{\mathrm{i,t}}$	0.84***	0.80***
	(8.31)	(17.13)
Observations	3,413,165	3,255,696
Adjusted R^2	0.073	0.003

Table A.2: **Robustness check on Table 3: Sub-sample analysis** This table shows average monthly value-weighted returns of portfolios formed on size, book-to-market, and FIT in sub-samples. We form the portfolios in the same method as with Table 4. The portfolios are rebalanced every quarter and held in the formation quarter. Panel A to Panel C report portfolio returns in the first-half of our sample period: 1980-1998. Panel D to Panel F report portfolio returns in the second-half of our sample period: 1999-2017.

Panel A: Excess Returns, 1980-1998

	Growth					Neutral					Value				
	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1
Small	0.18	0.48	0.53	0.99	0.82	0.71	0.90	1.05	1.25	0.54	0.74	0.91	1.18	1.51	0.77
	(0.43)	(1.22)	(1.32)	(2.35)	(5.25)	(2.14)	(2.64)	(3.06)	(3.60)	(5.40)	(2.14)	(2.63)	(3.49)	(4.28)	(5.09)
Big	0.46	0.64	0.96	1.51	1.09	0.48	0.69	1.05	1.14	0.59	0.50	0.87	1.08	1.00	0.52
	(1.36)	(2.16)	(2.78)	(3.62)	(3.42)	(1.69)	(2.32)	(3.42)	(4.15)	(3.55)	(1.55)	(3.40)	(3.89)	(4.08)	(2.24)

Panel B: CAPM Alpha, 1980-1998

	Growth					Neutral					Value				
	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1
Small	−0.93	−0.63	−0.59	−0.17	0.76	−0.15	−0.02	0.16	0.38	0.53	−0.04	0.08	0.38	0.71	0.75
	(−4.13)	(−3.53)	(−2.69)	(−0.89)	(4.63)	(−0.77)	(−0.08)	(0.73)	(1.87)	(4.77)	(−0.14)	(0.35)	(1.74)	(2.81)	(5.17)
Big	−0.56	−0.31	−0.03	0.45	1.03	−0.28	−0.18	0.16	0.28	0.56	−0.26	0.14	0.28	0.32	0.61
	(−2.48)	(−2.61)	(−0.25)	(2.35)	(2.95)	(−1.61)	(−1.81)	(1.54)	(2.50)	(3.25)	(−1.09)	(0.83)	(1.80)	(2.32)	(2.55)

Panel C: Fama-French-Carhart 4-Factor Alpha, 1980-1998

	Growth					Neutral					Value				
	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1
Small	−0.40	−0.26	−0.20	0.23	0.63	−0.03	0.06	0.14	0.36	0.39	−0.23	−0.05	0.14	0.43	0.65
	(−3.54)	(−3.14)	(−2.02)	(2.42)	(3.91)	(−0.38)	(0.71)	(2.12)	(5.32)	(3.77)	(−2.18)	(−0.60)	(2.02)	(5.93)	(4.57)
Big	−0.15	−0.03	0.12	0.64	0.79	−0.26	−0.27	0.00	0.05	0.32	−0.76	−0.21	−0.17	−0.04	0.73
	(−0.73)	(−0.26)	(1.29)	(4.52)	(2.95)	(−1.33)	(−3.08)	(0.03)	(0.50)	(1.54)	(−4.40)	(−1.74)	(−1.32)	(−0.26)	(3.12)

	Growth					Neutral					Value				
	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1	FIT1 (Low)	2	3	4	4 − 1
Panel D: Excess Returns, 1999-2017															
Small	0.10	0.59	0.84	1.33	1.23	0.33	0.62	1.20	1.67	1.35	0.36	0.86	1.02	1.72	1.36
	(0.22)	(1.53)	(2.17)	(3.28)	(4.03)	(0.80)	(1.75)	(3.90)	(4.91)	(4.64)	(0.86)	(2.03)	(2.65)	(4.97)	(5.99)
Big	0.19	0.40	0.86	1.44	1.25	0.07	0.44	0.94	1.43	1.37	0.21	0.22	0.64	1.18	0.98
	(0.53)	(1.14)	(2.53)	(4.49)	(4.26)	(0.15)	(1.16)	(2.59)	(4.20)	(5.31)	(0.39)	(0.56)	(1.50)	(2.94)	(2.68)
Panel E: CAPM Alpha, 1999-2017															
Small	−0.59	−0.02	0.25	0.72	1.31	−0.24	0.10	0.68	1.17	1.42	−0.21	0.33	0.49	1.23	1.45
	(−3.13)	(−0.12)	(1.66)	(2.73)	(4.98)	(−1.02)	(0.51)	(3.24)	(3.57)	(5.63)	(−0.69)	(0.97)	(1.70)	(4.05)	(6.79)
Big	−0.33	−0.04	0.37	0.94	1.27	−0.45	0.00	0.51	0.96	1.41	−0.30	−0.21	0.20	0.72	1.02
	(−2.17)	(−0.25)	(2.71)	(3.56)	(4.67)	(−1.83)	(0.00)	(2.13)	(4.06)	(6.04)	(−0.80)	(−0.77)	(0.55)	(2.66)	(2.79)
Panel F: Fama-French-Carhart 4-Factor Alpha, 1999-2017															
Small	−0.64	−0.14	0.10	0.46	1.10	−0.39	−0.13	0.43	0.78	1.16	−0.51	0.01	0.16	0.81	1.32
	(−5.76)	(−1.10)	(0.82)	(2.72)	(4.96)	(−2.96)	(−1.72)	(5.56)	(5.82)	(6.98)	(−4.94)	(0.09)	(1.42)	(6.75)	(7.57)
Big	−0.21	0.01	0.44	0.88	1.09	−0.52	−0.04	0.42	0.88	1.40	−0.46	−0.33	0.04	0.47	0.93
	(−1.09)	(0.07)	(2.80)	(3.70)	(4.69)	(−2.63)	(−0.34)	(3.07)	(5.69)	(5.70)	(−1.79)	(−2.02)	(0.20)	(1.98)	(2.62)

Table A.3: **Correlation of market-adjusted FIT between size and book-to-market quintiles.** This table shows correlation between market-adjusted FIT of size and book-to-market quintile portfolios. To form the portfolios, we sort all NYSE, AMEX, and NASDAQ stocks into size and book-to-market quintiles based on NYSE quintile breakpoints at each June-end and hold the portfolios in the next four quarters. In each quarter, we calculate value-weighted FIT for each quintile portfolio and adjust for the market-level value-weighted FIT. Panel A reports correlations between market-adjusted FIT of size quintiles. Panel B reports correlations between market-adjusted FIT of book-to-market quintiles.

Panel A: Correlations between size quintiles					
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	1.00				
Quintile 2	0.83	1.00			
Quintile 3	0.68	0.82	1.00		
Quintile 4	0.24	0.25	0.60	1.00	
Quintile 5	−0.85	−0.90	−0.89	−0.51	1.00
Panel B: Correlations between book-to-market quintiles					
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	1.00				
Quintile 2	0.22	1.00			
Quintile 3	−0.14	0.70	1.00		
Quintile 4	−0.94	−0.17	0.13	1.00	
Quintile 5	−0.78	0.13	0.55	0.76	1.00

Table A.4: **Robustness check on Table 5, using alternative PSFs** In the calculation of factor-level FIT, we use FIT derived from different settings of partial scaling factors (PSF). In Panel A, we set PSF to one for both inflows and outflows. In Panel B, we set PSF based on our estimation in Table A.1. Specifically, PSF is 0.837 for inflows and 0.803 for outflows. t-statistics are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: PSF = 1		
DepVar:	SMB	HML
FIT_{SMB}	0.53***	
	(4.83)	
FIT_{HML}		0.72***
		(3.52)
Observations	151	151
Adjusted R^2	0.13	0.07
Panel B: PSF from Table A.1		
DepVar:	SMB	HML
FIT_{SMB}	0.63***	
	(4.83)	
FIT_{HML}		0.86***
		(3.51)
Observations	151	151
Adjusted R^2	0.13	0.07

Table A.5: **Robustness check on Table 6, using alternative PSFs for factor-level FIT.** In the calculation of factor inflow, we use FIT derived from different settings of partial scaling factors (PSF). In Panel A, we set PSF to be ones for both inflows and outflows. In Panel B, we set PSF based on our estimation in Table A.1. Specifically, PSF is 0.837 for inflows and 0.803 for outflows. t-statistics are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: PSF = 1		
Depvar:	SMB	HML
past five-year FIT_{SMB}	−1.69***	
	(−2.96)	
past five-year FIT_{HML}		−4.62**
		(−2.08)
Observations	33	33
Adjusted R^2	0.03	0.09
Panel B: PSF from Table A.1		
Depvar:	SMB	HML
past five-year FIT_{SMB}	−2.00***	
	(−2.90)	
		−5.57**
past five-year FIT_{HML}		(−2.07)
Observations	33	33
Adjusted R^2	0.03	0.09

Table A.6: **Robustness check on Table 7, using alternative PSFs for fragilities.** In Panel A, we set PSF to one for both inflows and outflows. In Panel B, we set PSF based on our estimation in Table A.1. Specifically, PSF is 0.837 for inflows and 0.803 for outflows. Control variables include lagged factor volatilities in past four quarters and VXO at previous quarter-end. t-statistics are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(4)
	Panel A: PSF = 1					
	SMB			HML		
DepVar:	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$
$\sqrt{G_t}$	0.45***	0.27***		1.35***	0.53***	
	(4.69)	(2.62)		(6.06)	(2.68)	
$\triangle\sqrt{G_t}$			0.51***			0.72***
			(4.18)			(3.57)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	147	127	127	147	127	127
Adjusted R^2	0.13	0.31	0.40	0.20	0.60	0.19
	Panel B: PSF from Table A.1					
	SMB			HML		
DepVar:	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$
$\sqrt{G_t}$	0.45***	0.27***		1.36***	0.53***	
	(4.56)	(2.62)		(6.05)	(2.68)	
$\triangle\sqrt{G_t}$			0.51***			0.72***
			(4.18)			(3.57)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	147	127	127	147	127	127
Adjusted R^2	0.12	0.31	0.40	0.20	0.60	0.19

Table A.7: **Robustness check on factor long-term reversal in Table 6** This table reports regression of factor return on past five-year factor-level FIT and control variables. The control variables are defined in Table 5, including the dividend-price ratio (DP), earnings-price ratio (EP), market volatility (MktVol), net equity expansion (Ntis), T-Bill rate (Tbl), Inflation (Infl), and the investment-capital ratio (IK) as in Welch and Goyal (2007).We use the average of quarterly control variables in the past five years. Each time we include one control variable in the regression. The control variables for each column are shown at the top. Panel A and Panel B report the univariate regression of annual factor returns on average control variables in past five years. Panel C and Panel D report the bivariate regression of annual factor returns on past five-year factor-level FIT and past five-year control variables. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of one lag. Parameter estiamtes significant at 10% level are shown in bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control Variable:	DP	EP	MktVol	NTIS	TBL	INFL	IK
DepVar: SMB_{t+1}				**Panel A**			
Control, past five-year average	0.00	0.00	**11.59**	0.09	0.05	2.22	**10.70**
	(0.23)	(0.41)	(2.01)	(0.07)	(0.13)	(0.98)	(3.00)
Intercept	0.01	0.01	−0.09	0.02	0.02	−0.00	**−0.36**
	(0.44)	(0.41)	(−1.61)	(1.21)	(0.82)	(−0.01)	(−2.87)
Observations	33	33	33	33	33	33	33
Adjusted R^2	0.00	0.00	0.10	0.00	0.00	0.02	0.12
DepVar: HML_{t+1}				**Panel B**			
Control, past five-year average	**−0.00**	**−0.00**	0.85	**2.56**	**0.93**	**7.41**	**12.75**
	(−1.97)	(−1.72)	(0.15)	(1.77)	(2.21)	(3.74)	(2.13)
Intercept	**0.09**	**0.08**	0.03	0.02	−0.01	−0.03	**−0.42**
	(2.30)	(2.17)	(0.41)	(1.07)	(−0.49)	(−1.04)	(−2.03)
Observations	33	33	33	33	33	33	33
Adjusted R^2	0.06	0.04	0.00	0.07	0.06	0.10	0.09
DepVar: SMB_{t+1}				**Panel C**			
past five-year FIT_{SMB}	**−2.12**	**−1.96**	**−1.56**	**−1.99**	**−2.87**	**−2.23**	**−3.40**
	(−2.11)	(−2.13)	(−2.45)	(−3.10)	(−2.50)	(−2.23)	(−4.07)
Intercept	0.05	0.04	−0.09	**0.04**	**0.03**	0.03	**−0.45**
	(0.93)	(0.92)	(−1.60)	(2.35)	(1.93)	(0.94)	(−4.41)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33	33	33	33	33	33	33
Adjusted R^2	0.07	0.07	0.20	0.07	0.08	0.07	0.27
DepVar: HML_{t+1}				**Panel D**			
past five-year FIT_{HML}	**−6.27**	**−6.00**	**−5.26**	**−4.82**	**−6.34**	**−6.21**	**−4.86**
	(−2.62)	(−2.51)	(−1.91)	(−1.89)	(−2.43)	(−2.29)	(−2.19)
Intercept	**0.10**	**0.08**	0.03	0.03	−0.00	−0.03	−0.25
	(2.28)	(2.15)	(0.49)	(1.49)	(−0.14)	(−0.59)	(−1.24)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33	33	33	33	33	33	33
Adjusted R^2	0.16	0.15	0.12	0.12	0.16	0.15	0.15

Table A.8: **Robustness check on factor volatility and factor fragility: Other controls** This table reports robustness check on Table 7 with more control variables. In addition to lagged VXO and lagged factor volatilities in past four quarters, we control for time-trend and one-quarter lagged predictors of stock market returns as in Table 5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	SMB		HML	
DepVar:	σ_{t+1}	$\triangle\sigma_{t+1}$	σ_{t+1}	$\triangle\sigma_{t+1}$
$\sqrt{G_t}$	0.55**		1.06***	
	(3.97)		(4.34)	
$\triangle\sqrt{G_t}$		0.47***		0.86***
		(3.50)		(4.06)
Controls	Yes	Yes	Yes	Yes
Observations	127	127	127	127
Adjusted R^2	0.39	0.42	0.65	0.19

Table A.9: **Robustness check on factor volatility and factor fragility: Excluding financial crisis period.** In this table, we exclude sample period in year 2008 and 2009, and run the same set of regressions as in Table 7. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		SMB			HML	
DepVar:	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$	σ_{t+1}	σ_{t+1}	$\triangle\sigma_{t+1}$
$\sqrt{G_t}$	0.40***	0.26**		1.32***	0.55***	
	(3.25)	(2.15)		(6.63)	(2.78)	
$\triangle\sqrt{G_t}$			0.60***			0.57***
			(3.94)			(2.76)
$\text{VXO}_t/100$		0.01***	0.01***		0.00	0.00
		(2.85)	(3.12)		(0.47)	(0.31)
σ_t		0.18*	−0.83***		0.46***	−0.46***
		(1.68)	(−8.23)		(4.21)	(−4.55)
σ_{t-1}		0.07	0.19*		0.09	0.19*
		(0.73)	(1.95)		(0.91)	(1.67)
σ_{t-2}		−0.06	−0.07		0.16	0.13
		(−0.63)	(−0.81)		(1.54)	(1.18)
σ_{t-3}		0.05	0.07		−0.06	−0.07
		(0.55)	(0.80)		(−0.64)	(−0.87)
Observations	139	119	119	139	119	119
Adjusted R^2	0.08	0.23	0.39	0.24	0.57	0.20

Table A.10: **Aggregate mutual fund size and factor volatility.** This table reports the regression of factor volatility on contemporaneous aggregate mutual fund size. The sample period is from 1965 to 2017. In Panel A, the dependent variable is factor volatility measured by deviation of daily factor returns in a given year. The independent variable is the ratio of aggregate equity funds TNA to total market capitalization of common stocks. In Panel A, both dependent and independent variables are standardized by their time-series standard deviations. In Panel B, the dependent variable is annual change of factor volatility, and the independent variable is annual change of the ratio of aggregate equity funds TNA to total market capitalization of common stocks. We relax our mutual fund selection filter by allowing all mutual funds with CRSP investment objective code that starts with "ED" to enter our sample. t-statistics are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Level of factor volatility		
DepVar:	σ_{SMB}	σ_{HML}
TNA/MKT	0.33**	0.36***
	(2.52)	(2.75)
Intercept	2.20***	1.47***
	(10.60)	(10.38)
Observations	53	53
Adjusted R^2	0.09	0.11
Panel B: Change of factor volatility		
DepVar:	$\triangle\sigma_{\text{SMB}}$	$\triangle\sigma_{\text{HML}}$
$\triangle$(TNA/MKT)	0.07**	0.09***
	(2.43)	(3.30)
Intercept	−0.00	−0.00*
	(−1.31)	(−1.79)
Observations	53	53
Adjusted R^2	0.09	0.16

B Mutual Fund Flow-induced Trading and Other Anomalies

In this section, we extend our analysis of the effect of flow-induced trading on another 11 anomalies in Stambaugh, Yu, and Yuan (2012). To this end, we first form quintile portfolios based on each of the 11 anomalies. The two extreme quintiles of each anomaly are refered as the long leg and the short leg of the corresponding anomaly, respectively.

As in Section 3, we split each of the anomaly long-legs and short-legs into two groups: the inflow group with positive FIT and the outflow group with negative FIT. We report the value-weighted returns of the portfolios formed on the anomaly variables and FIT in Table B.1. We find large return heterogeneity within and across anomaly long-legs and short-legs. For example, controlling for the corresponding characteristics, stocks with positive FIT outperform other stocks with negative FIT by 39 bps to 92 bps per month across the 22 extreme portfolios. Besides, we observe the "reverted" premia across all the 11 anomalies. That is, the short-leg components with higher FIT outperform the long-leg components with lower FIT.

In Table B.2, we regress quarterly anomaly long-short returns on the contemporaneous anomaly-level FIT as in Table 5. As one can see, the correlations between anomaly returns and anomaly-level FIT are significant at 5% level for 9 out of 11 anomalies. That is, the factor-level FITs are significant drivers of time-variation in returns of those anomalies.

In Table B.3, we examine the relationship between anomaly returns and past flows into the anomalies. At the beginning of each quarter, we rank anomalies in ascending order by past anomaly-level FIT, calculated as the value-weighted FIT of the long leg minus the value-weighted FIT of the short leg. Then we assign the bottom 3 (top 3) anomalies into low (high) FIT group. We track the average returns of anomalies in each group in the quarter. We find that anomalies with higher past FIT significantly underperform anomalies with lower FIT in the past. For instance, the group of anomalies with highest-FIT in the past 8 quarters underperform the bottom-FIT anomaly group by 0.84% per month ($t = 4.15$), in term of the Fama-French-Carhart four-factor alpha.

For reader's convenience, we list the 11 anomalies, which are grouped by portfolio rebalancing frequency:

1. Annual-Rebalanced Anomalies

Net stock issues: Ritter (1991) and Loughran and Ritter (1995) find that equity issuances are associated with lower stock returns in the subsequent five years after issuance. We measure net stock issuance as $\log(\mathrm{shrout}_{\mathrm{i,t-1}}/\mathrm{shrout}_{\mathrm{i,t-2}})$, where $\mathrm{shrout}_{\mathrm{i,t-1}}$ is the split-adjusted number of shares outstanding of stock i as of the fiscal year ending in calendar year $t-1$.

Composite equity issues: Daniel and Titman (2006) provide another measure for equity issuance, which captures the part of a firm's increase in market capitalization that is not attributable to its stock returns. We compute composite equity issues as $\log(\mathrm{ME}_{\mathrm{i,t-1}}/\mathrm{ME}_{\mathrm{i,t-6}}) - \mathrm{CRet}_{\mathrm{i,t-6,t-1}}$, where $\mathrm{ME}_{\mathrm{i,t-1}}$ is the market capitalization of stock i as of the fiscal year ending in calendar year $t-1$ and $\mathrm{CRet}_{\mathrm{i,t-6,t-1}}$ is the cumulative returns of stock i from year $t-6$ to year $t-1$.

Total accruals: Sloan (1996) finds that firms with high accruals earn lower future stock returns than firms with low accruals. We calculate total accruals as

$$\frac{(\triangle \mathrm{ACT}_{\mathrm{i,t-2,t-1}} - \triangle \mathrm{CHE}_{\mathrm{i,t-2,t-1}}) - (\triangle \mathrm{LCT}_{\mathrm{i,t-2,t-1}} - \triangle \mathrm{DLC}_{\mathrm{i,t-2,t-1}})}{\mathrm{CEQ}_{\mathrm{i,t-1}}},$$

where $\triangle$ACT is the change in current assets, $\triangle$CHE is the change in cash and short-term investments, $\triangle$LCT is the change in current liabilities, $\triangle$DLC is the change in debt included in current liabilities, and CEQ is the total common/ordinary equities.

Net operating assets: Hirshleifer, Hou, Teoh, and Zhang (2004) find that high net operating assets is associated with lower future stock returns. We calculate net operating assets as

$$\frac{(\mathrm{AT_{i,t-1}} - \mathrm{CHE_{i,t-1}}) - (\mathrm{AT_{i,t-1}} - \mathrm{DLC_{i,t-1}} - \mathrm{DLTT_{i,t-1}} - \mathrm{MIB_{i,t-1}} - \mathrm{PSTK_{i,t-1}} - \mathrm{CEQ_{i,t-1}})}{\mathrm{AT_{i,t-2}}},$$

where AT is total assets, CHE is cash and short-term investments, DLC is debt in current liabilities, DLTT is long-term debt, MIB is minority interest, PSTK is book value of preferred stocks, and CEQ is book value of common equity.

Gross profitability: Novy-Marx (2013) document that stocks with high gross profitability earn higher future returns than those with low gross profitability. We compute gross profitability as revenues (Compustat item: REVT) minus cost of goods sold (Compustat item: COGS), scaled by total assets (Compustat item: AT).

Investment-to-assets: Lyandres, Sun, and Zhang (2008) find that firms with higher investment-to-asset ratio earn lower subsequent stock returns. We calculate investment-to-asset ratio as $(\triangle\mathrm{PPENT_{i,t-2,t-1}} + \triangle\mathrm{INVT_{i,t-2,t-1}})/\mathrm{AT_{i,t-2}}$, where $\triangle$PPENT is the change in property, plant, and equipment, and $\triangle$INVT is the change in inventories.

Asset growth: Cooper, Gulen, and Schill (2008) find that firms' acquisitions of assets, measured by the asset growth, are associated with lower subsequent stock returns. We compute asset growth as $(\mathrm{AT_{i,t-1}} - \mathrm{AT_{i,t-2}})/\mathrm{AT_{i,t-2}}$.

2. Quarterly-Rebalanced Anomalies

Failure probability: Campbell, Hilscher, and Szilagyi (2008) show that financially distressed stocks have high failure probability, and earn lower subsequent stock returns. They estimate failure probability in a dynamic logit model based on firms' accounting and market information. We compute failure probability following Chen, Novy-Marx, and Zhang (2011).

O-score: O-score (Ohlson, 1980) is also a proxy for financial distress. We compute O-score following Chen, Novy-Marx, and Zhang (2011).

Return on assets: Fama and French (2006) show that more profitable firms earn higher subsequent stock returns than less profitable firms. We measure the profitability by quarterly return on assets, which is the ratio of the quarterly income before extraordinary items (Compustat item: IBQ) to the total assets at the quarter-end (Compustat item: ATQ).

3. Monthly-Rebalanced Anomaly

Momentum: Jegadeesh and Titman (1993) document that stocks with high past returns outperform stocks with low past returns over 3- to 12-month holding periods. To implement the momentum strategy, at the beginning of month t, we form momentum portfolios based on cumulative stock returns from month $t-6$ to month $t-2$ (skip the most recent month), and hold the momentum portfolios from month t to month $t+5$. We deal with overlapping portfolios following Jegadeesh and Titman (1993).

Table B.1: **Returns of anomaly long- and short-legs split by FIT.** This table reports average monthly value-weighted returns of portfolios formed on anomaly variables and FIT. We focus on the 11 anomalies studied in Stambaugh, Yu, and Yuan (2012). In Appendix Section B, we describe the definitions of anomaly variables. We form quintile portfolios based on the anomaly variables. The first column reports average monthly Long-Short returns of each anomaly in the period of January 1980 to December 2017. In each quarter, we also split all stocks into positive-FIT group (inflow group) and negative-FIT group (outflow group). The two FIT portfolios are held in the formation quarter and rebalanced quarterly. We then intersect the long legs and short legs of the 11 anomalies with the two FIT portfolios. We calculate value-weighted portfolio returns in the holding period of April 1980 to December 2017. In Panel A, we report excess returns of the portfolios. In Panel B and C, we report portfolio returns adjusted for the exposure on market factor and Fama-French-Carhart four-factor. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags.

Panel A: Excess Return

Anomaly	Long-Short	Long Leg			Short Leg		
		Inflow	Outflow	In-Out	Inflow	Outflow	In-Out
Failure probability	0.51	1.14	0.37	0.77	0.76	−0.16	0.92
	(1.96)	(5.36)	(1.84)	(5.12)	(2.08)	(−0.38)	(4.04)
Ohlson's O	0.24	1.04	0.33	0.71	0.86	0.01	0.86
	(1.21)	(4.45)	(1.46)	(5.45)	(2.66)	(0.02)	(4.48)
Net stock issues	0.44	1.12	0.54	0.59	1.00	−0.06	1.06
	(2.68)	(5.08)	(2.65)	(4.01)	(3.73)	(−0.19)	(6.68)
Composite stock issues	0.44	1.15	0.50	0.66	0.91	−0.09	0.99
	(2.82)	(5.77)	(2.53)	(5.33)	(3.36)	(−0.32)	(6.17)
Total accruals	0.33	1.13	0.47	0.66	1.01	0.07	0.94
	(2.62)	(4.16)	(1.94)	(4.71)	(3.93)	(0.24)	(6.76)
Net operating assets	0.45	1.21	0.47	0.74	0.87	−0.02	0.89
	(4.29)	(4.29)	(1.90)	(4.29)	(3.44)	(−0.08)	(5.61)
Momentum	0.48	1.17	0.51	0.66	0.75	0.12	0.63
	(2.54)	(5.10)	(2.37)	(5.47)	(1.99)	(0.30)	(2.50)
Gross profitability	0.40	1.20	0.54	0.67	0.93	0.15	0.78
	(2.48)	(4.78)	(2.59)	(4.67)	(3.72)	(0.57)	(4.94)
Asset growth	0.33	1.07	0.53	0.54	0.86	0.13	0.73
	(1.69)	(4.40)	(2.46)	(3.78)	(2.85)	(0.40)	(3.67)
Return on assets	0.49	1.30	0.44	0.86	0.74	−0.24	0.98
	(1.75)	(5.33)	(2.01)	(5.25)	(1.95)	(−0.54)	(4.41)
Investment-to-assets	0.26	1.11	0.49	0.62	0.91	0.15	0.76
	(2.20)	(4.66)	(2.13)	(4.62)	(3.25)	(0.59)	(4.41)

Panel B: CAPM Alpha

Anomaly	Long-Short	Long Leg Inflow	Long Leg Outflow	Long Leg In-Out	Short Leg Inflow	Short Leg Outflow	Short Leg In-Out
Failure probability	0.82	0.57	−0.16	0.72	−0.10	−1.05	0.95
	(3.29)	(4.10)	(−1.80)	(4.50)	(−0.51)	(−4.04)	(3.89)
Ohlson's O	0.41	0.33	−0.32	0.65	0.05	−0.81	0.86
	(2.17)	(2.48)	(−3.35)	(4.47)	(0.28)	(−4.30)	(4.63)
Net stock issues	0.61	0.50	−0.06	0.56	0.21	−0.79	1.00
	(3.50)	(4.51)	(−0.61)	(3.88)	(1.55)	(−5.13)	(5.75)
Composite stock issues	0.71	0.59	−0.06	0.66	0.06	−0.88	0.94
	(5.23)	(5.65)	(−0.71)	(5.23)	(0.44)	(−6.85)	(5.77)
Total accruals	0.36	0.38	−0.25	0.62	0.22	−0.68	0.91
	(2.59)	(3.50)	(−2.56)	(4.34)	(1.73)	(−4.49)	(5.99)
Net operating assets	0.42	0.40	−0.28	0.68	0.14	−0.75	0.89
	(4.03)	(2.99)	(−2.37)	(3.90)	(1.19)	(−5.55)	(5.19)
Momentum	0.52	0.51	−0.11	0.63	−0.33	−0.96	0.62
	(2.91)	(4.41)	(−1.35)	(5.14)	(−1.44)	(−3.44)	(2.44)
Gross profitability	0.42	0.52	−0.06	0.58	0.32	−0.48	0.81
	(2.37)	(4.49)	(−0.47)	(3.93)	(2.27)	(−3.53)	(4.51)
Asset growth	0.55	0.38	−0.12	0.51	0.00	−0.70	0.70
	(2.79)	(3.42)	(−1.08)	(3.81)	(0.00)	(−4.16)	(3.21)
Return on assets	0.77	0.60	−0.19	0.79	−0.20	−1.22	1.02
	(2.80)	(3.76)	(−1.79)	(4.42)	(−0.92)	(−3.66)	(4.35)
Investment-to-assets	0.35	0.42	−0.18	0.60	0.10	−0.58	0.68
	(2.97)	(3.64)	(−2.13)	(4.48)	(0.73)	(−4.08)	(3.78)

Panel C: Fama-French-Carhart 4-factor Alpha

Anomaly	Long-Short	Long Leg Inflow	Long Leg Outflow	Long Leg In-Out	Short Leg Inflow	Short Leg Outflow	Short Leg In-Out
Failure probability	0.49	0.48	−0.17	0.64	0.14	−0.70	0.85
	(2.69)	(3.59)	(−2.04)	(3.93)	(0.76)	(−3.58)	(3.74)
Ohlson's O	0.55	0.41	−0.17	0.58	0.04	−0.80	0.84
	(3.45)	(3.63)	(−2.00)	(3.95)	(0.23)	(−4.35)	(4.73)
Net stock issues	0.47	0.48	−0.04	0.52	0.29	−0.63	0.92
	(3.58)	(4.31)	(−0.48)	(3.80)	(2.64)	(−4.95)	(5.75)
Composite stock issues	0.53	0.54	−0.04	0.58	0.13	−0.62	0.75
	(4.10)	(4.39)	(−0.55)	(4.58)	(1.03)	(−4.99)	(4.35)
Total accruals	0.40	0.43	−0.07	0.49	0.28	−0.62	0.90
	(2.74)	(3.82)	(−0.65)	(3.42)	(2.41)	(−4.25)	(5.80)
Net operating assets	0.45	0.46	−0.07	0.54	0.15	−0.59	0.74
	(4.22)	(3.46)	(−0.79)	(2.88)	(1.33)	(−4.47)	(4.17)
Momentum	−0.11	0.50	−0.03	0.53	0.24	−0.27	0.50
	(-0.98)	(4.28)	(−0.30)	(4.38)	(1.02)	(−1.39)	(1.92)
Gross profitability	0.52	0.56	0.04	0.52	0.26	−0.47	0.73
	(3.90)	(5.64)	(0.33)	(3.55)	(1.89)	(−4.24)	(4.92)
Asset growth	0.22	0.24	−0.14	0.38	0.20	−0.38	0.57
	(1.69)	(2.29)	(−1.46)	(2.83)	(1.41)	(−2.65)	(2.63)
Return on assets	0.63	0.64	−0.05	0.69	−0.07	−0.85	0.78
	(2.76)	(5.38)	(−0.47)	(4.11)	(−0.36)	(−3.53)	(4.18)
Investment-to-assets	0.22	0.30	−0.18	0.48	0.12	−0.48	0.60
	(1.92)	(2.50)	(−2.11)	(3.43)	(0.94)	(−3.74)	(3.39)

Table B.2: **Anomaly returns and contemporaneous anomaly-level FIT.** This table reports regressions of quarterly anomaly long-short returns on contemporaneous anomaly-level FIT based on the 11 anomalies examined in Stambaugh, Yu, and Yuan (2012). The dependent variables are quarterly long-short returns of anomalies. We construct anomaly variables as described in Appendix Section B, and we form quintile portfolios based on anomaly variables. The independent variables are anomaly-level FIT, which are defined as value-weighted average FIT of stocks in the long legs of anomalies minus that of anomaly short legs. The sample period is 1980Q1 to 2017Q4.

Anomaly	Variable	Coef.	t-statistics	Adjusted R^2
Failure probability	Intercept	0.00	0.37	0.11
	FIT	0.40	4.39	
Ohlson's O	Intercept	0.01	2.31	0.04
	FIT	0.49	2.57	
Net stock issues	Intercept	0.02	3.63	0.03
	FIT	1.03	2.51	
Composite stock issues	Intercept	0.01	2.57	0.05
	FIT	1.12	2.85	
Total accruals	Intercept	0.01	2.32	0.01
	FIT	0.35	1.58	
Net operating assets	Intercept	0.01	4.04	0.01
	FIT	0.38	1.34	
Momentum	Intercept	−0.01	−0.84	0.05
	FIT	1.00	3.08	
Gross profitability	Intercept	0.01	3.00	0.05
	FIT	0.82	2.86	
Asset growth	Intercept	0.01	1.72	0.06
	FIT	0.88	3.16	
Return on assets	Intercept	0.02	2.50	0.04
	FIT	1.12	2.63	
Investment-to-assets	Intercept	0.01	1.79	0.06
	FIT	0.86	3.35	

Table B.3: **Returns of anomalies sorted on past anomaly-level FIT.** This table reports the average monthly returns of anomaly portfolios sorted on past anomaly-level FIT from April 1982 Q1 to December 2017. The universe of anomalies includes the 11 anomalies examined in Table B.1 and a long-short strategy based on book-to-market ratio. Anomaly returns refer to the returns of the long-short portfolios by the extreme quintile portfolios. We define anomaly-level FIT in quarter t as the value-weighted FIT of the long leg minus the value-weighted FIT of the short leg in that quarter. We then form anomaly portfolios as follows. At the beginning of each quarter t, we rank the 12 anomalies in ascending order by their average FIT between quarter $t-k$ and quarter $t-1$ ($k = 1, 2, 4$, and 8). We assign the the bottom 3 and the top 3 anomalies into low FIT group and high FIT group, respectively, and we calculate the average anomaly returns for each group in quarter t. We report raw returns of the anomaly portfolios in Panel A. We adjust the anomaly portfolio returns for exposures to the market factor, the Fama-French three factors, and the Fama-French-Carhart four factors, respectively, and we report the factor-adjusted performance in Panel B, C, and D. t-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags.

Panel A: Raw Returns				
Sorting variable:	Low	Medium	High	Low-High
AnomalyFIT$_{t-1}$	0.45	0.40	0.34	0.11
	(2.58)	(3.80)	(2.30)	(0.52)
AnomalyFIT$_{t-2,t-1}$	0.49	0.41	0.28	0.22
	(2.80)	(3.60)	(2.13)	(1.03)
AnomalyFIT$_{t-4,t-1}$	0.60	0.40	0.20	0.40
	(3.32)	(3.92)	(1.50)	(2.11)
AnomalyFIT$_{t-8,t-1}$	0.75	0.36	0.14	0.610
	(3.82)	(3.43)	(1.03)	(2.78)
Panel B: CAPM Alpha				
Sorting variable:	Low	Medium	High	Low-High
AnomalyFIT$_{t-1}$	0.63	0.54	0.44	0.19
	(3.92)	(4.89)	(3.09)	(0.96)
AnomalyFIT$_{t-2,t-1}$	0.69	0.56	0.34	0.35
	(4.13)	(5.18)	(2.64)	(1.81)
AnomalyFIT$_{t-4,t-1}$	0.78	0.55	0.28	0.51
	(4.32)	(5.37)	(2.17)	(2.57)
AnomalyFIT$_{t-8,t-1}$	0.97	0.49	0.21	0.76
	(5.22)	(4.64)	(1.68)	(3.63)

Panel C: Fama-French Three-factor Alpha				
Sorting variable:	Low	Medium	High	Low-High
AnomalyFIT$_{t-1}$	0.58	0.49	0.47	0.11
	(3.54)	(5.02)	(3.27)	(0.51)
AnomalyFIT$_{t-2,t-1}$	0.61	0.53	0.36	0.26
	(4.03)	(5.23)	(2.74)	(1.29)
AnomalyFIT$_{t-4,t-1}$	0.70	0.50	0.32	0.38
	(4.32)	(5.94)	(2.49)	(2.12)
AnomalyFIT$_{t-8,t-1}$	0.89	0.46	0.22	0.67
	(5.58)	(4.67)	(1.75)	(3.29)
Panel D: Fama-French-Carhart Four-factor Alpha				
Sorting variable:	Low	Medium	High	Low-High
AnomalyFIT$_{t-1}$	0.55	0.36	0.20	0.35
	(3.58)	(3.84)	(1.50)	(1.64)
AnomalyFIT$_{t-2,t-1}$	0.57	0.40	0.09	0.50
	(3.87)	(4.20)	(0.80)	(2.50)
AnomalyFIT$_{t-4,t-1}$	0.63	0.39	0.06	0.57
	(4.23)	(5.12)	(0.44)	(3.07)
AnomalyFIT$_{t-8,t-1}$	0.79	0.36	−0.05	0.84
	(5.22)	(4.01)	(−0.41)	(4.15)