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Naïve Style-Level Feedback Trading in Passive Funds

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Abstract

Passive exchange-traded funds (ETFs) are ideally suited to style-level feedback trading because of their high liquidity, ease of short selling, and pure play on investment styles. I find strong evidence of short-term style-momentum trading in ETFs. Institutional investors that use ETFs do not act as arbitrageurs by trading against style momentum. Institutions, especially less sophisticated ones, are themselves style-momentum traders. Moreover, recent style-level demand predicts style-level return reversals. These findings suggest that uninformed positive feedback trading by less sophisticated market participants can destabilize financial markets in the short run.

I. Introduction

Passive exchange-traded funds (ETFs) are inherently attractive to short-term traders as a trading vehicle because of their high liquidity, ease of short selling, and pure play on investment styles (Broman and Shum (2018), Cong and Xu (2019), and Evans, Moussawi, Pagano, and Sedunov (2019)). Investors can gain exposure to broad core styles (e.g., value or growth), sector styles (e.g., technology or financials), and more recently, factor-based styles. Unlike traditional passive index funds, ETFs do not charge redemption fees (or otherwise restrict frequent trading),[1] and they generally have lower expense ratios, are more tax efficient, and offer intraday liquidity. Not surprisingly, index funds are predominantly used in buy-and-hold strategies (Goetzmann and Massa (2002)).

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[1]Many mutual funds, including index funds, either charge a redemption fee (up to a maximum of 2%) or impose restrictions on the frequency of round-trip trades (e.g., selling within 30 or 60 days of the purchase date).

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These characteristics make ETFs especially attractive to positive-feedback traders. Several theoretical models predict that positive-feedback traders can destabilize stock prices and thereby threaten the efficiency of financial markets (e.g., De Long, Shleifer, Summers, and Waldmann (1990), Barberis and Shleifer (2003), Barberis, Greenwood, Jin, and Shleifer (2015), and Jin and Sui (2019)). In particular, in Barberis and Shleifer's (2003) model, a group of investors (labeled *style-switchers*) naïvely allocates more capital to styles that recently performed well and withdraws capital from styles that performed poorly. In doing so, these investors temporarily push prices away from fundamentals. Extrapolating past price changes into the future is an important stylized fact for a broad cross section of investors, including professional investors (e.g., Greenwood and Shleifer (2014)). Edelen, Ince, and Kadlec (2016) conjecture that institutional investors could be the uninformed positive-feedback traders in models by De Long et al. (1990), among others. In this article, I examine style-level feedback trading in ETFs, both in the aggregate and specifically among institutional investors.

Positive-feedback trading can be rational if investors learn about the skill of a fund manager over time by observing the fund's realized performance (Berk and Green (2004)). Although there is an extensive literature on the flow–performance relationship in active mutual funds,[2] there is currently no consensus on whether investors engage in style-level positive-feedback trading. Barber, Huang, and Odean (2016) show that fund flows are significantly more responsive to deviations from style returns than to the style returns themselves. Thus, mutual fund investors appear to chase past style returns when, instead, they could be rationally chasing superior talent. This explanation is, however, irrelevant for ETFs that passively track a transparent benchmark.

Existing evidence on style-level feedback trading by institutional investors is also mixed. Choi and Sias (2009) find that institutional industry demand is unrelated to lagged industry returns after controlling for institutional herding. Frijns, Gilbert, and Zwinkels (2013) show that whereas growth fund managers typically engage in style-level positive-feedback trading, value funds engage in negative-feedback trading. A potential concern of inferring style-level demand aggregated from individual stock holdings is that ruling out stock-level explanations, such as an investor trading on stock characteristics (e.g., size, value, quality, or industry) or on private information, is very difficult. By contrast, ETFs provide a unique setting for examining the determinants of style-level demand without any confounding stock-level effects.

My analysis of style-level feedback trading is based on a sample of 285 passive U.S. equity ETFs in well-defined investment styles between 2003 and 2017. Collectively, these funds managed approximately $2 trillion in assets at the end of 2017. I begin by showing that ETF investors, in aggregate, engage in style-level positive-feedback trading. Specifically, I examine the relation between fund-level demand (e.g., net flows to Vanguard's small-cap value ETF), or style-level demand (e.g., the equal- or value-weighted net flow of small-cap value ETFs), and lagged fund returns. I interpret a positive (negative) relationship as positive-feedback

[2]See, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), Coval and Stafford (2007), and Spiegel and Zhang (2013).

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(or momentum) trading and a negative relationship as negative-feedback (or contrarian) trading. To illustrate, a 1-standard-deviation increase in fund returns is associated with a 2.42% increase in next month's net flows after controlling for fund characteristics and time fixed effects. This effect is economically strong relative to the average net flow of 2.76% per month. Comparable results are obtained at the style level by equal-weighting (or value-weighting) the left- and right-hand-side variables of the regression. A decomposition of the flow–performance relationship shows that this holds for both inflows (i.e., funds with high prior returns receive inflows) and outflows (i.e., funds with poor prior returns experience redemptions). The net flow–performance relationship does, however, decay very rapidly. The third monthly return lag remains positive, but it is marginally significant at best. This is consistent with recent survey-based evidence suggesting that positive-feedback traders' expectations depend most strongly on the most recently experienced returns (Greenwood and Shleifer (2014)).

In a frictionless economy, fully rational arbitrageurs should trade against style momentum (e.g., Barberis et al. (2015)). However, arbitrage is likely to be constrained in practice by various market frictions, such as i) the reluctance to take on idiosyncratic risk in open-end fund structures (Shleifer and Vishny (1997)), which matters even for well-diversified ETFs (Daniel, Mota, Rottke, and Santos (2020)); ii) difficulty inferring the degree of persistence in style-switcher demand (Barberis and Shleifer (2003)); iii) constraints on leverage and collateral (e.g., Liu and Longstaff (2004), Brunnermeier and Pedersen (2009)); and iv) coordination risk among arbitrageurs (Abreu and Brunnermeier (2003)), especially in the case of momentum strategies that lack a fundamental anchor (Stein (2009)).

To investigate the characteristics of institutional trading in ETFs, I construct two measures based on quarterly 13F filings. The first is net institutional buying over a quarter scaled by the number of shares outstanding (a value-weighted metric); the second is the fraction of institutions increasing portfolio weights to an ETF (an equal-weighted metric). An important advantage of the latter is that it is unlikely to be affected by the actions of underlying investors because institutional investors typically scale their positions up proportionally in response to flows from investors (e.g., Khan, Kogan, and Serafeim (2012), Lou (2012)), in which case the weight allocated to any given ETF is unaffected.

In contrast to the sophisticated institutional investor hypothesis, my results indicate that institutions trade on style momentum over 1-quarter horizons: A 1-standard-deviation increase in fund returns is associated with a 0.14- to 0.19-standard-deviation increase in institutional demand after controlling for lagged institutional trading, fund characteristics, and time fixed effects. These effects are comparable in magnitude to those obtained for monthly net flows. Moreover, I find no significant evidence to suggest that institutions engage in contrarian trading over intermediate horizons. These results are more consistent with the idea that the average institutional ETF investor is an uninformed positive-feedback trader rather than a sophisticated arbitrageur.

It remains possible that a group of less sophisticated institutions engages in short-term style-momentum trading while another group of more sophisticated institutions does not, and that these effects partially wash out when aggregated across institutions. I therefore reexamine the institutional demand–performance

relationship for subsets of institutions based on their level of sophistication. The existing literature has linked investor sophistication to several characteristics that predict abnormal performance, such as investor activeness (Cremers and Petajisto (2009)), investor holding period (Cella, Ellul, and Giannetti (2013), Albagli (2015), and Cremers and Pareek (2015)), or a combination of the two (Cremers and Pareek (2016)). In particular, Cremers and Pareek (2016) show that highly active investors with long holding periods outperform other institutions. Consistent with the idea that less sophisticated institutions are more likely to be uninformed positive-feedback traders, I find a stronger institutional demand–performance relation for less active and more short-term-oriented institutions. The overall sample of institutional ETF users is also tilted toward less sophisticated institutions that own a relatively large fraction of outstanding shares (14%) relative to the most sophisticated institutions (5%). My results therefore align with previous studies suggesting that institutional ETF users are less sophisticated, on average, relative to institutions that do not use ETFs (Joenväärä and Salehi (2018), Sherrill, Shirley, and Stark (2017)).

Style-switcher demand also has important asset pricing implications. If style-switcher demand for ETFs reflects uninformed positive-feedback trading, as in De Long et al. (1990), among others, and if it is strong enough to affect prices, then switcher demand should negatively predict future returns. To test this idea, I regress fund returns on lagged measures of style-level demand (the average net flow, or net institutional demand, of *other* ETFs in the same style) while controlling for time fixed effects and fund characteristics. Style-level demand predicts future returns negatively and significantly over the following 6 to 12 months. To better isolate the component of style-level demand related to past performance (i.e., style-switcher demand), I use the expected style-level demand conditional on lagged returns and other determinants. The return-predictability results remain strong even in this case. Finally, a long–short trading strategy that bets against recent style-level demand yields significant abnormal returns, confirming that switcher demand is uninformed and strong enough to push prices away from fundamentals.

These findings are related to a growing literature on the market impact of investor flows. Lou (2012) shows that flow-induced trading by mutual fund managers, as proxied by the expected fund flow conditional on prior performance, is associated with temporary price impacts on the underlying stocks. Frazzini and Lamont (2008) demonstrate that retail investors tend to direct capital to mutual funds that hold overvalued stocks. Lastly, Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) argue that mutual fund flows exacerbate cross-sectional mispricing. In contrast, I provide direct evidence of a specific trading strategy used by uninformed investors (i.e., style switching in equity markets) and the associated price impact. In a similar vein, Ben-Rephael, Kandel, and Wohl (2012) show that retail investor shifts between equity and bond funds are associated with a significant price impact for the aggregate stock market that is fully reversed within a year. My results highlight, instead, the potentially destabilizing role of uninformed institutional demand.

A large body of literature depicts institutions as relatively sophisticated investors that act as arbitrageurs except when limited by market frictions. Conversely, my findings suggest that a significant subset of institutional ETF users consists of institutions that are more likely to act as uninformed feedback traders. The notion

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that short-term institutional demand may have a destabilizing impact on market efficiency does have precedence in the existing literature (e.g., Coval and Stafford (2007), Frazzini and Lamont (2008), Dasgupta, Prat, and Verardo (2011), and Edelen et al. (2016)). In particular, Edelen et al. (2016) show that institutions often trade contrary to well-known stock return anomalies, although their findings have recently been challenged on the grounds that they are not robust to the window during which institutional trading is measured or the weighting method used (Calluzzo, Moneta, and Topaloglu (2019)). An important distinction of my article is that I provide consistent evidence for both equal- and value-weighted measures of institutional demand in a setting that does not require any assumptions regarding when institutions gain access to anomaly characteristics. Moreover, I provide more granular evidence on the types of institutions that engage in feedback trading.

II. Institutional Details and Hypotheses Development

ETFs feature an open-ended structure that allows investors to create new shares or redeem existing shares via the primary market. This process is only available to institutional investors known as *authorized participants* (APs) that have signed an agreement with the ETF sponsor. APs can buy or sell ETF shares in creation units directly from the ETF sponsor in exchange for the underlying basket of securities at the end of the trading day. The size of a creation unit ranges from 25,000 to 100,000 shares, with dollar values ranging from $570,000 to $8.39 million. Based on a survey of ETF sponsors, Antoniewicz and Heinrichs (2015) report that the average number of APs for domestic equity ETFs is 35, although the average number of APs that are deemed active is only 7. Although APs do not receive compensation from ETF sponsors, some APs are clearing brokers and receive payment for trading in the primary market on behalf of clients.

A. Defining Net Flows

I calculate net fund flow as the difference between *actual* dollar inflows (share creations) and outflows (share redemptions) at time t, scaled by lagged assets under management (AUM):

$$\text{ACTUAL_NFLOW}_{i,t} = \frac{\text{INFLOW}_{i,t} - \text{OUTFLOW}_{i,t}}{\text{AUM}_{i,t-1}}. \tag{1}$$

ETFs are required to disclose the data on monthly inflows and outflows in regulatory filings (Form N-SAR) with the U.S. Securities and Exchange Commission (SEC). A handful of ETFs are organized as unit investment trusts (UITs), which are not required to disclose this information. In such cases, I instead compute the *implied* net fund flow as follows:

$$\text{IMPLIED_NFLOW}_{i,t} = \frac{\sum_{d=1}^{N_t} (\text{SHR}_{i,d} - \text{SHR}_{i,d-1})\text{NAV}_{i,d}}{\text{AUM}_{i,t-1}}, \tag{2}$$

where $\text{SHR}_{i,d}$ is the number of shares outstanding for ETF i on day d, and $\text{NAV}_{i,d}$ is the underlying portfolio net asset value (NAV). The daily dollar flow

$((\text{SHR}_{i,d} - \text{SHR}_{i,d-1})\text{NAV}_{i,d})$ is aggregated over the specified time period t (e.g., a month).[3]

Net flows signal *relative* nonfundamental demand for the ETF compared with its underlying portfolio[4] that generated a profitable arbitrage opportunity (Brown, Davies, and Ringgenberg (2021)). For example, suppose that noise-trader demand for a financial sector ETF in the secondary market pushes the ETF price above the NAV price. Arbitrageurs would then find it profitable to buy the underpriced basket, exchange it for new overpriced ETF shares, and then sell the newly created ETF shares in the secondary market. Despite the clear theoretical link between nonfundamental demand and the resulting arbitrage trade, the initial demand shock may have taken place earlier if limits to arbitrage prevented arbitrageurs from exploiting the mispricing. Settlement issues can also lead to timing misalignments.[5] To ensure that the timing of net flows is properly aligned with that of the underlying demand shocks and maximize the use of actual reported net flows (equation (1)), I focus primarily on the monthly horizon in the empirical tests.

B. Defining Institutional Demand

Net flows are initiated by institutional investors because only APs or their institutional clients are permitted to transact in the primary market for ETFs. The initial demand shock may have, however, originated with either retail or institutional investors. Although retail investors own a significant fraction of outstanding ETF shares (58% on average in my sample), anecdotal evidence suggests that institutions are responsible for up to 80% of trading in the secondary market (Aggarwal and Schofield (2012)). To obtain a more specific measure of institutional ETF demand that reflects both secondary and primary market trading, I turn to 13F portfolio holdings.

Because my central hypothesis centers around how investors modify their portfolios in response to past style-level performance, I examine changes in holdings rather than levels. The first measure is *net institutional buying* scaled by the number of shares outstanding:

$$\%\text{INST_SHARES}_{i,q} = \frac{\sum_{j=1}^{N_j} \left(\text{SHARES}_{i,j,q} - \text{SHARES}_{i,j,q-1}\right)}{\text{SHR}_{i,q-1}}. \tag{3}$$

Here, $\text{SHARES}_{i,j,q}$ is the number of shares owned by institution j at the end of quarter q, and $\text{SHR}_{i,q-1}$ is the total number of shares outstanding for ETF i at $q-1$. Net institutional buying is a measure of absolute (rather than relative) demand because it is positive when institutional investors buy more shares from retail (and

[3]This definition is more accurate than the standard definition in the mutual fund literature, which assumes that flows occur at the end of the month (e.g., Sirri and Tufano (1998)).

[4]Said differently, a positive nonfundamental shock can imply a positive shock to the ETF, a negative shock to the underlying portfolio, or a positive shock to both that affects the ETF more than it does the underlying portfolio.

[5]Some funds use T + 1 accounting, whereby share creations and redemptions are recorded 1 day after trade execution, whereas others use T accounting (Staer (2017)). APs have also been shown to strategically delay creating or redeeming shares until T + 6 to take advantage of clearinghouse failure-to-deliver rules and avoid the costs associated with short selling (Evans et al. (2019)).

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other non-13F) investors on the secondary market or when institutional investors create new ETF shares on the primary market.

Recognizing that a few large institutional institutions may drive net institutional buying, I also consider an alternative measure that provides an equally weighted account of institutions' actions. The second measure is the *fraction of institutions increasing portfolio weights* to ETF *i*:

$$(4)\quad \%\text{INST_WGHT}_{i,q} = \frac{\#\text{NR_INST_INCREASE_WGHT}_{i,q}}{\#\text{NR_INST_INCREASE_WGHT}_{i,q} + \#\text{NR_INST_DECREASE_WGHT}_{i,q}}.$$

An important advantage of this measure is that it is less likely to be affected by the actions of underlying investors, such as retail investors directing capital to mutual funds holding overvalued stock (Frazzini and Lamont (2008)). This is because institutional investors typically scale up their positions proportionally in response to flows from their underlying investors (e.g., Khan et al. (2012), Lou (2012)), in which case the overall weight allocated to an ETF is unaffected. Eq. (4) is also a more direct measure of style switching because a higher value indicates that institutions are allocating a greater proportion of their own capital to a given ETF, or style.

C. Hypothesis Development

Several theoretical models predict that uninformed positive-feedback (or momentum) traders can destabilize stock prices and thereby threaten the efficiency of financial markets (e.g., De Long et al. (1990), Barberis and Shleifer (2003), Barberis et al. (2015), and Jin and Sui (2019)). In Barberis and Shleifer's (2003) model, there are multiple risky assets, and each risky asset belongs to one of two styles. Style switchers express demand at the investment style level, and they naïvely allocate more money to styles that recently performed well and simultaneously withdraw money from styles that recently performed poorly. In doing so, they push prices away from fundamentals in the short term.

Passive ETFs are inherently attractive to style-level momentum traders as a trading vehicle because of their pure play on investment styles, high liquidity, and ease of short selling (Broman (2016), Broman and Shum (2018), and Evans et al. (2019)). These features make ETFs more attractive to style-momentum traders compared with their underlying securities. Net flows, reflecting *relative* nonfundamental demand for an ETF vis-à-vis its underlying securities (Brown et al. (2021)), should therefore be positively related to past style-level returns.

Hypothesis 1a (H1a). Net flows are positively related to past style-level returns.

A common element in models of positive-feedback trading is the existence of a group of investors with extrapolation-based beliefs that recent price changes will continue into the future. Recent work, including Vissing-Jorgensen (2003), Amromin and Sharpe (2013), Greenwood and Shleifer (2014), and Kuchler and Zafar (2019), provides convincing evidence of return extrapolation. In particular, Greenwood and Shleifer (2014) analyze the return expectations of 6 data sources

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using investor surveys and find consistent evidence that a broad cross section of investors, including professional investors, extrapolates past returns. They also show that investors' expectations depend strongly on the returns experienced most recently.

Hypothesis 1b (H1b). More recent style returns predict net flows more strongly than distant returns.

In a frictionless economy, fully rational arbitrageurs should trade against style momentum (see, e.g., Barberis et al. (2015)). However, because of various market frictions, arbitrage is likely to be constrained in practice.[6] In the context of delegated investing, fund investors are likely to withdraw capital following poor performance, in which case fund managers may neglect seemingly profitable strategies with high idiosyncratic risk, especially if the duration of mispricing is uncertain or long (Shleifer and Vishny (1997)). Idiosyncratic risk is a concern for even well-diversified ETFs because characteristic-sorted portfolios, such as ETFs tracking value, growth, or quality styles, are exposed to unpriced risk factors that are difficult to hedge out in practice (Daniel et al. (2020)). It is also difficult for arbitrageurs to infer the degree of persistence in style-switcher demand (Barberis and Shleifer (2003)). In addition, arbitrage can be limited by funding and leverage constraints, including collateral constraints for short positions (Liu and Longstaff (2004)), that deprive arbitrageurs of debt capital at certain times (e.g., Brunnermeier and Pedersen (2009)). Even in the presence of well-informed and well-financed arbitrageurs, mispricing can persist because of coordination risk between arbitrageurs (Abreu and Brunnermeier (2003)), especially in the case of momentum strategies that lack a fundamental anchor (Stein (2009)). Thus:

Hypothesis 2 (H2). Institutional demand is not positively related to past style returns.

III. Data and Methods

The ETF data used in this study come from several sources. I first compile an initial list of U.S.-traded ETFs from the Morningstar Direct survivor-bias-free database that meet the following criteria: The fund must i) invest in U.S. equities; ii) be passively managed; iii) be benchmarked against a standard investment style, sector, or industry; and iv) be physically replicated.

The second criterion excludes all actively managed funds, also referred to by Easley, Michayluk, O'Hara, and Putniņš (2020) as *active-in-form* ETFs. Active-in-form ETFs feature fund managers who attempt to earn alpha and whose investment decisions are not constrained by any benchmark or for which the benchmark is custom-built based on proprietary algorithms. Such funds are excluded because they are expected to have a positive net flow–performance relationship when investors learn about the skill of the fund manager (or the customized benchmark)

[6]For consistency with the existing literature, I use *arbitrage* hereafter to refer to real-world arbitrage trades that are profitable but risky. There is no "true" arbitrage trade to exploit here because the distortions caused by feedback traders do not imply a violation of the law of one price.

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over time by observing the fund's realized performance (Berk and Green (2004)). Active ETFs (without a benchmark) are identified by the actively managed indicator variable in Morningstar. Active ETFs with a proprietary weighting scheme are identified by the index-weighting-method variable in Bloomberg. To identify any remaining active ETFs, such as those that employ proprietary screens to identify under- or overvalued companies, I manually remove funds for which the word *proprietary* is mentioned in the index methodology document.

The third and fourth criteria eliminate funds that are unlikely to be used as building blocks for style-level feedback strategies, such as strategies linked to sector rotation, tactical allocation, hedge fund tracking, or covered call strategies. Other niche styles are also excluded, such as those based on spin-offs, buybacks, firms with a recent initial public offering (IPO), and firms with significant insider trading. Leveraged ETFs are removed because they are only designed to achieve their desired leverage over a 1-day holding period (e.g., Charupat and Miu (2011)), which is too short for implementing style-level feedback strategies. Finally, I only include fund observations after the fund's AUM exceeds $15 million and funds that have at least 24 months of available data because the flow characteristics of these funds are likely to be different from those of more established funds.

Overall, these exclusion criteria decrease the number of ETFs in the sample to 285. The total AUM of U.S. equity ETFs was $1.978 trillion in Dec. 2017 (ICI (2018)), whereas the AUM of my sample of 285 funds was $1.823 trillion, or roughly 92% of the total. The sample period for my main tests is from Jan. 2003 to Dec. 2017.

To identify the investment style for broad-based ETFs, I use the ubiquitous Morningstar 3-by-3 style box that characterizes funds along size and value–growth dimensions. The Morningstar style box is publicly available, and it is widely used by practitioners. Moreover, these style boxes are updated monthly, and they are based entirely on fund holdings. For sector funds, I instead used Morningstar's 11-sector classification. Finally, I combine strategies related to profitability and low risk (or combinations of the two) into a single style designated *quality.*

In terms of data sources, I obtain monthly reported inflows and outflows from Morningstar Direct. ETF prices, volumes, and returns are from CRSP, whereas underlying portfolio NAV and the number of shares outstanding are from Bloomberg.[7] Finally, I use the Thomson Reuters 13F database to obtain institutional portfolios. Section 13F of the Securities Exchange Act of 1975 requires all institutions with investment discretion of over $100 million to report their holdings to the SEC on a quarterly basis. SEC regulations stipulate that all holdings of common stock (including ETFs) greater than 10,000 shares or $200,000 must be disclosed.

[7]To ensure accuracy, I cross-check the data from Bloomberg with those of Morningstar (for NAV and shares outstanding) and the CRSP Mutual Fund Database (for NAV). Appendix IA1 in the Supplementary Material provides additional details.

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A. Descriptive Statistics

Summary statistics are provided in Table 1. In Dec. 2017, there were a total of 285 U.S. equity ETFs: 128 in core styles, 129 in sector styles, and the remaining 28 in the quality style. The mean (median) AUM was $2.96 billion ($0.36 billion). As this mean and median indicate, the AUM is highly skewed in the cross-section of funds. Most underlying benchmarks are from well-known index providers, such as Standard & Poor's (S&P) (103 funds), Dow Jones (36), Russell (31), MSCI (29), NASDAQ (18), CRSP (13), and Morningstar (13).

Table 1 provides summary statistics for measures of ETF demand (i.e., net flows and net institutional demand). These measures are winsorized each year at the 1st and 99th percentiles to mitigate the impact of outliers. Monthly net fund flows are, on average, 2.76%, but volatility is high (12.32%). There are also some notable differences between style categories. Compared with ETFs in core styles, sector ETFs have more volatile flows (13.56% vs. 11.47%). ETFs in the quality style have the highest average net flows (3.69% per month), which is consistent with the rising popularity of smart-beta funds in recent years.

Net institutional buying is, on average, 5.23% per quarter. Like net flows, volatility is also high (18.87%), particularly for sector funds (23.30%). The fraction of institutions increasing portfolio weights to an ETF is, on average, 54.94%, which is comparable across the various style categories. Thus, an equally weighted

TABLE 1

Descriptive Statistics

In Table 1, the number of funds (#) is reported at the end of the sample period (Dec. 2017). Descriptive statistics for the remaining variables are based on the full sample from Jan. 2003 to Dec. 2017. The following variables are included: assets under management (AUM), the monthly net flow (in %), the quarterly net institutional buying during a calendar quarter scaled by the number of shares outstanding at the beginning of the quarter, and the quarterly fraction of institutions increasing portfolio weights to an exchange-traded fund (ETF).

		AUM (billions)		NFLOW		%INST_SHARES		%INST_WGHT	
Style	#	Mean	Median	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Core	128	4.49	0.48	2.78	11.47	3.96	13.80	53.62	12.76
Large value	19	2.85	0.52	2.48	9.55	4.54	15.37	52.94	12.28
Large blend	27	11.06	0.74	2.68	9.73	3.71	12.57	52.84	12.03
Large growth	19	4.41	0.47	2.58	9.04	4.28	13.71	55.26	12.84
Mid-value	7	1.36	0.30	2.41	8.81	3.87	11.11	53.53	13.54
Mid-blend	9	4.47	0.80	4.98	19.02	5.00	17.62	55.04	12.88
Mid-growth	8	1.32	0.41	2.44	10.28	3.52	12.23	53.06	13.40
Small value	14	1.25	0.18	2.42	14.06	2.72	9.13	52.22	12.77
Small blend	14	3.40	0.38	2.92	12.36	4.06	15.52	54.80	13.68
Small growth	11	1.67	0.25	2.54	11.22	3.53	14.39	53.48	12.40
Sector	129	1.30	0.42	2.61	13.56	6.24	23.30	56.03	13.65
Cyclical Super Sector									
Materials	7	0.80	0.53	2.63	13.39	5.81	20.73	55.91	13.40
Construction cyclical	10	1.04	0.35	2.45	17.21	8.21	29.89	58.35	14.13
Financial	19	1.24	0.23	3.33	16.77	8.72	32.14	57.63	14.20
Real estate	13	2.44	0.84	2.79	10.38	5.89	19.33	55.43	14.63
Sensitive									
Communications	4	0.42	0.41	2.15	12.61	4.90	17.89	54.60	12.10
Energy	15	1.38	0.42	2.72	13.02	5.52	20.94	56.06	13.47
Industrials	14	0.82	0.26	2.30	12.65	5.65	20.07	55.70	13.33
Technology	17	1.28	0.33	2.69	13.85	6.25	21.36	55.97	13.36
Defensive Super Sector									
Construction defensive	6	1.45	0.45	2.39	11.20	5.06	19.02	54.86	13.90
Health care	18	1.34	0.53	2.19	11.50	5.28	19.69	55.91	12.82
Utilities	6	1.44	0.62	2.14	11.80	4.37	22.17	51.87	13.10
Quality	28	2.71	0.42	3.69	9.18	7.87	17.64	57.54	14.18
All	285	2.96	0.36	2.76	12.32	5.23	18.87	54.94	13.32

TABLE 2

The Relationship Between Net Flows and Institutional Demand

Table 2 reports the results for regressions of quarterly net flows on contemporaneous measures of institutional demand. In Panel A, institutional demand is measured by the net institutional buying during a calendar quarter scaled by the number of shares outstanding at the beginning of the quarter. In Panel B, institutional demand is computed as the fraction of institutions increasing portfolio weights to an exchange-traded fund (ETF). Different rows correspond to different subsamples. Institutional demand in the first row is computed for the full sample, whereas in subsequent rows, it is computed separately for institutions classified as having high versus low i) active share, ii) holding duration, and iii) holding turnover. To ease interpretation across specifications, both the left- and right-hand-side variables are standardized to mean 0, variance 1 across the full sample. The model R^2 can be expressed as follows: $R^2 = \text{cov}\left(Y_{i,t}, \widehat{Y}_{i,t}\right)/\text{var}(Y_{i,t}) = \text{cov}\left(Y_{i,t}, X_{1,t}\widehat{b}_1\right)/\text{var}(Y_{i,t}) + \text{cov}\left(Y_{i,t}, X_{2,t}\widehat{b}_2\right)/\text{var}(Y_{i,t})$. Therefore, the normalized covariance can be interpreted as a decomposition of model R^2, with the covariance values corresponding to the fractions of the model sum of squares attributable to a particular X variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are double-clustered by fund and calendar time (t-stats in parentheses).

Variable	Coeff. $(\widehat{b})$	t-Stat.	Decomposing R^2 $\frac{\text{cov}\left(Y_{i,t}, X_t\widehat{b}\right)}{\text{var}(Y_{i,t})}$	R^2	No. of Obs.
Panel A. $NFLOW_{i,q} = a + b_1 \%INST_SHARES_{i,q} + e_{i,q}$					
%INST_SHARES	0.522***	(11.15)		0.273	10,790
High active share	0.314***	(18.69)	0.121	0.298	10,790
Low active share	0.394***	(11.28)	0.177		
High holdings duration	0.309***	(12.92)	0.119	0.274	10,790
Low holdings duration	0.363***	(8.64)	0.155		
Low holdings turnover	0.273***	(12.18)	0.100	0.273	10,790
High holdings turnover	0.390***	(10.79)	0.178		
Panel B. $NFLOW_{i,q} = a + b_1 \%INST_WGHT_{i,q} + e_{i,q}$					
%INST_WGHT	0.375***	(16.73)		0.140	10,366
High active share	0.111***	(6.96)	0.024	0.147	10,366
Low active share	0.333***	(13.58)	0.123		
High holdings duration	0.183***	(10.01)	0.048	0.134	10,366
Low holdings duration	0.268***	(13.21)	0.086		
Low holdings turnover	0.203***	(11.48)	0.057	0.141	10,366
High holdings turnover	0.261***	(14.37)	0.084		

account of institutional trading does not reveal any meaningful unconditional differences between the styles. Interestingly, net institutional buying explains a significant fraction of the variation in net flows: The model R^2 is 27% (see Table 2). The equal-weighted measure of institutional trading is also significantly related to net flows, but the model R^2 is lower at 14%. The stronger relationship between net flows and net institutional buying should be expected because both are value-weighted measures of investor demand. These results imply that institutional demand for investment styles (via ETFs) is highly correlated with relative non-fundamental demand for ETFs (as measured by net flows).

B. Methodological Choices

I model investor demand for ETFs as follows:

$$\text{INV_DEMAND}_{i,t} = a_0 + \sum_{k=1}^{12} b_k \text{RET}_{i,t-k} + c_1 \text{CONTROLS}_{i,t-1} + \text{FE} + \varepsilon_{i,t}, \tag{5}$$

where $\text{INV_DEMAND}_{i,t}$ is the monthly net flow (equations (1) and (2)) or the quarterly net institutional demand (equations (3) and (4)). If ETFs are more attractive to style-level positive-feedback traders compared with their underlying securities, then the coefficients on lagged returns ($b_{1,k}$) should be significantly positive (H1a).

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Moreover, more recent returns should have a greater impact than distant returns ($b_k > b_j$ for $k < j$; H1b). To retain parsimony for the monthly net flow specification, I estimate separate coefficients only for the first 3 return lags and then restrict the coefficients within each quarter (lags 4–6, 7–9, and 10–12) to be the same.[8] For the specification of quarterly institutional demand, I include 4 quarterly lags.

The controls are largely standard to the existing literature and include 12 monthly (or 4 quarterly) lags of the dependent variable, the average ETF premium (to capture persistent mispricing not fully arbitraged away during the prior period), an index of ETF liquidity based on the first principal component of three liquidity proxies (i.e., proportional quoted spreads, Amihud's price impact, and turnover; see Broman and Shum (2018)), fund size, fund age, and the net expense ratio. Additional details regarding the variable definitions are provided in the Appendix.

For the pooled OLS specification, equation (5) also includes fixed effects (FE) for investment styles (3-by-3 size/valuation styles, 11 sectors, and 1 quality style; 9 + 11 + 1 = 21) and time periods. Standard errors are double-clustered by fund and time.

IV. ETF Flows and Style-Level Feedback Trading

The baseline results for the monthly net flow–performance relationship are reported in Panel A of Table 3. Column 1 is estimated with pooled OLS without control variables, whereas column 2 includes controls. In either case, the results are largely the same: The first 2 return lags are positive and significant at the 1% level, or better, but the magnitudes rapidly decline ($b_1 = 0.46$, $b_2 = 0.17$ in column 2). The net flow–performance relationship is even stronger in the Fama–MacBeth regression (column 3). In this case, the first 3 return lags are positive and highly significant ($b_1 = 0.62$, $b_2 = 0.32$, $b_3 = 0.14$). Because equation (5) includes time fixed effects, the positive net flow–performance relationship implies that ETF investors' feedback trading is primarily a cross-sectional phenomenon. This result is consistent with Barberis and Shleifer's (2003) model, in which style switchers allocate capital based on relative performance in the cross section of styles (H1a). The rapid decay in the flow–performance relationship is consistent with the notion that style switchers pay more attention to returns experienced most recently (H1b).

Interestingly, the net flow–performance relationship is partially reversed over intermediate horizons. In the pooled OLS with controls, the coefficients are negative and at least marginally significant for intermediate lags from 4 to 6 and 7 to 9. There are two possible interpretations of these negative coefficients. First, as shown by Brown et al. (2021), net flows reflect *relative* nonfundamental demand for the ETF compared with its underlying securities. Consequently, the negative flow–performance relationship over intermediate horizons may signal that ETF investors continue to trade on style momentum but not as strongly as the investors in the underlying stocks do. Alternatively, it may reflect ETF investors trading on style momentum in the short run before switching to style-contrarian trading over

[8] Table IA2 in the Supplementary Material provides the full set of results with 12 monthly lags and controls.

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TABLE 3
Fund Flows and Style-Level Feedback Trading

Table 3 reports the results from regressions of monthly flows (net flows in Panel A; inflows or outflows in Panel B) on lagged monthly returns (continuous or quartile dummies), lagged flows over the prior 12 months, and control variables. Return quartiles are based on returns over the prior 12 months, with weights given by the coefficient estimates from column 2. Control variables include the net expense ratio, age, assets under management (AUM), the average monthly premium, and an index of exchange-traded fund (ETF) liquidity. For variable definitions, see the Appendix. In the pooled OLS specifications, I include fixed effects for calendar time and style (3 × 3 size/valuation styles, 11 sectors, and 1 quality style; 9 + 11 + 1 = 21). Style-level regressions (equal- or value-weighted averages of left- and right-hand-side variables) are estimated for styles with a minimum of 5 ETFs. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are double-clustered by fund and calendar time in columns 1–3 and by style and calendar time in columns 4 and 5 (*t*-stats in parentheses).

Panel A. Net Flows

	Fund-Level Regressions			Style-Level Regressions	
	Pooled OLS		Fama–MacBeth	Equal Weighted	Value Weighted
Variables	1	2	3	4	5
RET, $t-1$	0.445***	0.457***	0.616***	0.426***	0.280***
	(8.77)	(9.32)	(7.96)	(5.12)	(3.88)
RET, $t-2$	0.178***	0.172***	0.320***	0.130**	0.078
	(4.34)	(4.36)	(4.27)	(2.26)	(1.22)
RET, $t-3$	0.015	0.014	0.136**	−0.018	0.038
	(0.34)	(0.34)	(2.41)	(0.29)	(0.83)
RET, $[t-4, t-6]$	−0.057***	−0.046**	−0.074**	−0.066*	−0.095*
	(2.67)	(2.14)	(2.12)	(1.97)	(2.00)
RET, $[t-7, t-9]$	−0.080***	−0.068***	−0.035	−0.039	−0.066**
	(4.16)	(3.60)	(1.02)	(1.20)	(2.18)
RET, $[t-10, t-12]$	−0.028	−0.020	−0.012	−0.034	−0.029
	(1.24)	(0.89)	(0.31)	(1.22)	(0.91)
Y, $t-1$	0.054*	0.033	−0.012	0.090**	−0.089**
	(1.87)	(1.04)	(0.71)	(2.71)	(2.45)
Y, $t-2$	0.072***	0.059**	0.009	0.063	0.043
	(3.02)	(2.26)	(0.65)	(1.42)	(1.21)
Y, $t-3$	0.080***	0.070***	0.043***	0.056*	0.088
	(4.15)	(3.29)	(3.55)	(1.76)	(1.59)
Y, $[t-4, t-6]$	0.045***	0.038***	0.027***	0.020	0.029
	(6.09)	(4.29)	(3.79)	(1.29)	(1.55)
Y, $[t-7, t-9]$	0.036***	0.030***	0.022***	0.008	0.023*
	(6.58)	(5.31)	(4.05)	(0.58)	(1.94)
Y, $[t-10, t-12]$	0.014**	0.011*	0.013***	−0.001	−0.008
	(2.30)	(1.97)	(2.66)	(0.08)	(0.42)
Controls	No	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Style fixed effects (21)	Yes	Yes	No	No	No
Adj./avg. R^2	0.110	0.124	0.363	0.256	0.161
No. of obs.	31,710	31,695	31,695	2,587	2,587

Panel B. Inflows and Outflows

	Inflows			Outflows		
Variables	1	2	3	4	5	6
RET, $t-1$	0.222***	0.246***		−0.170***	−0.164***	
	(3.83)	(4.45)		(4.84)	(4.70)	
RET, $t-2$	0.066	0.078		−0.004	−0.001	
	(1.40)	(1.65)		(0.13)	(0.03)	
RET, $t-3$	−0.060	−0.053		0.034	0.033	
	(1.11)	(0.98)		(0.96)	(0.90)	
RET, $[t-4, t-6]$	−0.077***	−0.066**		0.031*	0.029	
	(2.94)	(2.51)		(1.75)	(1.64)	
RET, $[t-7, t-9]$	−0.036	−0.027		0.042***	0.040***	
	(1.47)	(1.18)		(2.85)	(2.83)	
RET, $[t-10, t-12]$	0.005	0.011		0.033*	0.032*	
	(0.20)	(0.44)		(1.80)	(1.72)	

(continued on next page)

TABLE 3 (continued)
Fund Flows and Style-Level Feedback Trading

Panel B. Inflows and Outflows (continued)

	Inflows			Outflows		
Variables	1	2	3	4	5	6
Q1 RET, $[t-1, t-12]$						1.206***
						(5.80)
Q2 RET, $[t-1, t-12]$			0.204			0.393*
			(0.68)			(1.83)
Q3 RET, $[t-1, t-12]$			1.123***			0.275
			(3.63)			(1.62)
Q4 RET, $[t-1, t-12]$			2.376***			
			(5.99)			
$Y, t-1$	0.232***	0.212***	0.212***	0.285***	0.275***	0.275***
	(11.72)	(9.97)	(9.95)	(9.96)	(9.70)	(9.77)
$Y, t-2$	0.126***	0.116***	0.116***	0.137***	0.132***	0.131***
	(6.34)	(5.76)	(5.85)	(7.51)	(7.29)	(7.23)
$Y, t-3$	0.153***	0.144***	0.144***	0.143***	0.139***	0.139***
	(9.49)	(8.87)	(8.77)	(7.93)	(7.77)	(7.79)
$Y, [t-4, t-6]$	0.055***	0.051***	0.051***	0.050***	0.047***	0.048***
	(8.57)	(8.29)	(8.22)	(7.58)	(7.24)	(7.25)
$Y, [t-7, t-9]$	0.032***	0.029***	0.029***	0.020**	0.019**	0.019**
	(4.25)	(3.97)	(4.12)	(2.50)	(2.30)	(2.27)
$Y, [t-10, t-12]$	0.029***	0.029***	0.029***	0.039***	0.038***	0.038***
	(4.32)	(4.34)	(4.46)	(4.56)	(4.43)	(4.35)
Controls	No	Yes	Yes	No	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects (21)	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.525	0.533	0.533	0.620	0.621	0.620
No. of obs.	31,682	31,667	31,667	31,682	31,667	31,667

intermediate horizons. To disentangle these two possibilities, it is necessary to analyze measures of absolute (rather than relative) investor demand. I revisit this issue in Section V.

Levy and Lieberman (2016) argue that the net flow–performance relationship is much weaker in ETFs than in active mutual funds. They reach this conclusion by comparing the model R^2 from style-level regressions of value-weighted net flows at the weekly horizon[9] on value-weighted returns, estimated separately for ETFs and active mutual funds. They include the current return, up to 1 lag of flows and returns, but no fixed effects. Including the current return in explaining flows is problematic because a positive relationship can arise from within-period positive-feedback trading, investors forecasting within-period returns, or the price impact of flows (e.g., Sias, Starks, and Titman (2001)). The standard approach in the literature is to include lags of up to at least 1 year (e.g., Coval and Stafford (2007), Barber et al. (2016)). From the perspective of testing for style-level feedback trading, it is also important to focus on cross-sectional variations in returns by controlling for time fixed effects.

Nevertheless, the adjusted R^2 for ETFs (11% in column 1) is lower than what is typically reported for active mutual funds. Dannhauser and Pontiff (2019) report a

[9]The use of weekly flows is problematic because of timing misalignments, as discussed in Section IIA. Nevertheless, in unreported tests, I obtain results that are comparable to those in Table 3 when estimating equation (5) at the weekly horizon.

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model R^2 of 19.5% (3.9%) for active mutual funds (passive index funds) when controlling for 12 monthly lags of returns and flows. However, the low R^2 for ETFs and passive index funds is primarily explained by a lack of explanatory power coming from lagged flows, not lagged returns. Active mutual fund flows are highly persistent (resulting in their high R^2 values) because of the persistence of retirement account contributions (Del Guercio and Tkac (2002)). By contrast, the weak flow persistence of ETFs and passive index funds is likely a reflection of their infrequent use in retirement accounts (Brown, Liang, and Weisbenner (2007), Mitchell, Mottola, Utkus, and Yamaguchi (2006), and Pinsker (2017)). For ETFs, the lack of persistence may also be related to their active use in various trading strategies (Broman and Shum (2018), Easley et al. (2020), and Huang, O'Hara, and Zhong (2020)).

The coefficient estimates themselves provide a direct assessment of the strength of style-level feedback trading. To illustrate, a 1-standard-deviation increase in returns (5.30%) at $t - 1$ is associated with an increase in net flows of 2.42% or 3.24% in columns 2 and 3, respectively. This effect is large when compared with the average monthly net flow of 2.76%. The strength of the net flow–performance relationship at the 1-month horizon is also between 2 and 4 times stronger than what is typically reported in the mutual fund literature[10] (e.g., Barber et al. (2016), Dannhauser and Pontiff (2019)). The magnitudes remain similar across various subsamples, including ETFs in broad core styles (with or without purely passive funds), ETFs in well-defined twin styles (the corner styles in Morningstar's 3-by-3 matrix), and sector funds (see Table IA4 in the Supplementary Material).

To properly benchmark my results relative to those of Levy and Lieberman (2016) and confirm that feedback trading is truly a style-level phenomenon, I estimate regressions in which both the left- and right-hand-side variables are averaged at the style level (with a minimum of 5 ETFs per style). The equal-weighted results in column 4 of Table 3 are not materially different from the fund-level results in terms of the magnitude and significance of past style returns (b_1 = 0.43, t-stat. = 5.12), whereas the value-weighted results in column 5 are somewhat weaker but still highly significant (b_1 = 0.28, t-stat. = 3.88). The main difference is the substantial increase in the adjusted R^2 (more than doubling in column 4 compared with column 2), which confirms the presence of a common style-specific factor in flows related to past performance (and other determinants).

Another difference is that equal-weighted style flows are more persistent than fund-level flows at the 1-month lag (coefficient = 0.09 vs. 0.03 in columns 4 and 2), whereas value-weighted style flows exhibit mean-reversion (coefficient = –0.09 in column 5). The persistence of equally weighted metrics of investor demand, controlling for time effects, has been interpreted as evidence of herding (e.g., Sias (2004)). Mean-reversion in value-weighted net flows may instead be related to the

[10]Because net flows are defined as dollar net flows scaled by lagged AUM, it is possible that differences in the flow–performance relationship between ETFs and mutual funds are, at least partially, driven by differences in the denominator (AUM). To account for this, I estimate the net flow–performance relationship for mutual funds during the 1990–2000 period when the total AUM of U.S. equity mutual funds was like that of U.S. ETFs during the 2003–2017 period. The strength of the flow–performance relationship during this earlier time period is very similar to that reported by Barber et al. (2016). See Appendix IA3 in the Supplementary Material for additional details.

use of large and highly liquid ETFs for short-term strategies. Broman and Shum (2018) provide evidence of a liquidity clientele among institutional investors: Liquidity is strongly related not only to higher short-term institutional ownership (vis-à-vis the dollar-weighted average of the underlying portfolio) but also to lower institutional investors' holding durations. In Section V, I present similar results on short-term persistence (mean-reversion) in equal-weighted (value-weighted) measures of net institutional demand.

A. Inflows and Outflows

Net flows reflect the difference between two nearly equally large components, new share creations (inflows) and redemptions (outflows), that might well follow different patterns and aggregation into net flows. If, on the one hand, style switchers finance their shifts into a style by withdrawing capital primarily from the fund's distant style (e.g., value vs. growth), as conjectured by Barberis and Shleifer (2003), then past style performance should be symmetrically related to higher inflows and lower outflows. If, on the other hand, switchers finance a shift into a particular style by withdrawing capital from several underperforming styles, then past style performance should have a weaker impact on outflows. To explore this idea, I estimate the flow–performance relationship separately for inflows and outflows as the dependent variable.

The results in Panel B of Table 3 confirm the existence of style-level feedback trading for both inflows (funds with high prior performance receive inflows) and outflows (funds with poor prior performance experience redemptions). With controls, the first return lag is positive and significant for inflows and negative and significant for outflows. To put the economic magnitude into perspective, a 1-standard-deviation increase in returns (5.30%) is associated with 1.31% higher inflows and 0.87% lower outflows. Although there is a modest asymmetry in the effect of past performance on ETF inflows versus outflows, the difference is insignificant. I do find stronger asymmetry when using cross-sectional return quintile dummies: ETFs in the top quintile of past 12-month fund returns experience 2.37% higher inflows (relative to the omitted bottom group), whereas funds in the bottom quintile experience 1.21% higher outflows (relative to the top group). The difference is significant at the 1% level. This asymmetry between inflows following outperformance and outflows following underperformance is more consistent with style switchers withdrawing capital from several poorly performing styles.

V. Institutional Demand and Style-Level Feedback Trading

Institutions are typically depicted as relatively sophisticated investors that act as arbitrageurs, except when limited by market frictions. In this case, institutional ETF users should not engage in style-level momentum trading (H2). To examine this hypothesis, I reestimate equation (5) with net institutional buying (%INST_SHARES), or the fraction of institutions increasing portfolio weights to an ETF (%INST_WGHT), as the dependent variable and all explanatory variables redefined at the quarterly frequency. The results are reported in Table 4. To ease the

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TABLE 4

Institutional Demand and Style-Level Feedback Trading

Table 4 reports the results from regressions of quarterly institutional demand on lagged quarterly returns and institutional demand over the prior 4 quarters and control variables. In columns 1 and 2, institutional demand is measured by net institutional buying during a quarter scaled by the number of shares outstanding at the beginning of the quarter. In columns 3 and 4, institutional demand is measured by the fraction of institutions increasing portfolio weights to an exchange-traded fund (ETF). Control variables include the net expense ratio, age, assets under management (AUM), the average quarterly premium, and an index of ETF liquidity. For variable definitions, see the Appendix. All variables are standardized across the full sample to ease the interpretation of coefficients across specifications. Columns 1 and 3 include fixed effects for calendar time and style (3 × 3 size/valuation styles, 11 sectors, and 1 quality style; 9 + 11 + 1 = 21). Columns 2 and 4 correspond to Fama–MacBeth regressions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are double-clustered by fund and calendar time (*t*-stats in parentheses).

	Y = %INST_SHARES		*Y* = %INST_WGHT	
	Pooled OLS	Fama–MacBeth	Pooled OLS	Fama–MacBeth
Variables	1	2	3	4
RET, *q* − 1	0.145***	0.151***	0.141***	0.192***
	(5.40)	(5.44)	(4.05)	(4.11)
RET, *q* − 2	−0.029	−0.014	−0.014	−0.063
	(1.02)	(0.47)	(0.45)	(1.45)
RET *q* − 3	−0.024	−0.020	−0.009	−0.059
	(1.22)	(0.72)	(0.39)	(1.65)
RET, *q* − 4	−0.036**	−0.049	−0.049**	−0.128***
	(2.06)	(1.46)	(2.07)	(3.19)
Y, *q* − 1	−0.084***	−0.140***	0.100***	0.106***
	(3.04)	(5.72)	(5.01)	(5.79)
Y, *q* − 2	0.012	−0.025	0.075***	0.078***
	(0.46)	(1.16)	(4.72)	(4.01)
Y, *q* − 3	−0.005	−0.005	0.076***	0.079***
	(0.22)	(0.22)	(6.13)	(6.03)
Y, *q* − 4	0.008	0.001	0.068***	0.078***
	(0.42)	(0.04)	(5.83)	(6.12)
Controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects (21)	Yes	No	Yes	No
Adj./avg. R^2	0.094	0.261	0.252	0.372
No. of obs.	10,582	10,582	10,448	10,448

interpretation of coefficients between specifications, I standardize all variables across the full sample.

In contrast to the sophisticated institutional investor hypothesis (H2), both measures of net intuitional demand are positively related to past returns, suggesting that institutions trade on style momentum. In the pooled OLS regression for %INST_SHARES (column 1), the coefficient on lagged returns is positive (0.145) and highly significant (*t*-stat. = 5.40). This implies that a 1-standard-deviation increase in quarterly returns is associated with a 0.145-standard-deviation (or $0.145 \times \sigma(\%\text{INST_SHARES}) = 0.145 \times 0.199 = 2.89\%$) increase in net institutional buying. Similar results are obtained using the Fama–MacBeth regression (column 2). Columns 3 and 4 are estimated for %INST_WGHT. The strength of the institutional demand–performance relationship remains similar (for pooled OLS) or even stronger (for Fama–MacBeth).

In models of feedback trading with both fully and partially rational arbitrageurs and without market frictions (e.g., De Long et al. (1990)), fully rational arbitrageurs seek to exploit naïve investors by trading on style momentum in the short run before switching to contrarian trading in the intermediate run even as naïve investors continue betting on momentum. In a similar vein, Brunnermeier and

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Nagel (2004) show that hedge funds were heavily invested in tech stocks leading up to the dot-com bubble but reduced their positions prior to the bust. My results do not support such a sophisticated view of institutional investors' capabilities. In particular, the second and third quarterly return lags are always insignificant, which suggests that institutions in the aggregate do not engage in contrarian trading over intermediate horizons.[11]

In line with the time-series properties of equal- and value-weighted net flows, %INST_WGHT (an equal-weighted metric) is also persistent at the first lag, whereas %INST_SHARES (a value-weighted metric) is mean-reverting. Sias (2004) and Choi and Sias (2009) interpret a positive relationship between current and lagged equal-weighted institutional demand as evidence of herding. Although my results also suggest that institutions herd, in this case to investment styles by trading ETFs, there is an important difference. Namely, I continue to find strong evidence of style-momentum trading even after accounting for herding. This finding contrasts with Choi and Sias (2009), who find no independent effect of lagged returns on institutional industry demand after controlling for industry herding. A concern with inferring style-level demand aggregated from individual stock holdings is that it is very difficult to rule out stock-level explanations. For example, an investor purchasing shares in Microsoft could be trading on stock-level characteristics (e.g., value, quality, momentum, or industry) or on private information. Not surprisingly, the contradictory findings between growth-oriented institutions (as momentum traders) and value-oriented institutions (as contrarian traders) hold both at the stock level (Badrinath and Wahal (2002)) and when aggregating stock positions to the style level (Frijns et al. (2013)). In contrast, ETFs provide a unique setting for examining the determinants of style-level demand without any confounding stock-level effects.[12]

A. Classification of Institutional Investors

It remains possible that a group of less sophisticated institutions engages in short-term style-momentum trading, whereas another group of more sophisticated institutions does not, and that these effects partially wash out when aggregated across institutions. To further explore this idea, I split institutions into different groups based on their level of sophistication.

The existing literature has linked investor sophistication to several characteristics that predict abnormal performance, such as investor activeness (Cremers and Petajisto (2009)), investor holding period (Cella et al. (2013), Albagli (2015), and Cremers and Pareek (2015)), or a combination of the two (Cremers and Pareek (2016)). In particular, Cremers and Pareek (2016) show that highly

[11] Although the fourth quarterly lag is negative and significant in some specifications, this is not necessarily a sign of sophistication because style-momentum strategies have historically generated negative abnormal returns starting at the 1-quarter horizon. See Table IA5 in the Supplementary Material for additional details and results.

[12] In Table IA6 of the Supplementary Material, I show that net institutional demand is positively related to lagged quarterly returns, especially for institutions with a value or a blend tilt, whereas the relationship is weaker but still positive for growth institutions.

active investors with long holding periods outperform other institutions, whereas short-term institutions underperform regardless of their degree of activeness. They argue that institutions may be able to spot mispricing that is reversed only over a long horizon, which requires conviction and patience on the part of the investor. Long-term investing can also benefit from opportunities to buy relatively illiquid or deep-value stocks on the cheap (Amihud, Mendelson, and Pedersen (2005)).

Activeness, as measured by ACTIVE_SHARE, is the extent to which an institutional investor's stock holdings deviate from its benchmark. Because institutional investors do not report their benchmarks, I use market capitalization weights for all common stocks from the CRSP as the benchmark, as suggested by Doshi, Elkamhi, and Simutin (2015). For each institution-quarter, ACTIVE_SHARE is the sum of the absolute differences between the institutional investor's portfolio weight and the CRSP value weight of the underlying stocks divided by 2 (Cremers and Petajisto (2009)).

Although we cannot directly observe the investor's investment horizon, it is nonetheless revealed over time through the investor's trading behavior. I construct two different proxies. First, HOLDING_DURATION is defined as the weighted-average length of time that the investor has held 13F securities in its portfolio after adjusting for intermediate buys and sells due to, for example, tax selling or window dressing (Cremers and Pareek (2015)). Second, HOLDING_TURNOVER is computed as the dollar value of quarterly trades of 13F securities scaled by the total market value of the portfolio averaged over the prior 4 quarters (Gaspar, Massa, and Matos (2005), Cella et al. (2013)). Additional details on variable construction are provided in the Appendix.

Next, I sort institutions into two groups according to their investment horizon (above or below the median) and then on activeness in quarter $q-1$. The sorts are based on a sample of institutions that have used ETFs at least once in the previous 24 months. Because large institutions are more likely to report aggregated holdings across several separately managed portfolios in their 13F filings (Blume and Keim (2014)), I perform the sorts separately for small institutions (those below the 80th percentile in terms of the total market value of holdings) and big institutions (the rest). Big institutions own the majority of outstanding ETF shares (31% vs. 11%), but they are less active on average (with an active share of 67% vs. 82%).

As discussed in Section IIIA, net institutional demand explains a significant fraction of the variation in net flows: The model R^2 is 27% (14%) for the value-weighted (equal-weighted) measure of institutional demand. Table 2 also provides the results of regressions of net flows on net institutional demand by type of institution. A decomposition of the model R^2 shows that the contribution of net institutional demand by less sophisticated institutions (low active share, low holding duration, and high holding duration) is between 0.3 and 2 times greater than that for more sophisticated institutions. This implies that the demand for investment styles by less sophisticated institutions is more highly correlated with relative nonfundamental demand for ETFs (as measured by net flows). This is consistent with my conjecture that less sophisticated institutions are more likely to act as uninformed style switchers.

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B. Institutional Investor Sophistication and Style-Momentum Trading

To test whether the propensity to engage in style-level feedback trading differs between different types of institutions, I reestimate equation (5) with institutional demand measured separately by more sophisticated institutions (long investment horizon and high activeness), less sophisticated institutions (short investment horizon and low activeness), and a middle category in which investment horizon and activeness are not in agreement. Panel A of Table 5 presents the results for net institutional buying as the dependent variable, and Panel B provides the results for the fraction of institutions increasing portfolio weights to an ETF.

The coefficient on the 1-quarter lagged returns increases monotonically as we go from the most sophisticated institutions (between 0.04 and 0.06, with *t*-stats around 3) to the least sophisticated (between 0.14 and 0.15, with *t*-stats around 5). Return lags beyond the first quarter are generally insignificant for both the most and least sophisticated institutions. Said differently, the least sophisticated institutions exhibit the strongest tendency to trade on style-level momentum in the short run and do not switch to contrarian trading over the intermediate horizon. The evidence is becoming increasingly clear: Institutional ETF users, especially the least sophisticated institutions, are likely to be naïve style-momentum traders themselves. Moreover, the least sophisticated institutions own a relatively large fraction of outstanding shares (14%) relative to the most sophisticated institutions (5%), which suggests that the sample of institutional ETF users is tilted toward less sophisticated institutions.

The lack of sophistication among institutional ETF users has precedence in the existing literature. Joenväärä and Salehi (2018) and Sherrill et al. (2017) show that institutional investors that use ETFs underperform institutions that do not. My results also agree with Edelen et al. (2016), who find that institutions trade contrary to several well-known asset pricing anomalies. Their findings are, however, sensitive to the window during which institutional trading is measured and the weighting method used (Calluzzo et al. (2019)). An important distinction of my article is that by focusing on feedback strategies, I do not have to make assumptions regarding when institutions gain access to the data (return data are available immediately, unlike accounting data). Irrespective of whether I use equal- or value-weighted metrics, my conclusions remain the same. Importantly, I also provide more granular evidence of the types of institutions that engage in feedback trading.

VI. Style-Switcher Demand and Return Predictability

The evidence thus far suggests that a large cross-section of investors engages in short-term positive feedback trading using passive ETFs. If, on the one hand, style-switcher demand for ETFs reflects uninformed feedback trading, as in De Long et al. (1990), among others, and if it is strong enough to affect prices, then style-switcher demand should negatively predict future returns. If, on the other hand, switcher demand is sophisticated in the sense that it reflects how (fundamental) information is impounded into asset prices, then style-switcher demand should not be negatively related to subsequent returns. These predictions generally apply to various measures of style-level demand.

TABLE 5

Style-Level Feedback Trading by Institutional Investor Type

Table 5 reports the results from regressions of quarterly institutional demand by investor type on lagged quarterly returns and institutional demand over the prior 4 quarters and control variables. Institutional demand is calculated separately for institutions with high versus low holding duration, holding turnover, and active share. The subsample in columns 1 and 4 is based on the most sophisticated institutions (i.e., high holding duration/low holding turnover and high active share), whereas that in columns 3 and 6 is based on the least sophisticated institutions. In Panel A, institutional demand is measured by net institutional buying during a quarter scaled by the number of shares outstanding at the beginning of the quarter. In Panel B, institutional demand is measured by the fraction of institutions increasing portfolio weights to an exchange-traded fund (ETF). Control variables include the net expense ratio, age, assets under management (AUM), the average quarterly premium, and an index of ETF liquidity. For variable definitions, see the Appendix. All variables are standardized across the full sample to ease the interpretation of coefficients across specifications. All specifications include calendar time and style fixed effects. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are double-clustered by fund and time (*t*-stats in parentheses).

	High Holdings Duration × High Active Share		Low Holdings Duration × Low Active Share	Low Holdings Turnover × High Active Share		High Holdings Turnover × Low Active Share
Variables	1	2	3	4	5	6
Panel A. Y = %INST_SHARES						
RET, $q-1$	0.044**	0.096***	0.151***	0.063***	0.094***	0.135***
	(2.56)	(3.72)	(4.89)	(3.09)	(3.51)	(5.00)
RET, $q-2$	−0.029*	−0.038	−0.000	−0.010	−0.040	−0.011
	(1.80)	(1.23)	(0.02)	(0.67)	(1.35)	(0.54)
RET, $q-3$	−0.014	−0.034*	−0.000	−0.021	−0.026	−0.004
	(0.93)	(1.80)	(0.02)	(1.28)	(1.18)	(0.18)
RET, $q-4$	−0.032*	−0.020	−0.021	−0.041*	−0.018	−0.035**
	(1.85)	(1.09)	(1.41)	(1.95)	(1.02)	(2.33)
Y, $q-1$	−0.092***	−0.064*	−0.136***	−0.059***	−0.063*	−0.151***
	(3.95)	(1.76)	(5.28)	(3.00)	(1.76)	(3.87)
Y, $q-2$	−0.022	0.006	−0.037*	−0.005	0.009	−0.056**
	(1.00)	(0.18)	(1.78)	(0.37)	(0.28)	(2.53)
Y, $q-3$	−0.002	−0.006	−0.001	0.012	−0.003	−0.015
	(0.14)	(0.23)	(0.04)	(0.92)	(0.08)	(0.64)
Y, $q-4$	0.009	0.001	0.014	0.012	0.006	0.016
	(0.69)	(0.04)	(0.66)	(0.78)	(0.27)	(1.06)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects (21)	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.056	0.060	0.086	0.101	0.060	0.083
No. of obs.	10,093	10,572	10,276	10,159	10,503	10,497
Panel B. Y = %INST_WGHT						
RET, $q-1$	0.061**	0.108***	0.146***	0.057**	0.116***	0.147***
	(2.63)	(3.81)	(4.56)	(2.64)	(3.99)	(4.85)
RET, $q-2$	−0.022	−0.015	0.013	−0.020	0.002	−0.005
	(1.11)	(0.65)	(0.41)	(0.81)	(0.07)	(0.18)
RET, $q-3$	−0.004	0.009	−0.009	−0.016	0.007	−0.005
	(0.25)	(0.43)	(0.34)	(0.97)	(0.28)	(0.23)
RET, $q-4$	−0.012	−0.035**	−0.027	−0.004	−0.057**	−0.018
	(0.63)	(2.09)	(1.05)	(0.23)	(2.60)	(0.79)
Y, $q-1$	0.084***	0.070***	0.029	0.085***	0.054***	0.027*
	(4.64)	(4.36)	(1.49)	(3.84)	(3.07)	(1.70)
Y, $q-2$	0.039***	0.047***	0.021	0.073***	0.056***	0.041***
	(3.44)	(3.23)	(1.47)	(4.56)	(3.46)	(3.10)
Y, $q-3$	0.047***	0.043***	0.044***	0.046***	0.037***	0.023*
	(3.56)	(3.03)	(2.85)	(3.49)	(2.67)	(1.71)
Y, $q-4$	0.031**	0.042**	0.044***	0.027**	0.068***	0.036***
	(2.23)	(2.40)	(3.99)	(2.22)	(4.65)	(3.24)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects (21)	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.115	0.145	0.142	0.116	0.135	0.155
No. of obs.	9,486	10,374	10,059	9,528	10,239	10,304

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Brown et al. (2021) provide more nuanced predictions for the specific case of the ETF market in which APs use the share creation/redemption mechanism to trade on relative mispricing between an ETF and its underlying portfolio. In their model, net flows reflect *relative* nonfundamental demand for the ETF compared with its underlying basket of securities. By "nonfundamental," they mean something that is distinct from concurrent fundamentals, which could be either noise-trader demand, such as naïve style-switcher demand, or an under- or overreaction to fundamental news. If the ETF is more exposed to nonfundamental demand, then net flows negatively predict future ETF returns. In contrast, if the NAV is more exposed to nonfundamental demand (e.g., the underlying securities reflect fundamental information more slowly than the ETF), then net flows positively predict future ETF returns.

As a starting point, I measure style-level demand by the equally weighted monthly net flow, or the quarterly institutional demand, of other ETFs in the same style S as a given ETF i:

$$\text{OWN_STYLE_DEMAND}_{i,t} = \frac{1}{J-1} \sum_{j=1, j\neq i}^{J} \text{INV_DEMAND}_{j,t}, i, j \in S. \tag{6}$$

Admittedly, style-switcher demand is not the only component of style-level demand. Investors may also use ETFs for other strategies, such as gaining exposure to factors (Cong and Xu (2019) or hedging industry risk (Huang et al. (2020)). To better isolate the component of style-level demand related to style switching, I use the expected part of the Fama–MacBeth regression of net flows (or net institutional demand) on lagged returns and other determinants (see equation (5)) and then aggregate this measure to the style level by taking an equal-weighted average across all ETFs in the same style (excluding the focal ETF i), as in equation (6).[13]

To ensure that I am picking up cross-sectional variations in style-level demand, I also use the difference between own- and distant-style investor demand. Distant-style demand is defined analogously to equation (6), except that the own-style S is replaced by the distant-style D. For ETFs in core styles with a size and value–growth tilt (e.g., small growth), the distant style refers to the opposite size and value–growth tilt (in this case, large-cap value). For ETFs in sector styles (e.g., cyclical), the distant style includes all funds in the opposite super sector (defensive).[14]

A. Results: Predictive Regressions

I estimate pooled OLS regressions of future abnormal ETF returns (relative to the Fama–French–Carhart 4-factor model[15]) on measures of style-level investor demand, control variables, and time fixed effects to account for unobserved market conditions:

[13]The correlation between actual and expected style-level demand is very high, ranging from 0.72 to 0.80, suggesting that style-switcher demand is an important source of overall style-level demand.

[14]For ETFs in between value and growth (i.e., blend), I use the opposite size category. For mid-cap funds, the opposite includes both large and small. For the sensitive super sector, the opposite includes both cyclical and defensive.

[15]The factor loadings are estimated over the full sample. The (unreported) results are similar when using raw returns.

$$\text{PERFORMANCE}_{i,[t+1,t+\tau]} = a + b_1 \text{STYLE_DEMAND}_{i,t} + b_2 \text{CONTROLS}_{i,t} + \text{FE}_t + \varepsilon_{i,t}, \quad (7)$$

where CONTROLS includes the log of AUM, the ETF premium, the ETF return, and an index of ETF liquidity (as detailed in Section IIIB). To ease the interpretation of coefficient estimates, I standardize the right-hand-side variables across the full sample. The regression sample starts in 2006 when the median number of ETFs per style is at least 5.

The use of overlapping return periods is expected to generate residual correlation across time for a given fund. Moreover, the residuals are likely to be cross-sectionally correlated because ETF returns are likely to be exposed to unpriced factors at the style level (Daniel et al. (2020) or because STYLE_DEMAND is highly correlated in the cross section of ETFs in the same style *S* but not across time periods.[16] To account for this, I compute *t*-statistics using Driscoll and Kraay's (1998) standard errors, which can accommodate both sources of correlation. The lag length for the autocorrelation adjustment is set to equal the number of overlapping time periods. Comparable results are obtained if equation (7) is instead directly estimated at the style level by equally weighting the left- and right-hand-side variables (see Table IA7 in the Supplementary Material). The results for return predictability over various horizons (τ) are reported in Table 6.

There is a positive and highly significant relationship between equal-weighted style flows and concurrent fund returns. This is consistent with a significant price impact of style-level demand on returns, although it may also reflect within-period positive-feedback trading. More importantly, there is a negative and highly significant relationship between style flows and future returns at the 6- and 12-month horizons. Specifically, a 1-standard-deviation increase in style flows is associated with a –0.34% (–0.55%) ETF return over the next 6 (12) months. This suggests that nonfundamental demand shocks have a relatively long-lasting price impact. Focusing on expected style-level flows to better capture style-switcher demand does not change this conclusion. In this case, a 1-standard-deviation increase in expected style flows is associated with –0.44% (–0.61%) ETF return over the next 6 (12) months. The results remain virtually unchanged when using own-distant style flows, which confirms that the return predictability is primarily coming from cross-sectional variation in style-level demand.

As a benchmark for the return predictability associated with style-level flows, I compare them to fund-level net flows. Net flows are a weaker predictor of future ETF returns because the coefficient estimates are only around one-third of those for style flows. It is possible that style-level flows are a more precise proxy of nonfundamental demand shocks. The strength of style-level flows as a return predictor is not at all obvious, considering that fund-level net flows are only modestly positively correlated with own-style net flows (0.20). The correlation is even weaker between fund-level flows and relative (own-distant) style flows (0.13). These results complement the fund-level return predictability documented by Brown et al. (2021) for a broader sample of ETFs.

[16]The autocorrelation in style-level investor demand is generally low, ranging from 0.21 to 0.33 (net flows), 0.27 to 0.31 (fraction of institutions increasing portfolio weights), and –0.06 to 0.02 (net institutional buying).

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TABLE 6

Investor Demand and Return Predictability

Table 6 reports the results from regressions of abnormal exchange-traded fund (ETF) returns (adjusted for the Fama–French–Carhart 4 factors) on style-level measures of investor demand:

$$\text{PERFORMANCE}_{i,[t+1,t+\tau]} = a + b_1\text{STYLE_DEMAND}_{i,t} + b_2\text{CONTROLS}_{i,t} + \text{FE}_t + \varepsilon_{i,t},$$

where τ is the return horizon in months (Panel A) or quarters (Panel B). Specifically, [0] denotes the current time period, and [1, τ] denotes return horizons from 1 to τ periods in the future. Style-level demand is measured by i) the equally weighted net flow of *other* ETFs in the same style (OWN_STYLE_FLOW), ii) the expected style-level net flow (i.e., the expected part from Fama–MacBeth regressions of net flows on lagged returns and determinants), iii) the difference between own- and distant-style flows (OWN_DIST_STYLE_FLOW), iv) the difference between expected own- and distant-style-level net flows, and v) the fund-level net flow (NFLOW). The distant style refers to ETFs in the opposite style(s). In Panel B, investor demand is measured by the equal-weighted net institutional demand of other ETFs in the same style (based on net institutional buying or the fraction of institutions increasing portfolio weights to an ETF) at the quarterly horizon. All specifications include control variables (assets under management (AUM), premium, ETF returns, and an index of ETF liquidity) and calendar time fixed effects. To ease the interpretation of coefficients across specifications, all explanatory variables are standardized to mean 0, variance 1 across the full sample. The *t*-statistics are calculated using standard errors that are adjusted for serial and cross-sectional correlation based on Driscoll and Kraay (1998), with the maximum lag for autocorrelation determined by the number of overlapping periods per return horizon. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Monthly Horizon

	[0]	[1,1]	[1,3]	[1,6]	[1,12]
OWN_STYLE_FLOW	0.415***	−0.084*	−0.134	−0.338***	−0.545**
	(8.75)	(1.77)	(1.60)	(2.65)	(2.54)
R^2	0.051	0.030	0.027	0.031	0.035
No. of obs.	30,157	30,100	29,816	29,249	28,113
E(OWN_STYLE_FLOW)	0.330***	0.005	−0.174	−0.437***	−0.606**
	(5.25)	(0.09)	(1.54)	(2.64)	(2.37)
R^2	0.040	0.029	0.025	0.028	0.033
No. of obs.	27,733	27,488	27,204	26,637	25,502
OWN_DIST_STYLE_FLOW	0.300***	−0.106**	−0.146**	−0.376***	−0.629***
	(7.40)	(2.32)	(1.98)	(3.66)	(3.65)
R^2	0.042	0.031	0.028	0.032	0.036
No. of obs.	28,135	28,082	27,826	27,315	26,291
E(OWN_DIST_STYLE_FLOW)	0.180***	−0.024	−0.191**	−0.463***	−0.674***
	(3.58)	(0.52)	(1.97)	(3.28)	(3.27)
R^2	0.033	0.030	0.026	0.029	0.034
No. of obs.	25,993	25,765	25,509	24,998	23,975
NFLOW	0.313***	−0.026	−0.071*	−0.110**	−0.149*
	(9.95)	(1.06)	(1.78)	(2.00)	(1.67)
R^2	0.042	0.029	0.026	0.028	0.032
No of obs.	31,173	31,163	30,875	30,300	29,148

Panel B. Quarterly Horizon

	[0]	[1,1]	[1,2]	[1,4]
OWN_STYLE_ %INST_WGHT	0.778***	−0.304**	−0.639***	−0.994***
	(4.69)	(2.32)	(3.12)	(2.82)
R^2	0.055	0.038	0.036	0.040
No. of obs.	9,646	9,615	9,050	9,050
OWN_DIST_STYLE_ %INST_WGHT	0.468***	−0.272***	−0.620***	−1.007***
	(3.28)	(2.69)	(4.04)	(3.52)
R^2	0.046	0.039	0.038	0.041
No. of obs.	9,007	8,978	8,469	8,469
E(OWN_STYLE_ %INST_WGHT)	0.370*	−0.344**	−0.686***	−1.121***
	(1.95)	(2.40)	(3.25)	(3.56)
R^2	0.039	0.039	0.036	0.042
No. of obs.	9,499	9,431	8,867	8,867
OWN_STYLE_ %INST_SHARES	0.653***	−0.229	−0.515***	−0.845**
	(3.04)	(1.44)	(2.73)	(2.47)
R^2	0.050	0.037	0.034	0.038
No. of obs.	9,684	9,635	9,070	9,070
OWN_DIST_STYLE_ %INST_SHARES	0.426**	−0.275*	−0.498**	−0.916***
	(2.31)	(1.94)	(2.48)	(2.80)
R^2	0.044	0.040	0.036	0.040
No. of obs.	9,045	8,998	8,489	8,489
E(OWN_STYLE_ %INST_SHARES)	0.459**	−0.193	−0.549**	−1.008***
	(1.99)	(1.62)	(2.43)	(3.93)
R^2	0.040	0.037	0.033	0.039
No. of obs.	9,584	9,531	8,967	8,967

The negative relationship between investor demand and future returns also holds for both measures of net institutional demand. As before, the return predictability is strongest at the 6- and 12-month horizons. At the 12-month horizon, the impact of a 1-standard-deviation increase in style-level institutional demand is associated with a decrease in future ETF returns that ranges from –0.85 to –1.11%. The point estimates, and the *t*-statistics in particular, are somewhat stronger for equally weighted metrics of institutional demand. This is consistent with the existing literature, which emphasizes the greater predictive power of equal-weighted measures of investor demand relative to value-weighted measures (e.g., Sias, Turtle, and Zykaj (2015), Edelen et al. (2016)).

Overall, the return predictability results clearly highlight that style-level demand, especially the component linked to style-switcher demand, is negatively related to future returns. The results are robust to several measures of style-level demand, based on both net flows and net institutional demand. This suggests that uninformed style-level positive-feedback trading is strong enough to push prices away from fundamentals over an extended time period.

B. Betting Against Recent Style-Level Demand

To better gauge the economic significance of the style-level return predictability documented earlier over 6- to 12-month horizons, I now turn to a simple trading strategy. The base assets consist of 21 style portfolios (see Table 1 for a complete list). Style returns correspond to either the equal- or value-weighted averages of the underlying ETF returns. I sort the style portfolios into quartiles based on style-level investor demand over the prior P months (6 or 12). This is done by first computing net flows (or institutional demand) over the prior P months[17] and then equally weighting the measures at the style level. I consider holding periods (K) of 1, 3, and 6 months. For holding periods longer than a month, the strategy corresponds to a composite portfolio in which $1/K$ of the holdings are rebalanced each month (e.g., Novy-Marx and Velikov (2016)). I use partial rebalancing to make full use of all available data, given the relatively short sample period. Table 7 reports the Fama–French–Carhart 4-factor alphas for the low (Q1), high (Q4), and low – high (Q1 – Q4) portfolios for sorts on past style-level demand. The low-minus-high portfolio is a long–short strategy that buys styles with low demand and short-sells styles with high demand (i.e., the strategy bets *against* recent style-level demand).

As shown in Table 7, the long–short trading strategy generates consistently significant abnormal returns ranging from 4.3% to 5.4% per year for sorts on style-level net flows. This is true both for equal- and value-weighted style portfolio returns, for 6- and 12-month demand horizons, and across all 3 holding periods. Because the largest funds within a style are typically also the most liquid (often, even more so than their underlying portfolios on a dollar-weighted basis) (Broman and Shum (2018)), the value-weighted style portfolios are clearly implementable in practice. Likewise, sorts on style-level %INST_WGHT (an equally weighted metric) yield positive and

[17]The definitions are unchanged for net flows (equations (1) and (2)) and net institutional buying (equation (3)), except that the numerator (dollar flows or net number of shares bought) is computed over a window of P months, whereas the denominator (AUM or number of ETF shares outstanding) is lagged by $P - 1$ months. The fraction of institutions increasing portfolio weights to an ETF is computed as in equation (4) and then averaged over the prior P months.

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TABLE 7

Betting Against Style-Level Demand

Table 7 reports annualized Fama–French–Carhart 4-factor alphas for trading strategies based on style-level investor demand. The base assets consist of 21 style portfolios (3 × 3 size/valuation styles, 11 sectors, and 1 quality style; 9 + 11 + 1 = 21). Style returns correspond to either equal- or value-weighted averages of the underlying exchange-traded fund (ETF) returns. Investor demand (net flows or net institutional demand) is first computed over the prior *P* months (6 or 12) as in equations (1)–(4), and then equally weighted at the style level. The base assets are then sorted into quartiles based on style-level investor demand over the prior *P* months. For holding periods longer than a month (*K* = 3 or 6), I use partial rebalancing following the Jegadeesh and Titman (1993) methodology. Newey–West *t*-statistics with 12-month lags are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Holding Period (*K* = months)								
	K = 1			*K* = 3			*K* = 6		
Predictor	Q1	Q4	Q1 – Q4	Q1	Q4	Q1 – Q4	Q1	Q4	Q1 – Q4
OWN_STYLE_FLOW [$t-1, t-12$]									
Equal weighted	1.149	−3.826***	4.974**	2.139	−3.306***	5.445***	1.415	−2.873**	4.288**
	(0.74)	(3.09)	(2.56)	(1.51)	(2.80)	(3.15)	(1.16)	(2.45)	(2.85)
Value weighted	1.018	−3.597***	4.615**	1.641	−2.980**	4.621**	0.819	−2.578**	3.398**
	(0.59)	(2.78)	(2.12)	(1.05)	(2.55)	(2.39)	(0.61)	(2.30)	(2.07)
OWN_STYLE_FLOW [$t-1, t-6$]									
Equal weighted	−0.558	−5.314***	4.755***	1.325	−4.062***	5.386***	1.485	−3.388***	4.872***
	(0.45)	(6.48)	(3.66)	(1.05)	(5.12)	(4.05)	(1.41)	(4.05)	(4.00)
Value weighted	−0.497	−5.843***	5.346***	1.100	−4.169***	5.269***	1.183	−3.153***	4.335***
	(0.38)	(6.09)	(3.58)	(0.82)	(5.00)	(3.47)	(1.02)	(3.56)	(3.09)
OWN_STYLE_%INST_WGHT [$t-1, t-12$]									
Equal weighted	1.311*	−2.935*	4.246**	0.954	−2.835	3.789**	−0.821	−1.268	0.447
	(1.68)	(1.70)	(2.18)	(1.22)	(1.65)	(2.12)	(0.99)	(1.07)	(0.34)
Value weighted	0.931	−3.188**	4.119**	0.610	−2.834*	3.444**	−0.781	−1.508	0.727
	(1.06)	(2.03)	(2.26)	(0.68)	(1.81)	(2.03)	(0.93)	(1.16)	(0.50)
OWN_STYLE_%INST_WGHT [$t-1, t-6$]									
Equal weighted	−0.101	−4.135***	4.033***	0.044	−3.427**	3.471**	0.538	−2.478	3.016*
	(0.1)	(3.00)	(3.04)	(0.05)	(2.30)	(2.25)	(0.71)	(1.64)	(1.97)
Value weighted	−0.349	−4.251***	3.901***	−0.282	−3.336**	3.054*	0.237	−2.308	2.545
	(0.35)	(2.85)	(2.71)	(0.29)	(2.21)	(1.91)	(0.29)	(1.54)	(1.64)

(continued on next page)

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TABLE 7 (continued)

Betting Against Style-Level Demand

	Holding Period (K = months)								
	$K = 1$			$K = 3$			$K = 6$		
Predictor	Q1	Q4	Q1 – Q4	Q1	Q4	Q1 – Q4	Q1	Q4	Q1 – Q4
OWN_STYLE_%INST_SHARES $[t-1, t-12]$									
Equal weighted	0.281	−2.815	3.096*	0.494	−1.971	2.465*	−0.687	−1.146	0.458
	(0.22)	(1.58)	(1.85)	(0.44)	(1.31)	(1.68)	(0.61)	(0.88)	(0.35)
Value weighted	−0.116	−2.834	2.718	0.060	−1.775	1.835	−0.609	−1.227	0.618
	(0.09)	(1.59)	(1.55)	(0.05)	(1.21)	(1.22)	(0.56)	(0.96)	(0.48)
OWN_STYLE_%INST_SHARES $[t-1, t-6]$									
Equal weighted	0.728	−4.803**	5.530***	1.032	−3.585*	4.618**	0.347	−1.687	2.034
	(0.6)	(2.43)	(2.70)	(0.94)	(1.88)	(2.61)	(0.34)	(1.11)	(1.51)
Value weighted	0.471	−4.243**	4.714**	0.687	−3.097*	3.784**	−0.108	−1.429	1.321
	(0.4)	(2.18)	(2.29)	(0.61)	(1.63)	(2.10)	(0.1)	(0.93)	(0.98)

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significant abnormal returns (3.1%–4.2% per year) at the 1- and 3-month holding periods. Abnormal returns for sorts on style-level %INST_SHARES are comparable or even stronger, but only when institutional demand is measured over the prior 6 (but not 12) months. It is possible that the value-weighted signals of institutional demand are, compared with equal-weighted measures, more short-lived as return predictors.

Although the alphas are concentrated in the short leg of the strategy for sorts on style-level institutional demand and, to a lesser degree, for sorts on style-level net flows, this does not necessarily imply that short-sale constraints are the primary friction preventing arbitrageurs from exploiting the strategy. Short-selling ETFs is, in general, not an impediment given that ETF short interest already accounts for up to 20% of the total dollar value of short interest in U.S. equity markets (Evans et al. (2019)). Short interest is particularly high for sector funds that are often used as a hedging vehicle (Huang et al. (2020)). A more important impediment to arbitrage may instead be idiosyncratic-style risk; because most ETFs in my sample correspond to characteristic-sorted portfolios, hedging unpriced (style-specific) factors is difficult in practice (Daniel et al. (2020)).

VII. Summary and Conclusions

In this article, I examine style-level feedback trading in ETFs and whether this demand is uninformed, as theorized by De Long et al. (1990), among others. Extrapolation of past price changes into the future is an important stylized fact for a broad cross section of investors (e.g., Greenwood and Shleifer (2014)). There is currently no consensus in the literature on whether mutual fund investors (Barber et al. (2016)), fund managers (Frijns et al. (2013)), or institutional investors (Choi and Sias (2009)) engage in style-level positive-feedback trading. By contrast, ETFs provide a unique setting for examining the determinants of style-level demand without any confounding stock-level effects.

Alternative explanations for positive-feedback trading based on investors' pursuit of superior talent are irrelevant for passive and transparent ETFs for which no skill is involved. Consistent with these predictions, I find that ETF investors, in aggregate, engage in style-momentum trading, allocating more money to well-performing styles in the cross section and withdrawing money from poorly performing styles. Style-momentum trading in ETFs is economically very strong over short horizons (up to a quarter) and holds for both inflows and outflows, which is consistent with style-switching behavior.

A large body of literature depicts institutions as relatively sophisticated investors that act as arbitrageurs, except when limited by market frictions. However, Edelen et al. (2016) conjecture that institutional investors could be uninformed positive-feedback traders themselves. To evaluate the role of institutions, I examine the relationship between net institutional demand and lagged returns in the aggregate as well as separately by institutional investor type. I show that institutional investors engage in style-momentum trading in the short run (up to a quarter), which is mostly driven by less sophisticated institutions (i.e., those with low active share, high holding turnover, and low holding duration). Moreover, less sophisticated institutions own a relatively large fraction of outstanding ETF shares (14%) relative to more sophisticated institutions (5%), which suggests that the sample of

institutional ETF users is tilted toward less sophisticated institutions. These results agree with Joenväärä and Salehi (2018) and Sherrill et al. (2017), who show that institutional investors that use ETFs underperform institutions that do not.

Finally, I examine whether the style-level demand for ETFs is strong enough to temporarily push prices away from fundamentals. Consistent with this prediction, I find that style-level net flows (or net institutional demand) for ETFs are negatively related to future returns over a period of 6 to 12 months. Similarly, a trading strategy that bets against recent style-level demand yields highly significant and positive abnormal return months. This evidence is consistent with the idea that the style-level demand for ETFs is uninformed as well as strong enough to push prices away from fundamentals.

Appendix. Variable Definitions

Fund Characteristics

Inflows, outflows, and net flows: Dollar inflows (from N-SAR when available), or the dollar value of monthly share creations (when N-SAR is not available), scaled by the lagged AUM [INFLOW]. Dollar outflows, or the dollar value of monthly share redemptions, scaled by lagged AUM [OUTFLOW]. Net flows is dollar inflows minus outflows scaled by lagged AUM [NFLOW].

AUM: Assets under management, or number of shares outstanding multiplied by NAV.

RET: Monthly ETF return inclusive of dividends.

Age: (Current date – inception date)/365.

Average premium:
$$\text{AVGPREM}_{i,t-1} = \frac{1}{N_{t-1}} \sum_{d=1}^{N_{t-1}} (\ln(\text{ETF}_{i,d}) - \ln(\text{NAV}_{i,d})),$$
where N_{t-1} = number of trading days in month $t-1$; $\text{ETF}_{i,d}$ = closing midpoint price on day d; and $\text{NAV}_{i,d}$ = net asset value per share.

Expense ratio: The percentage of fund assets used to pay for management fees and other operating expenses, including distribution (12b-1) fees and administrative fees.

Quoted spread:
$$\text{QSPR}_{i,t} = \frac{1}{N_t} \sum_{d=1}^{N_t} \ln\left[\frac{\text{ASK}_{i,d} - \text{BID}_{i,d}}{(\text{ASK}_{i,d} + \text{BID}_{i,d})/2}\right],$$
where ASK and BID refer to closing ask and bid prices of the ETF i on day d. N_t refers to the number of days in month t.

Price impact:
$$\text{AMIHUD}_{i,t} = \frac{1}{N_t} \sum_{d=1}^{N_t} \ln\left[\frac{|R_{i,d}|}{\text{DVOL}_{i,d}}\right],$$
where R is the closing mid-quote return (in %), and DVOL is the dollar volume ($millions) on day d. Daily observations beyond the 99.5th percentile are discarded.

Turnover:
$$\text{TO}_{i,t} = \frac{1}{N_t} \sum_{d=1}^{N_t} \ln\left[\frac{\text{VOL}_{i,d}}{\text{SHR}_{i,d}}\right],$$
where VOL is the share volume of ETF i on day d, and SHR is shares outstanding. Daily observations beyond the 99.5th percentile are discarded.

ETF_LIQ: The ETF liquidity index is computed as the first principal component across the 3 individual liquidity measures (– quoted spreads, – price impact, and + turnover).

Institutional Investor Characteristics

Active share:
$$\text{ACTIVE_SHARE}_{i,q} = 0.5 \times \sum_{j=1}^{N} \left(w_{i,j,q} - w_{j,q}^{VW}\right),$$
where $w_{i,j,q}$ = actual weight invested by institution i in security j at quarter-end q, and $w_{j,q}^{VW}$ is the market-cap weight of security j.

Investor holding duration:
$$\text{HOLDING_DURATION}_{i,j,T-1} = \frac{(W-1)H_{i,j}}{H_{i,j}+B_{i,j}} + \sum_{t=T-W+1}^{T-1} \left(\frac{(T-t-1)\alpha_{i,j,t}}{H_{i,j}+B_{i,j}}\right),$$
where $B_{i,j}$ = total percentage of 13-F security i (stock or ETF) bought by institution j between $t = T-W$ and $t = T-1$, where t, T are in quarters; $H_{i,j}$ = percentage of total shares outstanding of security i held by institution j at time $t = T-W$; $\alpha_{i,j,t}$ = percentage of total shares outstanding of i bought or sold by institution j between time $t-1$ and t, where $\alpha_{i,j,t} > 0$ for buys and $\alpha_{i,j,t} < 0$ for sells; and W = maximum holding duration (20 quarters, as in Cremers and Pareek (2016)). The duration measure is set to 0 for security i if it is not held by institution j at time $T-1$. To arrive at a measure of investor holding duration, I calculate a weighted average across all securities i based on the market value invested in the security by institution j. Before including institution j in the calculation, I require that j has existed for at least 2 years.

Investor holding turnover:
$$\text{HOLDING_TURNOVER}_{j,t} = \frac{\sum_{i \in Q} \left|N_{i,j,t}P_{i,t} - N_{i,j,t-1}P_{i,t-1} - N_{i,j,t-1}\Delta P_{i,t}\right|}{\left(\sum_{i \in Q} N_{i,j,t}P_{i,t} + N_{i,j,t-1}P_{i,t-1}\right)/2},$$
where $P_{i,t}$ and $N_{i,j,t}$ refer to the price and number of shares outstanding, respectively, of security i held by institution j in quarter t. For each institutional investor j, I start by computing the holding turnover every quarter based on its entire portfolio of 13-F securities (including stocks and ETFs), and then I

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Supplementary Material

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