What Drives the Size and Value Factors?

Abstract

I show that over 40% of movements in the Fama-French size and value factors are temporary price pressures. Since 1980, investors frequently made large capital reallocations across mutual funds of different size and value styles, generating large factor-level price pressures that completely reverse subsequently. Further corroborating the price pressure interpretation, flow-induced price movements happen exclusively in intraday (open to close) returns, but not in overnight (close to open) returns, consistent with the fact that mutual funds tend to trade during market hours. Overall, these findings imply that a sizeable fraction of factor movements do not represent fundamental risk.

Keywords: Fama-French Three Factor Model, Price Pressures, Style Investing

JEL classification: G10, G12, G23, G40

1 Introduction

Size and value factors play central roles in both academic and industry finance. In academia, the Fama-French three factor model – which augments the Capital Asset Pricing Model with size and value factors – are widely used to explain the cross-section of expected stock returns. The model is also referenced in the scientific background for the 2013 Nobel prize in economics (Nobel Prize Committee (2013)). In the asset management industry, investors have invested into those two factors for decades; as of 2018, value is the most popular smart beta strategy in the U.S. by assets under management.[2] In addition, size- and value-based stock style indices, such as the Russell 2000 Growth index, have been widely used in investment performance evaluation (Cremers, Petajisto, and Zitzewitz, 2013).[3]

However, since the original Fama and French (1992) paper, researchers incessantly debated how to interpret movements in these factors. Some researchers argue that factor movements are fundamental, reflecting either cash flow variation or rational time-varying risk premium (Fama and French, 1992, 1995; Gomes, Kogan, and Zhang, 2003; Zhang, 2005; Berk, Green, and Naik, 1999; McQuade, 2018). In his presidential address to the American Finance Association, John Cochrane argues that the very *existence* of factor structures automatically suggests rational, fundamental-based explanations:

> *Behavioral ideas ... do not easily generate this kind of coordinated movement across all assets that looks just like a rise in risk premium.*

At the same time, other researchers argue that factor movements reflect non-fundamental price pressures arising from large, correlated trading at the factor-level (Lakonishok, Shleifer, and Vishny, 1994; Gompers and Metrick, 2001; Barberis and Shleifer, 2003; Kozak, Nagel, and Santosh, 2018; Koijen and Yogo, 2019). After countless papers on these factors, there is still no consensus about whether they represent fundamental risk and why their premia changes over time.[4]

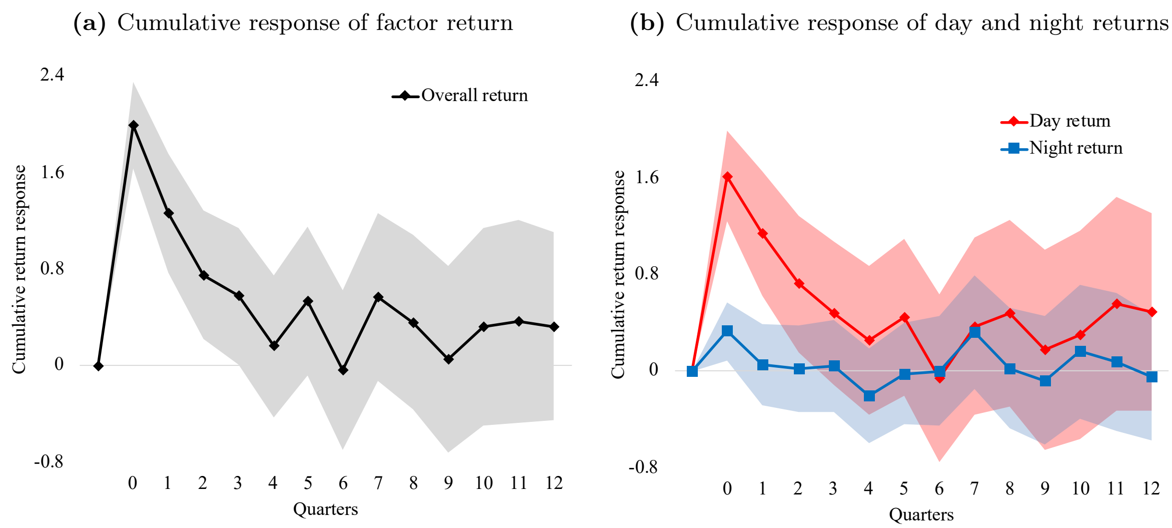
[2] See Exhibit 6 in Morningstar (2019). As for the size factor, Dimensional Fund Advisors have long provided funds that focus on small capitalization stocks.

[3] Mukhlynina and Nyborg (2020) show that some investment professionals use the Fama-French three factor model in valuation.

[4] A number of papers document time-variation in size and value factor premia (Cohen, Gompers, and Vuolteenaho, 2002; Greenwood and Hanson, 2012; Ilmanen, Israel, Moskowitz, Thapar, and Wang, 2019; Haddad, Kozak, and Santosh, 2020). See Fama and French (2020) for a recent discussion on the decline of value premium after 1991.

In this paper, I show novel evidence supporting the latter view: style-level mutual fund flows cause price pressures and reversions in the size and value factors, explaining over 40% of annual factor return variation. Since 1980, investors frequently reallocated capital across mutual funds of different size and value styles in a correlated fashion. Because fund managers trade stocks in response to flows, this led to large time-varying demand fluctuations in the stock factors. As shown in Panel (a) of Figure 1, these demand shocks create large price pressures that revert over the subsequent years. Further corroborating the price pressure interpretation, the flow-induced price movements happen exclusively in intraday (open to close) returns, but not overnight (close to open) returns, consistent with the fact that mutual funds tend to place trades during market open hours. Overall, my results imply that close to half of size and value factor movements are temporary price pressures and thus do not reflect fundamental risk.

Figure 1. Fund Flow-Induced Price Pressures in Factor Returns.
This figure shows the cumulative size and value factor return responses to mutual fund flow-induced trading. Panel (a) plots the cumulative response estimated on both factors together. In response to each 1% of in (out) flows, factor return is higher (lower) by approximately 2%, followed by complete reversal over the subsequent one to two years. Panel (b) plots the separate responses of day (open to close) and night (close to open) returns to flows. The shaded areas are two standard error bands. Estimation details of Panels (a) and (b) appear in Sections 2.3 and 3.3, respectively.



The empirical exercises proceed in three parts. In the first part, I show that fund flows generate large factor-level price pressures. Throughout the sample from 1980 to 2018, mutual fund flows are not idiosyncratic but highly correlated at the factor-level.[5] For instance, during the dotcom boom period of 1998Q2 to 2000Q1, mutual fund investor shifted their money into large cap-growth funds. As a result of these flows, mutual fund demand of growth stocks during this period was \$185 billion higher than value stocks, and the demand of large cap stocks was \$184 billion higher than small cap stocks. This resulting net trading in the value and size factors amounted to a total of 3.1% of the average U.S. stock market capitalization over this period.

These flows create large temporary price pressures in factors. Following Lou (2012), I compute flow-induced trading (FIT) in factors where FIT is defined as the non-discretionary trading by funds in response to flows. For both factors, FIT appear to generate substantial price pressures. One standard deviation of quarterly FIT generates contemporaneous factor returns of 2.88% to 3.78%, all of which reverses in the subsequent one to two years. These flow-induced price movements are several times larger than the unconditional quarterly premium of size and value factors which are only 0.28% and 0.77%, respectively, in my sample period, flow-induced price pressures can explain 47.1% of the overall variation in annual factor returns.

These factor-level findings are not simply repackaging the known fact that flows generate stock-level price pressures (Coval and Stafford, 2007; Lou, 2012). To see this, I follow Fama and French (1995) to perform a split-sample exercise. I randomly split stocks into two disjoint samples and use one to measure factor-level FIT and the other to construct factor returns. If price pressures only happen at the stock-level, we should not find relationships between the two. However, I find that factor-level FIT from one sample still robustly explains price pressures in the other sample.

In the second part, I tackle alternative hypotheses. While my findings are consistent with price pressures, I have not ruled out the possibility that there may be some other state variables driving both flows and returns. Asset pricing theory provides a rich set of possible state variables such as time-varying risk aversion Campbell and Cochrane (1999), cash flow growth risk Bansal and Yaron (2004), volatility Campbell, Giglio, Polk, and Turley (2018), disaster risk Gabaix (2012), intermediary constraints He and Krishnamurthy (2013), and so on. If the dependence of flows and returns on those state variables work out in a fortuitious way, all my findings can be explained even

[5] The mutual fund industry has long categorized equity funds along size and value dimensions. Morningstar, the dominant mutual fund investment advice provider, has used a 3×3 style-box box to classify funds along size and value dimensions since 1992. See `https://awgmain.morningstar.com/webhelp/glossary_definitions/mutual_fund/glossary_mf_ce_Equity_Style_Box.html`.

if flows do not directly cause price movements.

Because the state variables can be unspecified and unobservable, at first glance, this set of hypotheses seem impossible to test. However, there is an additional prediction about price pressures that is difficult to generate under these alternative hypotheses. Existing literature suggests that mutual funds tend to trade during market open hours and thus their trading primarily affect day (open to close) returns but not night (close to open) returns (Cushing and Madhavan, 2000; Lou, Polk, and Skouras, 2019; Bogousslavsky and Muravyev, 2019).[6] I also present further evidence that mutual fund trading impact day but not night returns throughout my sample period. Therefore, if the flow-induced factor movements are indeed price pressures, we should expect the effects to primarily show up in day returns.

After decomposing factor returns into day and night components, I verify that the flow-induced price pressures indeed happen primarily during the day. This is shown in Panel (b) of Figure 1, and is inconsistent with the alternative hypotheses. All the aforementioned state variables in alternative hypotheses tend to be slow-moving and do not generate differential predictions on day versus night returns.

The last part of the empirical exercise investigates the drivers of factor-level flows. Prior papers find that mutual fund flows tend to chase past fund returns and Morningstar ratings (Chevalier and Ellison, 1997; Coval and Stafford, 2007; Guercio and Tkac, 2008; Reuter and Zitzewitz, 2017; Evans and Sun, 2018; Ben-David, Li, Rossi, and Song, 2019). Following those papers, I use a panel regression to isolate the component of fund flows that can be explained by lagged fund returns and Morningstar ratings, and then examine how much of factor-level FIT variation can be explained by this component. One may anticipate that the explanatory power is low because, at the fund-level, return- and rating-chasing can only explain around 2% of flow variation. However, it turns out that much of fund-level flows are idiosyncratic and wash out at the factor-level. When aggregated at the factor-level, return- and rating-chasing can explain a substantial fraction of of annual flow variation (35 - 41%).

The main contribution of this paper is showing that close to half of size and value factor movements are non-fundamental price pressures. A secondary contribution is the development of a novel

[6] It is worth clarifying that while mutual fund *investors* can purchase and redeem mutual fund shares when markets are closed, the stock trading by mutual fund *managers* primarily happens during market hours.

way – using day versus night returns – to examine whether mutual fund flows create price pressures. In recent years, fund flows have been frequently used as mispricing instruments (Edmans, Goldstein, and Jiang, 2012; Khan, Kogan, and Serafeim, 2012; Dong, Hirshleifer, and Teoh, 2019). However, Wardlaw (2020) points out that some flow measures are incorrectly specified and lead to spurious findings. While his criticism does not apply to the fund flow measure in my paper, it is helpful for future researchers to have an independent way to test the validity of specific fund flow constructions.

This paper is related to a rich literature that demonstrates the effect of demand in prices. One stream of this literature uses stock index inclusion event studies (Shleifer, 1986; Harris and Gurel, 1986; Kaul, Mehrotra, and Morck, 2000; Wurgler and Zhuravskaya, 2002; Greenwood, 2005; Chang, Hong, and Liskovich, 2014), and another stream examines mutual fund and ETF flows (Coval and Stafford, 2007; Lou, 2012; Brown, Davies, and Ringgenberg, 2019). Frazzini and Lamont (2008) and Song (2017) show that mutual fund investors experience lower returns due to their reallocation of money across funds. In addition to stock price-based evidence, researchers have also found demand effects in options, government bonds, and corporate bonds (Garleanu, Pedersen, and Poteshman, 2008; Krishnamurthy and Vissing-Jorgensen, 2012; Greenwood and Vayanos, 2014; Choi, Hoseinzade, Shin, and Tehranian, 2020). Greenwood and Thesmar (2011) and Cella, Ellul, and Giannetti (2013) show that selling pressure by institutions lead to price fragility. Recently, Koijen and Yogo (2019) develop a structural approach to estimate the impact of institutional demand on asset prices.

The findings in this paper are consistent with the style investing hypothesis in Barberis and Shleifer (2003). A number of papers have shown evidence of style-level return momentum, reversals, and excess comovement consistent with this hypothesis (Teo and Woo, 2004; Froot and Teo, 2008; Wahal and Yavuz, 2013). Using daily data in Israel, Ben-Rephael, Kandel, and Wohl (2011) show that market-level flows to equity funds create short-term price pressures. Ben-Rephael, Kandel, and Wohl (2012) argues that aggregate net exchanges of equity funds represent proxies for market level sentiment and can explain aggregate market returns and reversals. A contemporaneous paper by Huang, Song, and Xiang (2019) also documents that flows explain size and value factor movements.[7]

[7] The first draft of my paper was posted on SSRN Feb 2 2017. Huang et al. (2019) first appeared on SSRN on Jan 20, 2019.

My paper adds to the existing literature by quantifying the large explanatory power of price pressures and by developing a novel approach to establish the price pressure interpretation.

Finally, this paper is also related to recent papers that aim to understand the difference between intraday and overnight returns (Cliff, Cooper, and Gulen, 2008; Berkman, Koch, Tuttle, and Zhang, 2012; Lou et al., 2019; Bogousslavsky and Muravyev, 2019; Hendershott, Livdan, and Rösch, 2020). While some of these papers examine differences in *average* factor returns during day versus night, my paper differs by focusing on explaining the *variation* of factor returns.

The rest of the paper proceeds as follows. Section 2 documents flow-induced price pressures in the size and value factors. Section 3 considers alternative hypotheses and tests the price pressure interpretation using day and night returns. Section 4 quantifies how much of factor-level flows can be explained by return- and rating-chasing. Section 5 concludes.

2 Factor-level Flows and Price Pressures

2.1 Data and Measures

Mutual fund flows. I obtain quarterly mutual fund return and flows of U.S. domestic equity funds from the CRSP survivorship bias-free mutual fund database. I use MFLINKS to group the CRSP share classes together at the fund level (Wermers (2000)). Fund flows are calculated as:

$$\text{Flow}_{j,t} = \frac{\text{TNA}_{j,t} - \text{TNA}_{j,t-1} \cdot (1 + \text{Ret}_{j,t})}{\text{TNA}_{j,t-1}} \tag{1}$$

where $\text{Ret}_{j,t}$ is the post-fee return of fund j in quarter t and $\text{TNA}_{j,t}$ is total net assets at the end of quarter t.[8]

Flow-Induced Trading in Stocks. Mutual funds approximately buy (or sell) their existing portfolios holdings in equal proportion when facing in (out) flows. To estimate this component of non-discretionary fund flow-induced trading, I follow Lou (2012) to calculate Flow-Induced Trading

[8] Note that this definition of fund flow is not subject to the critique in Wardlaw (2020).

(FIT) for each stock i in each quarter t as

$$\text{FIT}_{i,t} = \frac{\sum_{\text{fund } j} \text{SharesHeld}_{i,j,t-1} \cdot \text{Flow}_{j,t}}{\sum_{\text{fund } j} \text{SharesHeld}_{i,j,t-1}} \tag{2}$$

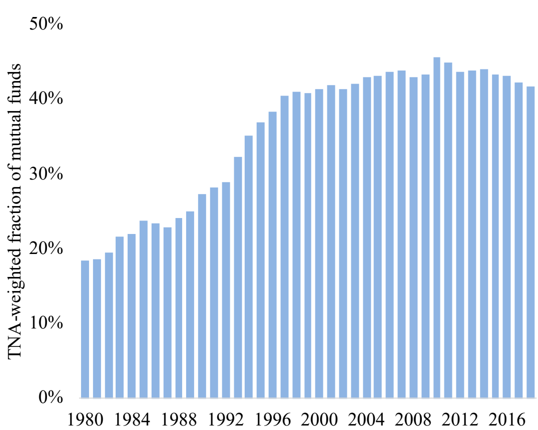
where $\text{SharesHeld}_{i,j,t-1}$ is the split-adjusted number of shares of stock i held by fund j at the end of quarter $t-1$. Mutual fund holdings data are obtained from Thomson Reuters S12.[9]

Summary statistics. Summary statistics of fund flows and FIT appear in Table 1. Over the sample period, the importance of the mutual fund sector in the U.S. equity market steadily increased, as the fraction of market held by mutual funds rose from 2.2% in 1980 to 22.9% in 2018. The sample covers a total of 7,474 unique funds and 317,677 fund-quarters. There is substantial variation of FIT across stocks and the average interquartile range of FIT across all quarters is 4.98%.

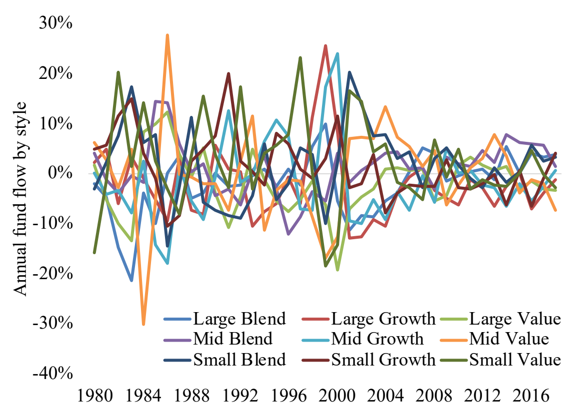
2.2 Factor-level Flow-Induced Trading

Figure 2. The Importance of Size- and Value-Related Styles in Mutual Funds. Panel (a) plots the TNA-weighted fraction of domestic equity mutual funds with style-related terms (e.g., "small cap", "growth") in their fund names. Panel (b) plots the annual fund flows for the 3 × 3 styles based on Morningstar style boxes. The flows are demeaned by year to focus on cross-sectional dispersion.

(a) Fraction of funds with style-related names



(b) Annual mutual fund flows by Morningstar style



If mutual fund flows are idiosyncratic, the induced trading demand in stocks should wash out at

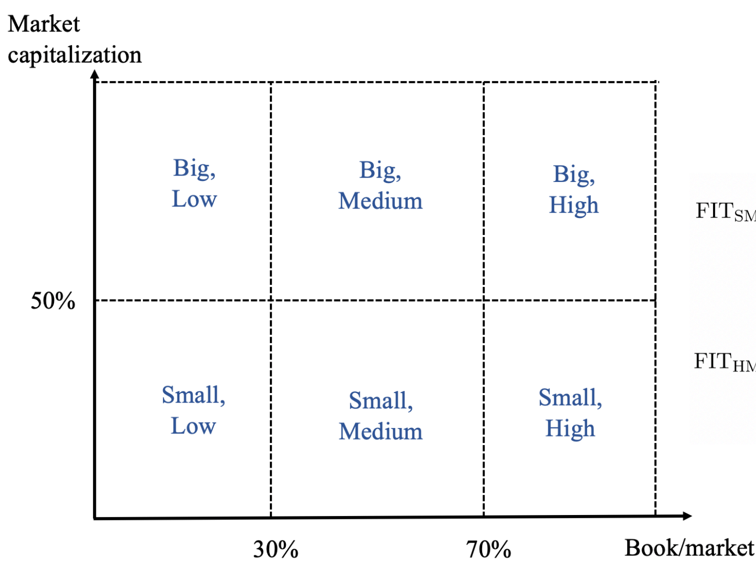
[9]In calculating FIT, the original Lou (2012) paper applies slightly different scaling coefficients for in flows and out flows. Because the factor-level results are barely affected by this, for simplicity, I use the same scaling factor of 1 for all flows.

Table 1. Summary Statistics of Mutual Funds and Flow-Induced Trading (FIT). This table summarizes the sample of 1980 to 2018, constructed by joining U.S. domestic equity funds in CRSP with the fund holdings in Thomson Reuters S12. FIT is defined as the non-discretionary trading in stocks induced by fund managers proportionally expanding or contracting their existing holdings in response to fund flows (Lou, 2012).

Year	Mutual Fund Data				Flow Induced Trading (FIT)			
	Num	AUM ($ million)		Fraction of	Num	Quarterly FIT distribution		
	Funds	Median	Mean	Total Market	Stocks	25%	50%	75%
1980	299	50.9	144.4	2.2%	1,969	-3.5%	-1.3%	2.2%
1981	301	54.4	138.2	2.2%	2,284	-2.4%	-0.6%	2.6%
1982	305	71.6	175.6	2.3%	2,300	-1.4%	1.0%	5.6%
1983	351	91.4	217.6	2.6%	2,655	-0.2%	3.2%	9.1%
1984	364	85.6	222.7	2.9%	2,950	-1.4%	1.6%	5.6%
1985	387	108.4	283.8	3.4%	3,382	-1.9%	1.6%	6.6%
1986	458	93.4	309.0	3.9%	4,150	-2.5%	0.7%	5.0%
1987	533	86.8	293.2	4.6%	3,991	-4.1%	0.1%	4.9%
1988	582	82.5	294.2	4.8%	4,263	-3.1%	-1.3%	0.7%
1989	659	86.9	339.3	4.9%	4,183	-2.3%	-0.7%	1.7%
1990	726	78.8	304.6	5.3%	4,035	-3.7%	-1.0%	1.7%
1991	843	99.2	401.0	6.0%	3,955	-1.4%	1.5%	4.6%
1992	980	109.7	456.5	6.7%	4,253	-0.2%	2.6%	6.2%
1993	1,290	110.4	514.1	8.1%	5,126	0.2%	3.0%	6.9%
1994	1,462	97.3	492.0	9.3%	5,906	0.0%	2.3%	5.8%
1995	1,557	129.3	677.1	11.1%	6,271	0.9%	3.2%	6.8%
1996	1,737	139.8	810.7	12.2%	6,809	0.9%	3.7%	7.5%
1997	1,955	147.9	985.7	13.4%	7,063	0.2%	2.9%	6.4%
1998	2,276	137.3	1,060.8	14.3%	7,170	-2.1%	0.4%	3.2%
1999	2,575	155.3	1,244.6	16.2%	6,900	-5.1%	-1.7%	1.6%
2000	2,964	137.2	1,097.0	15.5%	6,926	-1.6%	1.4%	5.2%
2001	3,094	117.8	914.2	16.6%	6,245	-0.3%	2.0%	5.0%
2002	3,174	96.3	708.8	17.0%	5,725	-1.0%	1.4%	5.2%
2003	3,210	137.3	955.3	17.6%	5,348	0.9%	3.9%	6.9%
2004	3,174	160.6	1,142.9	18.2%	5,278	-0.1%	2.0%	4.2%
2005	3,257	177.9	1,251.0	18.7%	5,237	-1.4%	0.3%	2.3%
2006	3,101	226.9	1,515.7	18.9%	5,154	-1.1%	0.6%	2.9%
2007	3,520	194.4	1,457.0	19.2%	5,136	-2.1%	-0.4%	1.4%
2008	3,867	107.7	838.2	19.8%	4,915	-2.5%	-0.8%	1.5%
2009	3,673	157.4	1,124.4	20.8%	4,585	-1.4%	0.4%	3.2%
2010	3,384	211.8	1,374.1	20.0%	4,410	-1.5%	0.1%	1.8%
2011	3,536	199.8	1,296.3	19.1%	4,243	-2.4%	-0.8%	1.1%
2012	3,374	226.9	1,499.8	19.6%	3,602	-2.0%	-0.7%	0.7%
2013	3,405	298.4	1,986.5	20.5%	3,963	-0.3%	1.3%	3.3%
2014	3,563	286.3	2,106.7	20.8%	3,990	-1.6%	0.0%	1.8%
2015	3,768	242.8	1,967.5	21.5%	4,128	-1.7%	-0.4%	1.0%
2016	3,870	234.0	2,080.3	22.6%	3,876	-1.9%	-0.5%	1.1%
2017	3,849	256.8	2,512.4	22.6%	3,898	-1.1%	-0.1%	1.0%
2018	3,645	248.0	2,460.5	22.9%	3,879	-0.7%	0.4%	2.1%

the factor-level. However, there is reason to suspect that flows contain large size and value factor components. First, mutual funds have long been classified into size and value-based style categories. Since 1992, Morningstar — the leading mutual fund investment advisor — has classified funds using the 3×3 size-value style box. Even before then, an average of 23% of funds had explicit mentions to size and value-related investment styles in their fund names, and that increased to 44% by 2010, as shown in Panel (a) of Figure 2. Second, investors often reallocate significant amount of capital across styles. Panel (b) of Figure 2 plot the annual fund flows in the 3×3 Morningstar fund styles. It is not uncommon for style-level flows to reach 10% or even 20% in a given year.[10]

Figure 3. Computing Flow-Induced Trading (FIT) for Fama-French Factors.
I follow the Fama-French procedure to sort stocks into 2×3 portfolios using lagged market capitalization and book-to-market ratios of NYSE stocks. After sorting, I compute the value-weighted FIT for each of the 2×3 portfolios, and then aggregate them into size and value factors as long-short portfolios following the equations on the right.



$$\mathrm{FIT}_{\mathrm{SMB}} = \frac{\mathrm{FIT}_{\text{small, high}} + \mathrm{FIT}_{\text{small, medium}} + \mathrm{FIT}_{\text{small, low}}}{3} - \frac{\mathrm{FIT}_{\text{big, high}} + \mathrm{FIT}_{\text{big, medium}} + \mathrm{FIT}_{\text{big, low}}}{3}$$

$$\mathrm{FIT}_{\mathrm{HML}} = \frac{\mathrm{FIT}_{\text{small, high}} + \mathrm{FIT}_{\text{big, high}}}{2} - \frac{\mathrm{FIT}_{\text{small, low}} + \mathrm{FIT}_{\text{big, low}}}{2}$$

I now compute quarterly Flow-Induced Trading (FIT) for the Fama-French size and value factors. As a reminder of their methodology, stocks are sorted into 2×3 portfolios using NYSE break points of market capitalization and book-to-market ratios (Figure 3). The market-cap break point is the 50^{th} percentile while the book-to-market break points are the 30^{th} and 70^{th} percentiles.[11] I then compute value-weighted average FIT for each of the 2×3 portfolios, and them compute FIT for

[10] Because Morningstar style assignments started in 1986, the styles during the first few years of the sample are back-filled.

[11] For the 24% of stocks (only 2.7% if value-weighted) without FIT data, I assume that FIT equals zero.

size and value factors as long-short factors:

$$\text{FIT}_{\text{SMB},t} = \frac{\text{FIT}_{\text{small, high},t} + \text{FIT}_{\text{small, medium},t} + \text{FIT}_{\text{small, low},t}}{3} - \frac{\text{FIT}_{\text{big, high},t} + \text{FIT}_{\text{big, medium},t} + \text{FIT}_{\text{big, low},t}}{3} \tag{3}$$

$$\text{FIT}_{\text{HML},t} = \frac{\text{FIT}_{\text{small, high},t} + \text{FIT}_{\text{big, high},t}}{2} - \frac{\text{FIT}_{\text{small, low},t} + \text{FIT}_{\text{big, low},t}}{2} \tag{4}$$

Figure 4 plots the factor-level FIT against the factor returns at an annual frequency. The flows are large and persistent. For instance, during the dotcom boom of 1998Q2 to 2000Q1, mutual fund investor bought into large cap-growth funds, and their reallocation led to net trading of \$185 billion out of the value factor and \$184 billion out of the size factor. This amounts to a total of -3.1% of the average U.S. stock market capitalization over this period. The size and value return factors also returned negatively during this period of time. After being burned by the dotcom bust, investors changed to favoring small cap and value funds instead, and the flows reversed directions until the financial crisis in late 2007.

2.3 Factor-Level Price Pressures and Reversals

As can be seen from Figure 4, the FIT into factors are highly correlated with factor returns. At the quarterly frequency, correlation is 51% for the size factor and 35% for the value factor. Whether this reflects price pressures, however, depends on whether the flow-induced price movements revert subsequently. To estimate the dynamic effect of FIT, I estimate a panel regression on both factors:

$$\text{Ret}_{f,t} = b_0 \cdot \text{FIT}_{f,t} + b_1 \cdot \text{FIT}_{f,t-1} + ... + b_{12} \cdot \text{FIT}_{f,t-12} + \text{Controls}_{f,t} + \epsilon_{f,t} \tag{5}$$
$$\text{where factor } f \in \{\text{size, value}\}$$

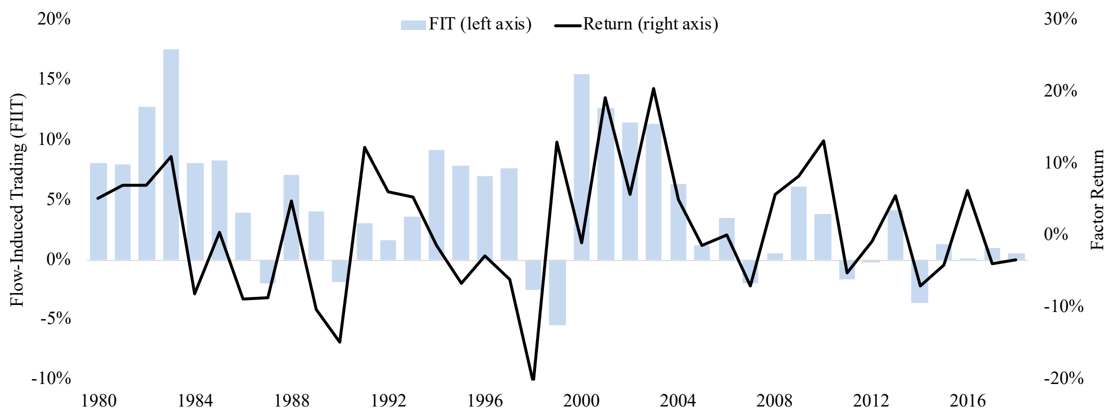
where the controls include 12 lags of factor returns and factor fixed effects.[12]

The results are shown in specification (1) of Table 2. In response to 1% of FIT, factor return responds by 1.99% contemporaneously, followed by strong reversions in the subsequent year. The

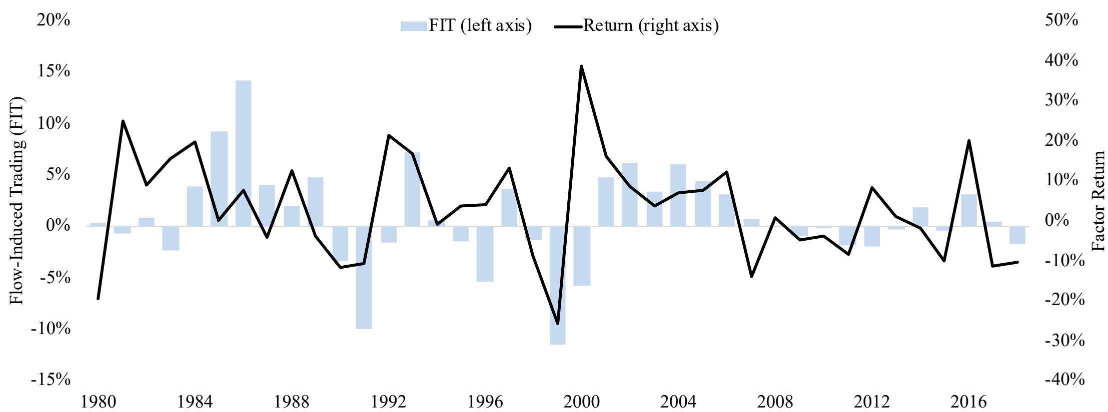
[12]To properly account for the changes in factor portfolio composition, the independent variables are constructed to align with the quarter t factor composition. That is, $\text{FIT}_{f,t-k}$ uses stock-level FIT from quarter $t-k$, but whether each stock belongs to the long or short side of a factor is determined by the quarter t factor definition. The composition of size factor changes relatively slowly, but the composition of value factor changes substantially over time. The results, however, are also robust to not taking into account this composition change.

Figure 4. Flow-Induced Trading (FIT) in Size and Value Factors.
The blue bars represent annual flow-induced trading (FIT) in the Fama-French factors while the black lines show the annual factor return realizations. FIT is defined as the non-discretionary trading in stocks induced by fund managers proportionally expanding or contracting their existing holdings in response to fund flows.

(a) Size Factor



(b) Value Factor



result is also similar when estimating the regression on the two factors separately, and those results are reported as specifications (2) and (3). To visualize the cumulative price path, Panels (a) and (b) of Figure 6 plot the cumulative return response to FIT ($\hat{b}_0, \hat{b}_0 + \hat{b}_1, ...$). Panel (a) plots the estimate using both factors and Panel (b) plots the separate estimates for each factor. In both cases, the price movements reverse entirely after one to two years, although the standard errors are wider when estimating two factors separately.

The effect on factors is not just statistically significant but also economically significant. Over the sample period, the unconditional quarterly premia of size and value are 0.28% and 0.77%,

Table 2. Flow-Induced Price Pressures in Factors.
I estimate panel regressions of quarterly factor returns on contemporaneous and 12 lags of factor FIT (flow-induced trading). I control for lagged factor returns. Specification (1) is estimated using the data of both factors and also controls for factor fixed effects. Specifications (2) and (3) are estimated using the data of the two factors separately.

	Dependent variable: Factor Return					
Sample:	Both factors		Size factor		Value factor	
	Independent variables:					
	FIT	Return	FIT	Return	FIT	Return
Lag	(1)		(2)		(3)	
0	1.99***		1.65***		2.42***	
	(0.18)		(0.19)		(0.37)	
1	−0.73***	0.03	−0.83***	0.06	−0.55	−0.05
	(0.22)	(0.06)	(0.25)	(0.08)	(0.44)	(0.08)
2	−0.51**	0.03	−0.44*	0.14*	−0.47	−0.07
	(0.23)	(0.05)	(0.26)	(0.08)	(0.42)	(0.08)
3	−0.18	−0.06	−0.16	0.01	−0.13	−0.10
	(0.22)	(0.04)	(0.27)	(0.08)	(0.40)	(0.06)
4	−0.42*	0.04	−0.27	0.16*	−0.78*	−0.02
	(0.22)	(0.05)	(0.28)	(0.09)	(0.43)	(0.06)
5	0.37	−0.08*	0.43	−0.08	0.37	−0.10
	(0.23)	(0.05)	(0.28)	(0.09)	(0.47)	(0.07)
6	−0.57**	0.05	−0.70**	0.04	−0.04	0.02
	(0.25)	(0.06)	(0.28)	(0.09)	(0.54)	(0.08)
7	0.61**	−0.06	0.34	0.17*	0.63	−0.19**
	(0.26)	(0.06)	(0.29)	(0.09)	(0.58)	(0.09)
8	−0.21	−0.05	−0.21	0.12	−0.15	−0.13
	(0.27)	(0.06)	(0.30)	(0.09)	(0.62)	(0.10)
9	−0.31	0.01	−0.10	0.03	−0.73	−0.02
	(0.28)	(0.07)	(0.30)	(0.09)	(0.64)	(0.11)
10	0.27	−0.02	0.57*	−0.05	0.35	−0.05
	(0.29)	(0.07)	(0.31)	(0.09)	(0.65)	(0.11)
11	0.04	−0.06	0.04	−0.13	0.04	−0.07
	(0.29)	(0.07)	(0.31)	(0.09)	(0.69)	(0.11)
12	−0.05	0.10	−0.24	0.09	0.28	−0.03
	(0.26)	(0.07)	(0.27)	(0.09)	(0.59)	(0.10)
Factor fixed effect	Yes		N/A		N/A	
No. obs	288		144		144	
Adjusted R^2	36.0%		43.6%		35.3%	
Marginal Adj R^2 of FIT	34.2%		43.1%		27.0%	

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

respectively. The price impact estimate in specification (1) implies that, if contemporaneous FIT is lower by one standard deviation, then quarterly factor return will be lower by 3.76% in size and 2.96% in value. This is several times larger than the unconditional premium.[13] In terms of R^2, in specification (1), the explanatory power of 36.0% almost entirely comes from the FIT whose marginal R^2 is 34.2%.[14]

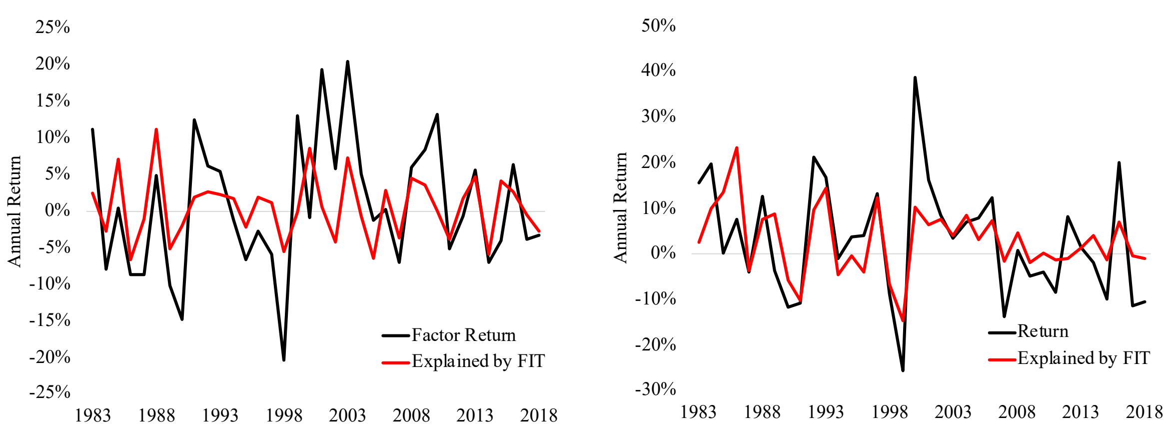
To visualize the explanatory power on factor returns, I compute the returns spanned by FIT:

$$\widehat{\text{Ret}}_{f,t}^{\text{explained}} = \hat{b}_0 \cdot \text{FIT}_{f,t} + \hat{b}_1 \cdot \text{FIT}_{f,t-1} + ... + \hat{b}_{12} \cdot \text{FIT}_{f,t-12} \tag{6}$$

where the estimated coefficients $\hat{b}_0, ..., \hat{b}_{12}$ come from specification (1) in Table 2. I then plot the explained against actual factor returns at an annual frequency in Figure 5. Clearly, FIT can explain a high fraction of factor returns except a few episodes, most notable of which is the dotcom boom and bust period of 1998 – 2002. Because flows are persistent at the quarterly frequency (Figure 12 in the Appendix), when aggregated to the annual frequency, the explanatory power of $\widehat{\text{Ret}}_{f,t}^{\text{explained}}$ on actual factor returns further increases to 47.1%.

Figure 5. Explanatory Power of Flows on Factor Returns.
These panels plot annual factor returns that is spanned by Flow-Induced Trading (red lines), as estimated in regression (6), against actual factor returns (black lines).

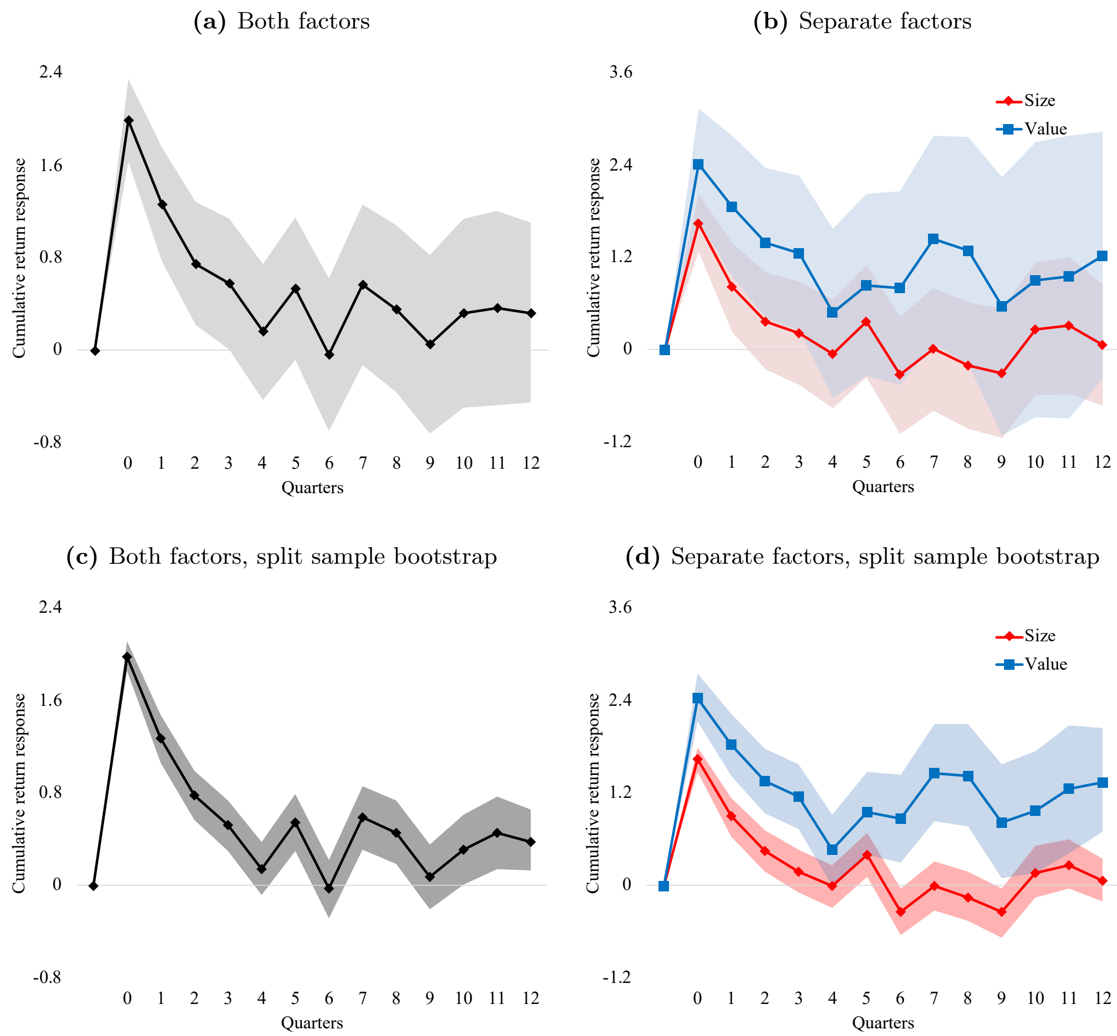
(a) Size factor **(b)** Value factor



[13] One standard deviation of quarterly FIT is 1.89% in size factor and 1.49% in value factor.

[14] In appendix A.1, I show that the results here are robust to using any combinations of factor and time fixed effects. In all those specifications, price pressures appear to revert fully after eight quarters.

Figure 6. Cumulative Factor Return Responses to Flow-Induced Trading (FIT). The four panels plot the cumulative response of factor returns to FIT. For instance, Panel (a) shows that, in response to each 1% of flows, contemporaneous factor returns change by around 2%, followed by complete reversal in the subsequent quarters. The response coefficients are estimated using panel regressions (equation (6)). Panels (a) and (c) are estimated using both factors and Panels (b) and (d) use size and value factor separately. The shaded areas are two standard error bands. In Panels (a) and (b), factors are formed using all stocks. In Panels (c) and (d), stocks are randomly split into equal-size samples A and B to create A-sample- and B-sample-based factors. I then estimate the responses of A-sample (or B-sample) factor return to B-sample (or A-sample) FIT. The shaded areas represent 95% distribution of the point estimates from 1,000 repetitions of this split-and-estimate procedure.



2.4 Are These Truly *Factor-Level* Price Pressures?

I interpret the results so far as systematically correlated fund flows generating *factor-level* price pressures. However, one may question whether this is merely a repackaging of the known fact that fund flows create price pressures at the individual *stock-level* (Coval and Stafford, 2007; Lou, 2012). To put it more bluntly: if flows generate price pressures in each individual stock, wouldn't one expect to find the same pattern in any stock portfolios?

To investigate whether the price pressures are truly at the factor-level, I follow Fama and French (1995) to use a split-sample procedure. In each quarter, I randomly split stocks into two equal-size disjoint samples A and B, and then construct factor FIT from sample A (or B) and factor return from sample B (or A). I then modify regression (6) to estimate whether FIT from one sample can explain factor returns from the other sample:

$$\text{Ret}_{f,t}^{\text{sample A}} = b_0^{B\to A} \cdot \text{FIT}_{f,t}^{\text{sample B}} + ... + b_{12}^{B\to A} \cdot \text{FIT}_{f,t-12}^{\text{sample B}} + \text{Controls}_{f,t}^{\text{sample A}} + \epsilon_{f,t}^{\text{sample A}}, \quad (7)$$

$$\text{Ret}_{f,t}^{\text{sample B}} = b_0^{A\to B} \cdot \text{FIT}_{f,t}^{\text{sample A}} + ... + b_{12}^{A\to B} \cdot \text{FIT}_{f,t-12}^{\text{sample A}} + \text{Controls}_{f,t}^{\text{sample B}} + \epsilon_{f,t}^{\text{sample B}}. \quad (8)$$

where control variables include factor fixed effects and lagged factor returns.

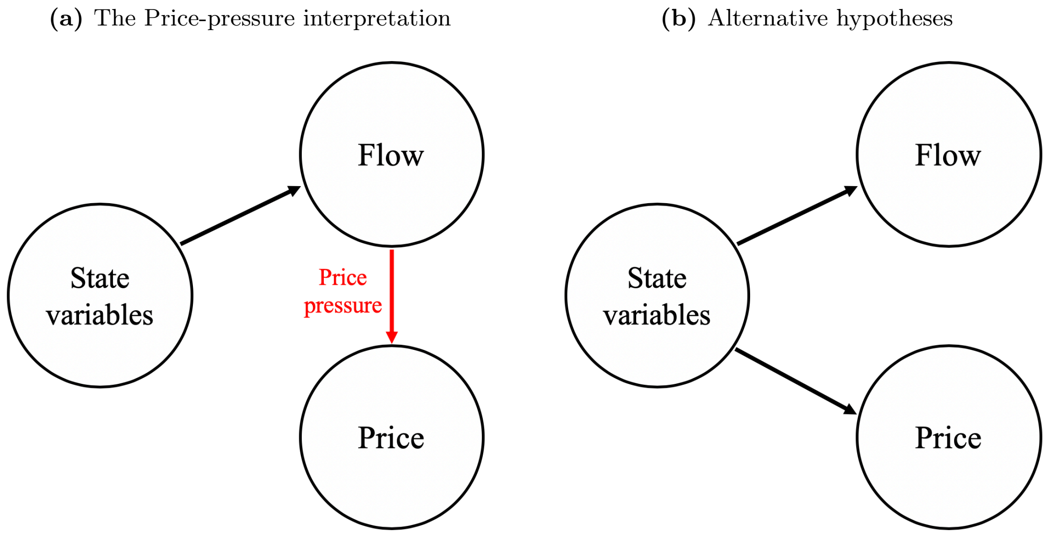
If the flow-induced price pressures only exist at the stock-level, because the two samples are disjoint, we should expect no effects. However, I repeat this split-and-estimate procedure 1,000 times and plot the average cumulative response functions in Panels (c) and (d) in Figure 6. The shaded areas are 95% confidence interval of the point estimates. The results are very similar to that in Panels (a) and (b), indicating that the price pressures are truly at the factor-level.

3 Intraday versus Overnight Evidence of Price Pressures

How confident should we be about the price pressure interpretation? My arguments so far are not different from the existing literature (Teo and Woo, 2004; Coval and Stafford, 2007; Ben-Rephael et al., 2011; Lou, 2012; Ben-Rephael et al., 2012). First, fund flows reflect trading by mutual fund investors who are predominantly retail and have been found to exhibit various unsophisticated behavior.[15] Second, the flows appear to generate contemporaneous price movements that revert over time, which is exactly what one would expect under the price pressure interpretation. For someone sympathetic to the non-fundamental view of factors, this might already be sufficiently convincing.

[15] As of 2020, households control 89% of mutual fund assets Institute (2020). Frazzini and Lamont (2008) document that mutual fund investors lose close to 1% of return due to their reallocate across funds even when not accounting for transaction costs.

Figure 7. Illustration of Alternative Hypotheses.
The arrows represent causal relationships between variables. Panel (a) illustrates the price pressure interpretation in this paper: flows directly cause price pressures (red arrow). Panel (b) illustrates the alternative hypotheses. Due to the dependence on common state variables, flows and prices will appear to be related, but flows do not directly cause price movements.



However, researchers have also proposed many rational explanations of the size and value factors, and it is immediately possible to come up with more (Gomes et al., 2003; Zhang, 2005; Berk et al., 1999; McQuade, 2018). Thus, in this section, I examine whether my findings can be explained by alternative hypotheses that do not involve price pressures.

3.1 What Are the Alternative Hypotheses?

Most alternative hypotheses fall under the “common state variable” formulation: both flows and prices may be driven by some state variables. This is illustrated by the diagram in Panel (b) of Figure 7: flows do not directly cause price movements. Rather, flows and returns both depend on common state variables. If the dynamic dependence work out in a fortuitous way, then all the aforementioned results can be explained.

There are many possible state variables proposed in the theoretical asset pricing literature, and many of them are difficult to measure. For instance, such variables can reflect time-varying preferences (Campbell and Cochrane, 1999), long-run cash flows (Bansal and Yaron, 2004), volatility Campbell et al. (2018), disaster risk (Gabaix, 2012), intermediary capital constraints (He and

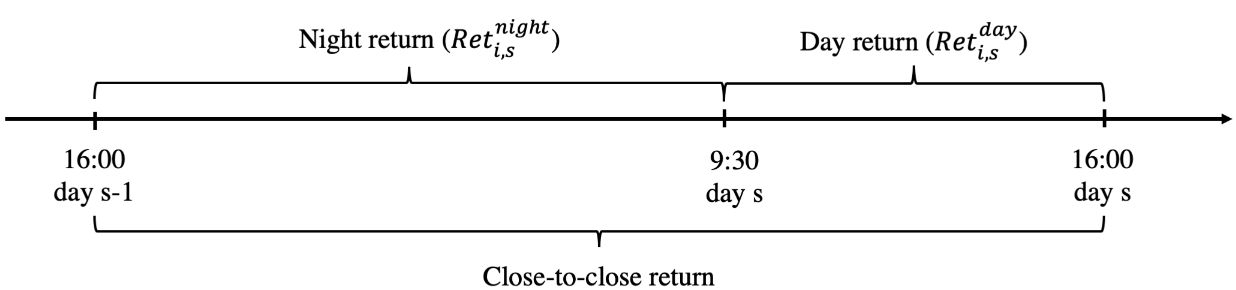
Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), and so on.

3.2 Identification Approach: Mutual Funds Trading Exerts More Price Impact During the Day

At first glance, these alternative hypotheses seem irrefutable as the state variables can be unspecified and unobservable. When facing such generic alternative hypotheses, the standard approach in causal identification is to focus on a subset of data where the source of variation is "cleaner" (Angrist and Pischke, 2008). However, this does not fit the purpose of this paper: we need to examine whether *most* of the factor movements associated with flows – which is over 40% of overall annual movements – are price pressures, not whether *a small subset* of them are price pressures. Restricting attention to less variation automatically precludes answering the broader question.

Despite the apparently difficulty in identification, more careful examination of the price pressure mechanism generates a further testable prediction that is difficult to reconcile with the alternative hypotheses. Because mutual funds tend to trade during market hours and especially towards the market close, price pressure should primarily happen in the day component of returns (open to close) rather than the night component (open to close). In contrast, the possible state variables in the alternative hypotheses are slow-moving. At a minimum, those mechanisms do not switch on and off at an intraday frequency, so they do not generate differential predictions in day versus night returns.

Figure 8. Illustration: Decomposition of Returns into Day and Night Components.



Testing this prediction critically depends on the assumption that mutual funds exert more price impact on day returns. Is is justified? The existing literature suggests this to be a valid assumption. First, Lou et al. (2019) find that institutional investors tend to exert more impact on day returns. In contrast, retail investors exert more impact on night returns, possibly because retail investors work during market hours and submit trades after market close which are then executed at the subsequent market open. Cushing and Madhavan (2000) and Bogousslavsky and Muravyev (2019) find evidence that many institutions tend to trade around or at the time of market closing and thus contribute to the day component of returns. Second, due to their institutional structure, mutual funds also have incentives to trade closer to market close time because when mutual fund investors redeem shares at net asset values that are based on closing prices.

However, the evidence in the existing literature is about institutions in general. There are many different types of institutions – mutual funds, pension funds, insurance, funds, etc. – and they may all behave differently. Therefore, I now further test whether mutual fund trades appear to have more impact on day but not night returns. As illustrated in Figure 8, I first decompose daily stock returns into day and night components:

$$\text{Ret}_{i,s}^{\text{day}} = \frac{\text{P}_{i,s}^{\text{close}}}{\text{P}_{i,s}^{\text{open}}} - 1, \tag{9}$$

$$\text{Ret}_{i,s}^{\text{night}} = \frac{1 + \text{Ret}_{i,s}^{\text{close-to-close}}}{1 + \text{Ret}_{i,s}^{\text{day}}} - 1, \tag{10}$$

where $\text{Ret}_{i,s}^{\text{close-to-close}}$ is the conventional close-to-close daily return of stock i on day s, while $\text{P}_{i,s}^{\text{open}}$ and $\text{P}_{i,s}^{\text{close}}$ are daily open and close prices.[16] After Trade-And-Quote (TAQ) data becomes available in 1993, I follow Lou et al. (2019) to use the volume-weighted average price during the first and last 30 minutes of trading hours (9:30 - 10:00 and 15:30 - 16:00) to measure open and close prices.[17] For the period before 1993, I use daily open and close prices from Bloomberg.

I obtain mutual fund trades by taking differences in split-adjusted quarterly mutual fund holdings from Thomson Reuters S12. I aggregate all mutual fund trades together at the stock-quarter level:

$$\text{Trade}_{i,\text{quarter } t} = \frac{\sum_{\text{fund } j}(\text{SharesHeld}_{i,j,t} - \text{SharesHeld}_{i,j,t-1})}{\text{SharesOutstanding}_{i,t-1}} \tag{11}$$

where $\text{SharesHeld}_{i,j,t}$ represent the number of shares of stock i held by fund j in quarter t. As controls, I also measure the trades by other 13F institutions in Thomson Reuters S34 and aggregate

[16] Following Lou et al. (2019) and Hendershott et al. (2020), the night return is defined by subtracting the day returns. Thus, dividends are automatically included in the night returns.

[17] My results are robust to using CRSP open and close prices as in Hendershott et al. (2020). Those results are available upon request.

them by the eight legal types in Brian Bushee's classification (Bushee, 2001). The eight types include banks, investment companies, independent investment advisors, insurance, public pension, private pension, endowment funds, and "other miscellaneous types". Because many mutual funds are contained within other 13F institutions, I use the mutual fund-13F mapping table provided by Thomson Reuters (S12 table type5) to subtract off the mutual fund trades from 13F trades. I then use panel regressions to infer whether mutual fund trades are more related to the day component of returns (aggregated at the quarterly frequency):

$$\mathrm{Ret}_{i,t}^{\mathrm{day}} = a^{\mathrm{day}} + b^{\mathrm{day}} \cdot \mathrm{Trade}_{i,t}^{\mathrm{Mutual\ fund}} + \mathrm{Controls}_{i,t} + \epsilon_{i,t}^{\mathrm{day}}, \tag{12}$$

$$\mathrm{Ret}_{i,t}^{\mathrm{night}} = a^{\mathrm{night}} + b^{\mathrm{night}} \cdot \mathrm{Trade}_{i,t}^{\mathrm{Mutual\ Fund}} + \mathrm{Controls}_{i,t} + \epsilon_{i,t}^{\mathrm{night}} \tag{13}$$

where the controls includes trades by the eight other types of 13F institutions. To control for the persistence of day and night returns documented in Lou et al. (2019), the controls also include three years of lagged day and night stock returns. I also control for quarter and stock fixed effects and cluster standard errors by quarter and stock. To focus on more relevant economic magnitudes, observations are weighted by the fraction of stock market cap occupied by each stock in each quarter.[18]

The full-sample regression results in Panel A of Table 3 confirm that mutual fund trades appear to only impact returns during the day. Each 1% of additional mutual fund trading is associated with 0.48% higher contemporaneous day return, but a slightly negative coefficient for the night return. The difference between the day and night coefficients is 0.58 with a t-statistic of 5.8. In Panel B, I split the sample into 5 equal-length periods and estimate the regression in each sub-sample. While the price impact coefficient on day return varies over time, the conclusion that mutual fund trades are only positively associated with day return is robust throughout the 38 year sample.

It is very unlikely that reverse causality can generate these findings. While mutual fund trading can chase returns, such as due to investing in momentum strategies or due to window dressing, existing evidence shows that they chase overall returns (Grinblatt, Titman, and Wermers, 1995; O'Neal, 2001). It is difficult to imagine why they would only chase day returns but not night

[18]This ensures that each quarter is given the same weight despite the overall increase of market cap over time. For instance, in 2018Q1, Apple stock is 2.25% of overall market capitalization. Thus this data point receives a weight proportional to 2.25% in the regression.

Table 3. The Effect of Mutual Fund Trades on Day and Night Returns.
I decompose quarterly stock returns into the day (open to close) and night (close to open) components, and then use panel regressions to estimate the impact of mutual fund trading on those returns. Panel A reports the estimate using the full sample while Panel B reports the estimates from five sub-periods. The regressions include controls for the trades by other 13F institutions, three years of lagged day and night stock returns, as well as quarter and stock fixed effects. Standard errors are clustered by quarter and stock. Mutual fund trades are normalized by lagged shares outstanding. Observations are weighted by the market cap of stocks as a fraction of overall market cap in each period. Due to requiring lagged returns, the sample starts in 1984.

Panel A: Full Sample

Dependent variable:	Day Return	Night Return	Difference
	(1)	(2)	(3)
Mutual Fund Trade	0.48***	−0.11*	0.58***
	(0.08)	(0.06)	(0.10)
Controls:			
Trade by Other Institutions	Yes	Yes	
Lagged Day Returns	Yes	Yes	
Lagged Night Returns	Yes	Yes	
Quarter Fixed Effect	Yes	Yes	
Stock Fixed Effect	Yes	Yes	
Num Obs	434,365	434,365	
Adjusted R^2	18.5%	19.5%	

Panel B: Regression coefficient on mutual fund trade, by Sub-Samples

Dependent variable:	Day Return	Night Return	Difference
	(1)	(2)	(3)
1984 - 1990	1.30***	0.20	1.10***
	(0.25)	(0.13)	(0.28)
1991 - 1997	0.67***	0.02	0.66***
	(0.20)	(0.09)	(0.22)
1998 - 2004	0.88***	−0.22	1.11***
	(0.19)	(0.29)	(0.35)
2005 - 2011	0.34***	−0.09	0.43***
	(0.09)	(0.05)	(0.10)
2012 - 2018	0.41***	−0.16***	0.57***
	(0.06)	(0.06)	(0.08)

*** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$

returns.

3.3 Factor-level Price Pressures Happen During the Day

Having shown that mutual fund trades primarily impact the day return, I test whether the flow-induced factor-level price pressures primarily happen during the day. If so, this will lend further support for the price pressure interpretation.

I first decompose quarterly size and value factor returns into day and night components. Figure 9 plots the times series of those two components at an annual frequency. Unlike that suggested by standard asset pricing theories, the day and night factors are drastically different, and this makes it possible to identify off of their differences.[19]

I now separately estimate the impact of factor-level FIT on day and night factor returns:

$$\mathrm{Ret}_{f,t}^{\mathrm{day}} = b_0^{\mathrm{day}} \cdot \mathrm{FIT}_{f,t} + b_1^{\mathrm{day}} \cdot \mathrm{FIT}_{f,t-1} + ... + b_{12}^{\mathrm{day}} \cdot \mathrm{FIT}_{f,t-12} + \mathrm{Controls}_{f,t} + \epsilon_{f,t}^{\mathrm{day}} \tag{14}$$

$$\mathrm{Ret}_{f,t}^{\mathrm{night}} = b_0^{\mathrm{night}} \cdot \mathrm{FIT}_{f,t} + b_1^{\mathrm{night}} \cdot \mathrm{FIT}_{f,t-1} + ... + b_{12}^{\mathrm{night}} \cdot \mathrm{FIT}_{f,t-12} + \mathrm{Controls}_{f,t} + \epsilon_{f,t}^{\mathrm{night}} \tag{15}$$

where the control variables include 12 quarters of lagged day and night factor returns, as well as factor fixed effects. Panel (b) of Figure 1 in the introduction section plots the cumulative response coefficients of day and night returns to FIT. Consistent with the price pressure interpretation, almost all price pressures appear in day returns and there is almost no effect in night returns. In Appendix A.2, I show this is also true when estimated on each factor individually. Therefore, the price impact of FIT appears to happen exclusively during the day, supportive of the price pressure interpretation.

4 What Drove the Flows?

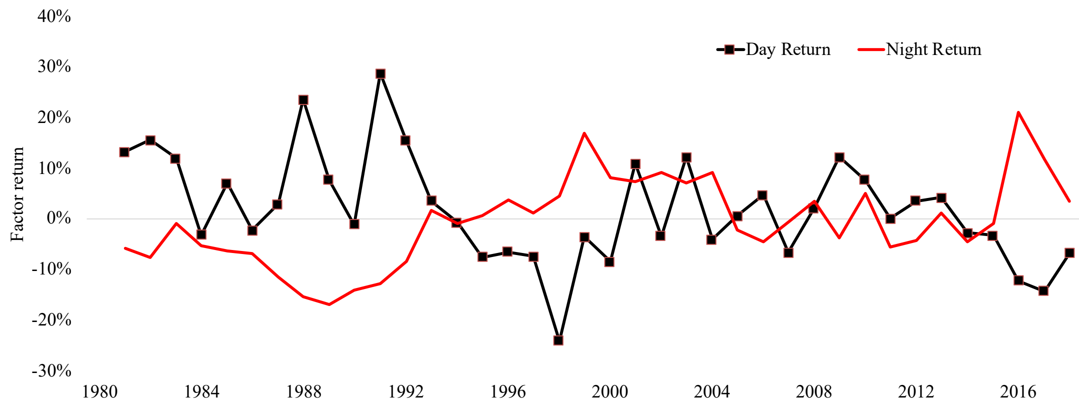
The results so far show that mutual fund flows drive factor-level price pressures. It is natural to then ask: what drove the flows in the first place?

Since Chevalier and Ellison (1997), it is well known that mutual fund flows chase past returns. More recently, researchers also found that investors mechanically chase Morningstar ratings (Guercio and Tkac, 2008; Reuter and Zitzewitz, 2017; Evans and Sun, 2018; Ben-David et al., 2019). In this

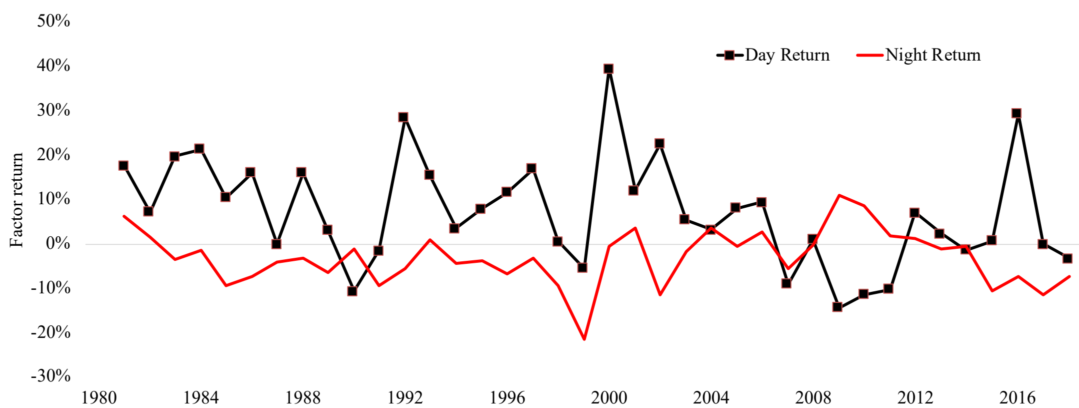
[19] Similar to Lou et al. (2019), I find that size and value factor premia primarily happen in day returns.

Figure 9. Annual Day and Night Return Components in Factors.
I decompose Fama-French factors returns into day (open to close) and night (close to open) components. The day component of annual factor returns is plotted in black and the night component is plotted in red.

(a) Size Factor



(b) Value Factor



section, I show that the combined effects of return- and rating-chasing can explain 35% and 41% of annual flows in size and value factors.

This high explanatory power may come as a surprise, because at the fund-level, return- and rating-chasing can only explain approximately 2% of flow variation. However, it turns out that much of fund-level flows are idiosyncratic and washes out when aggregated at the factor level.

4.1 Quantifying the Explanatory Power of Return- and Rating-Chasing

I first estimate return and rating chasing using a panel regression at the fund level:

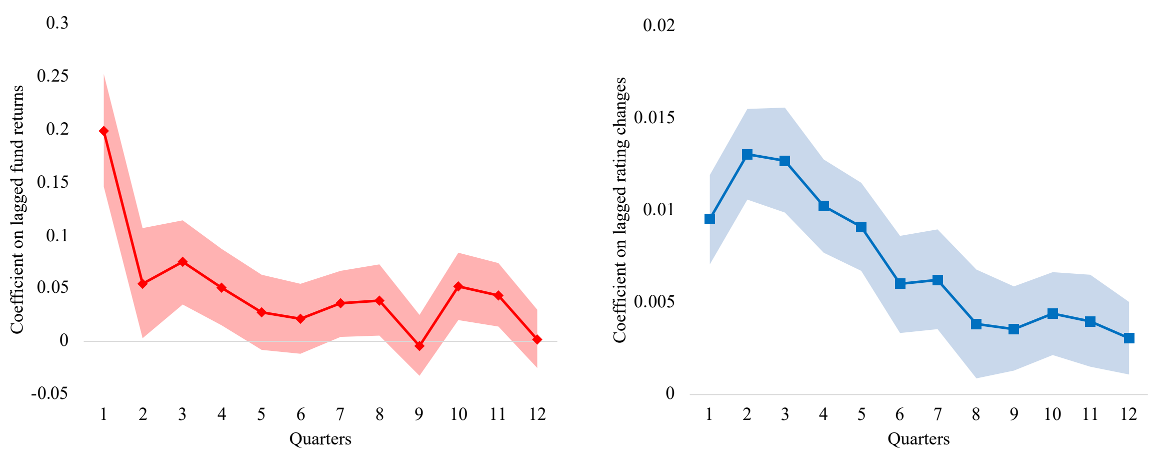
$$
\begin{aligned}
\mathrm{Flow}_{\mathrm{fund}\ j,t} = {} & \underbrace{b_1 \cdot \mathrm{FundRet}_{j,t-1} + ... + b_{12} \cdot \mathrm{FundRet}_{j,t-12}}_{\text{Return-chasing}} \\
& + \underbrace{c_1 \cdot \Delta\mathrm{Rating}_{j,t-1} + ... c_{12} \cdot \Delta\mathrm{Rating}_{j,t-12}}_{\text{Rating-chasing}} + \mathrm{Controls}_{j,t} + \epsilon_{j,t}
\end{aligned}
\tag{16}
$$

where $\mathrm{FundRet}_{j,t}$ and $\Delta\mathrm{Rating}_{j,t}$ are lagged fund returns and lagged Morningstar rating changes. Morningstar ratings are downloaded from Morningstar Direct.[20] The controls include quarter fixed effects and 12 quarterly lags of fund flows to account for serial correlation in fund flows. Observations are value-weighted by the fraction of TNA each fund occupies in each quarter.

Figure 10. Return- and Rating-Chasing in Mutual Fund Flows.
Panels (a) and (b) plot the dependence of quarterly fund flows on lagged fund returns and Morningstar rating changes, respectively. Shaded areas are two standard error bands.

(a) Coefficients on lagged returns

(b) Coefficients on lagged Morningstar rating changes



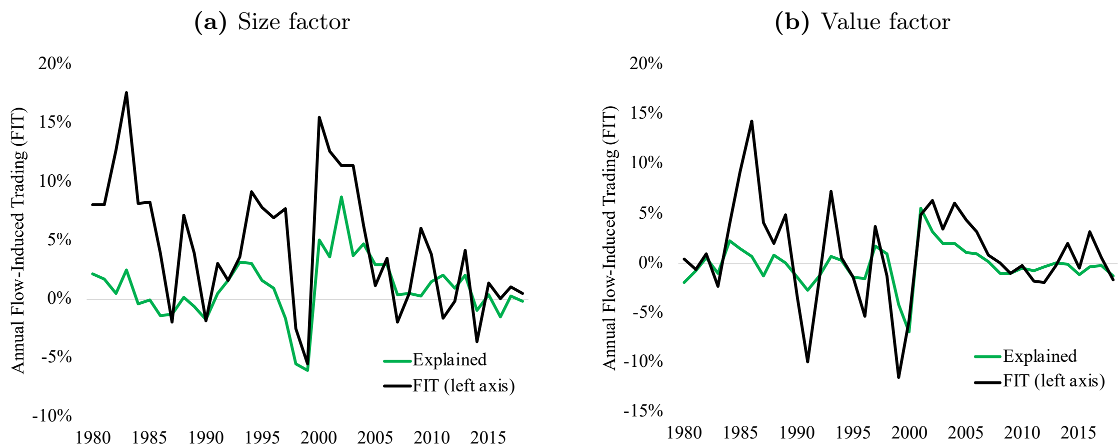
The regression coefficients are plotted in Figure 10. There is clear evidence of return and rating chasing. At the fund-level, the marginal R^2 of the lagged return and rating variables is 2%.

I then use the estimated coefficients in (16) to isolate flows explained by return- and rating-chasing. I aggregate those flows at the factor level and plot them against the total FIT in Figure

[20] Because ratings become available in 1986, the rating variables are set to zero before then.

11. Even though the marginal R^2 is low at the fund-level, at the factor-level, they can explain 35% and 41% of annual size and value factor FIT, respectively.

Figure 11. Factor-level FIT Explained by Return-Chasing and Rating-Chasing.
I use fund-level panel regressions to estimate the dependence of fund flows on lagged fund returns and Morningstar rating changes (equation (16)). I then only use the flows spanned by those explanatory variables to calculate flow-induced trading (FIT) at the factor-level and plot it in green. They represent the amount of factor-level FIT that can be explained by the return-chasing and rating-chasing behavior of mutual fund investors.



5 Summary

Size and value factors occupy an important place in finance. In academia, they are routinely used to explain the cross-section of returns. In industry, they are the first "factor investment" strategies. However, the interpretation of those factors is far from settled. While some argue that factor movements reflect fundamental – cash flow variation or time-varying discount rates – others argue that they are driven by correlated demand shocks at the factor level.

This paper presents novel evidence for the latter view. Over the period of 1980 to 2018, mutual fund investors frequently reallocated capital across mutual funds with different size and value styles. This resulted in large factor-level flows that generated price pressures that revert completely over the subsequent one to two years. These price pressures explain over 40% of annual factor variation. Further, consistent with the price pressure interpretation, the flow-induced price movements mostly happen during the day (open to close) when mutual funds trade, but not over night (close to open). This finding is very difficult to reconcile with alternative hypotheses that do not involve price pressures.

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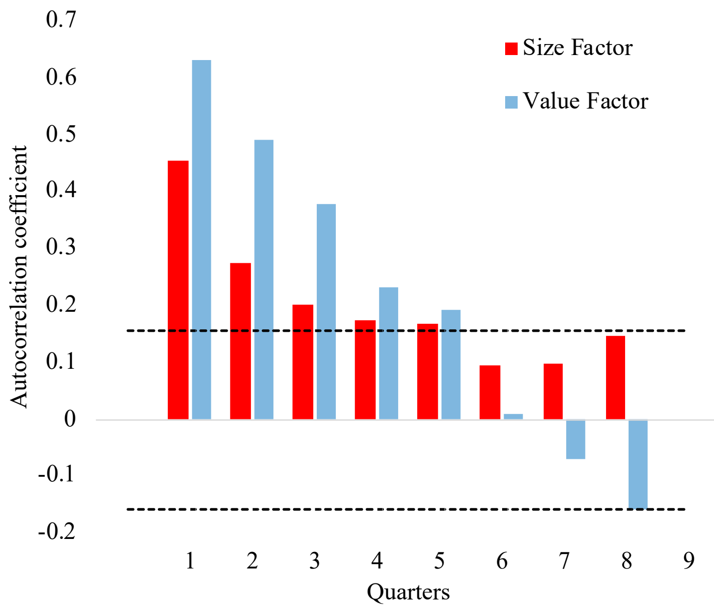
APPENDIX

A Additional Empirical Results

Figure 12. Autocorrelation of Quarterly Factor-level FIT. The dashed lines are two standard error bands.



A.1 Robustness of regression (6)

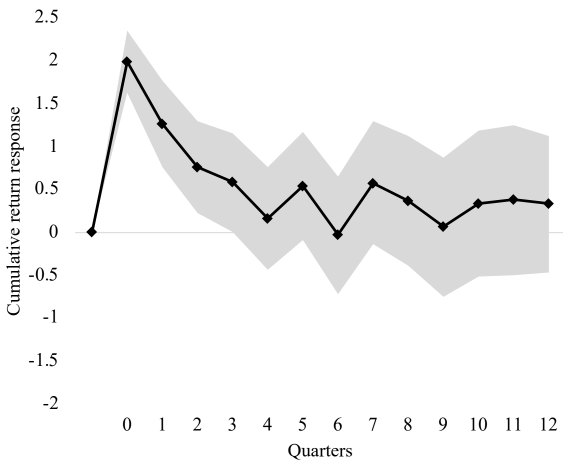
I re-estimate the price pressure panel regression (equation (6)) and vary whether factor and time fixed effects are included. I then plot the cumulative response of returns to FIT under all possible specifications in Figure 13. The results are broadly similar albeit larger standard errors when time fixed effects are included.

A.2 Day vs. Night Price Pressures

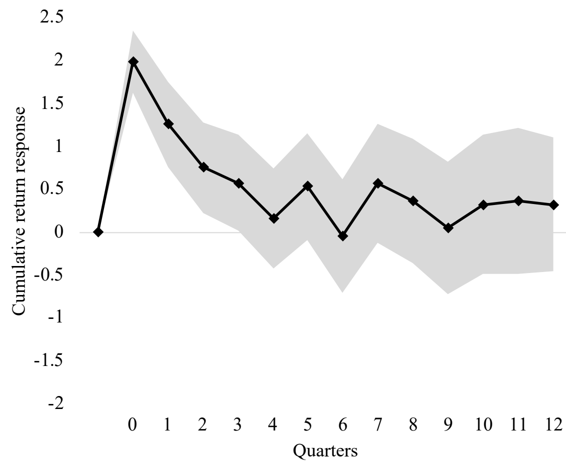
Price Pressure by Factor. In Section 3.3, I estimated the day and night price pressures of FIT in both factors together. Here, I estimate the same for size and value factors separately. The results are shown in Figure 14. The same pattern emerges, albeit with larger standard errors: for both factors, price pressures primarily happen during the day but not overnight.

Figure 13. Robustness Check: Price Pressure of Flow-Induced Trading (FIT)
. I re-estimate the panel regression of size and value factor returns on current and 12 lags of past FIT and returns (equation (6)), and I vary whether factor and/or quarter fixed effects are included. The figures plot the cumulative response of factor returns to FIT. Panel (a), which includes factor fixed effects, is the same as the Panel (a) in Figure 6.

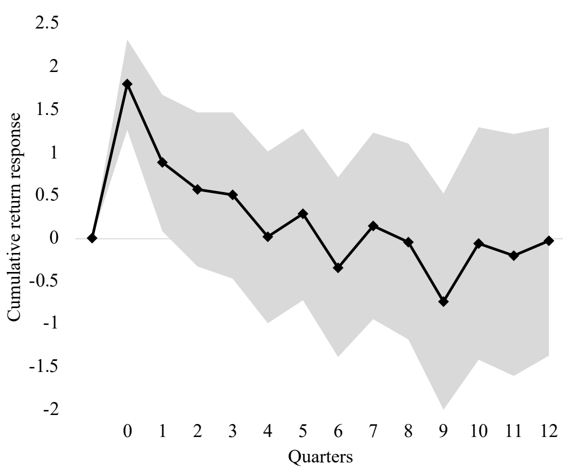
(a) Factor fixed effect



(b) No fixed effect



(c) Time fixed effect



(d) Both fixed effects

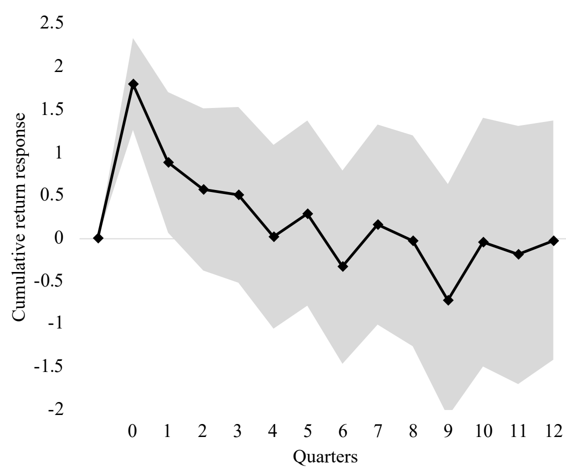


Figure 14. Flow-Induced Price Pressures in Day and Night Returns.
I separately estimate the cumulative size and value factor return responses to mutual fund flow induced trading pressures. The shaded areas indicate two standard errors.