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Corporate managers, price noise and the investment factor

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Abstract

This study investigates the impact of flows between bond and equity funds on investment factors over the period 1984–2015. It determines contemporaneous mispricing effects and a statistical reversal relation between these flows and both legs of the investment factor. The statistical reversal relationship between previous flows and the investment factor is economically significant. A one-standard-deviation shock to flows causes a 0.29% decrease in investment factor returns, which are reversed within 5 months. A trading strategy based on signals from past flows and the investment factor outperforms the market by 0.68% in the months following positive flows and produces significant alphas after accounting for well-known equity risk factors. The findings are interpreted as evidence in favor of a behavioral explanation, in which sentiment influences actual managerial decisions. When retail investors and managers are swept up in market euphoria, retail investors shift their holdings from bond to equity mutual funds, and high-investment firms invest more aggressively. Market-level euphoria has a different impact on high- and low-investment firms, and thus the investment factor can be influenced. Hence, the mispricing occurs during these periods, and the reversal relationship is especially pronounced for a high-investment portfolio versus a low-investment portfolio. As a result, during the months following periods of positive flows, the investment factor outperforms the market factor. Interestingly, this study's measure of flows, which serves as a proxy for market-level euphoria, outperforms other measures of investor sentiment.

Keywords: Corporate investment, Investment factor, Mutual funds, Fund flows, Net exchanges, Price noise, Market stress

JEL Classification: G11, G12, G14

Introduction

The time-series and cross-sectional relationships between corporate investments and stock returns are well-documented in the literature. Time-series evidence supports the notion that corporate investments are influenced by waves of investor optimism and pessimism. According to Arif and Lee (2014), periods of higher corporate investment correspond to periods of investor optimism and are followed by periods of lower aggregate stock returns. Managers increase (decrease) capital investments during periods of optimism (pessimism) because they overestimate (underestimate) the present value of expected future cash flows. Aggregate investments negatively predict future

market returns because managers, like investors, are frequently too optimistic (too pessimistic). They conclude that investor sentiment influences real managerial decisions, either because managers rationally exploit market misvaluations (“managerial catering” hypothesis) or because they are caught up in market euphoria (“expectation bias” hypothesis) and make more capital investments. They demonstrate the tendency for aggregate investment to increase during periods of high consumer confidence, high net inflows into equity markets, and high sentiment, as measured by the Baker–Wurgler sentiment index.

Baker et al. (2003)’s cross-sectional findings suggest that corporate investment is sensitive to nonfundamental changes in stock prices. Their main prediction is that stock prices will have a greater impact on the investment of “equity-dependent” firms, which require external equity to finance marginal investments. In particular, firms in the top quintile of equity dependence have investments that are nearly three times as sensitive to stock prices as firms in the bottom quintile. Standard corporate finance considerations suggest that equity-dependent firms tend to be young and have high leverage, low cash balance and cash flows, high cashflow volatility (and hence low incremental debt capacity), and strong investment opportunities. They discover average negative investment-future returns sensitivity, which becomes increasingly negative as equity dependence increases.

Similarly, prior research indicated a negative relationship between aggregate mutual fund flows, flows from the bond to equity mutual funds, and future market returns. According to Ben-Rephael et al. (2012), mutual fund trading activities generate non-fundamental price pressure on aggregate stock prices, which reverts in the short term. Accordingly, in bullish markets, equity mutual funds receive inflows that must be quickly equitized by fund managers. They are experiencing outflows in bearish markets, and managers reduce their positions because of redemption pressure. Due to the tendency of retail investors to herd, the directional trading of mutual funds is correlated. As a result, mutual funds’ collective actions generate short-term price pressure on aggregate stock prices. Correlated net inflows (outflows) cause upward (downward) price pressure and subsequent negative (positive) returns. Hence, the reversal relationship can be linked to price “noise” caused by uninformed trading stemming from sentiment.

In this vein, I investigate the impact of flows between the bond and equity funds on investment factors in the United States from 1984 to 2015. Based on previous evidence, I hypothesize that market euphoria affects retail investors’ and managers’ decisions. Retail investors are shifting their holdings from bond to equity mutual funds, and high-investment firms are investing more aggressively. “Aggressive” managers are caught up in market euphoria; thus, they invest more, and high-investment stocks are overpriced. Because high- and low-investment firms are assumed to be differentially impacted by market-level euphoria during these periods, high-investment firms earn higher returns than low-investment firms. Consequently, the investment factor may be influenced, and the contemporaneous relationship between net exchanges and the investment factor can be interpreted as negative. Subsequently, the reversal relationship is stronger and, therefore, returns for the high-investment portfolio are significantly lower than those for the low-investment portfolio. Hence, if both retail investors and managers are overly optimistic, I anticipate that an investment factor will perform particularly well in the coming

period (the lagged relationship between net exchanges and the investment factor can be assumed to be positive). Overall, I find contemporaneous mispricing effects and a statistical reversal relationship between net exchanges, flows from bonds to equity funds, and both legs of the investment factor. The statistical reversal relationship between previous net exchanges and the investment factor is economically significant. Moreover, a one-standard-deviation shock to net exchanges causes a 0.29% decrease in investment factor returns, which are all reversed within 5 months. A trading strategy based on signals from past net exchanges and the investment factor outperforms the market by 0.68% in the months following positive net exchanges and produces significant alphas after accounting for well-known equity risk factors. My findings are interpreted as evidence in favor of a behavioral explanation in which sentiment influences real managerial decisions. Interestingly, in the regressions, my measure of flows from bonds to equity funds, which serves as a proxy for market-level euphoria, outperforms other indicators of investor sentiment.

The rest of this paper is structured as follows. Section 2 discusses the relevant literature. Section 3 describes the data and presents summary statistics. Section 4 discusses my empirical findings regarding the relationship between factor portfolio returns, net exchanges, and market stress indicators. Finally, Sect. 5 concludes with a summary of the major findings.

Related literature

Retail investors are the most common mutual fund shareholders, and they are vulnerable to volatile market conditions. Based on data reported in the 2018 Investment Company Institute (ICI) Fact Book,¹ retail investors hold about 92% of all equity mutual funds, 90% of bond mutual funds, and 62% of money market mutual funds as of 2017. In bullish markets, for example, equity mutual funds receive inflows that must be quickly equitized by fund managers. The directional trading of mutual funds is correlated due to retail investors' herding behavior. Hence, the collective actions of fund managers generate short-term price pressure on aggregate stock prices. As a result, the direction of mutual fund trades may be predictable due to the price pressure problem associated with "crowded trades." The temporary price pressure hypothesis has recently received strong empirical support. The results of Arif et al. (2016) suggest that short sellers trade in the opposite direction of these flows based on the flow-induced price impact. When fund flows are in the opposite direction, short sellers have up to three times the ability to predict stock returns. Short sellers are extremely quick to mirror "unexpected" mutual fund trades that are not part of an ongoing pattern. The authors do not provide direct evidence on how short sellers can predict these moves, but it appears that short sellers are picking up on some important indirect signals. Consistent with the behavioral literature, mutual funds lose more to short sellers when retail investors are overoptimistic about equities. Ben-Rephael et al. (2012) investigated aggregate net equity fund exchanges in the United States and the monthly shifts between bond and equity funds. They discovered that aggregate stock market excess returns are contemporaneously positively, but

¹ https://www.ici.org/pdf/2018_factbook.pdf, Table 60.

negatively, correlated with lagged net exchanges. Within four (ten) months, 85% (100%) of the contemporaneous relation is reversed. Their findings are interpreted as supporting the notion of “noise” in aggregate market prices. Ben-Rephael et al. (2011) use aggregate daily flows to equity mutual funds in Israel and found empirical evidence supporting the “temporary price pressure hypothesis” regarding mutual fund flows: flow-induced trading activities of mutual funds create temporary price pressure that is then corrected. Within 10 trading days, half of the initial price change is reversed. Ben-David et al. (2021) found a causality between flow-based sentiment and returns, presenting evidence that mutual fund ratings generate correlated demand, which causes systematic price fluctuations. Meanwhile, Wen et al. (2019) discovered a robust negative relationship between retail investor attention and future stock price crash risk for a sample of Chinese A-share listed companies. Their empirical evidence suggests that retail investor attention can effectively reduce information asymmetry, resulting in a lower risk of a stock price crash.

Regarding return predictability, Lou (2012) provided a flow-based explanation for some well-known empirical patterns of return predictability. In particular, he showed that expected flow-induced trading by mutual funds positively (negatively) predicts future stock and fund returns in the short (long) run. The return pattern is consistent with the notion that arbitrageurs have limited capacity to absorb temporary demand shocks in the financial market, even if these shocks are fully expected. The flow-based explanation drives mutual fund performance persistence, the smart money effect, and, to a lesser extent, stock price momentum. According to Shive and Yun (2013), patient traders’ profit from mutual funds’ predictable, flow-induced trades. In anticipation of a 1%-of-volume change in mutual fund flows into a stock the following quarter, institutions in the same 13F category as hedge funds trade 0.29–0.45% of volume in the current quarter. A third of the trading is linked to a subset of 504 identified hedge funds. The effect is stronger when quarterly mutual fund portfolio disclosure is required and among hedge funds with more patient capital. A hedge fund with a one standard deviation higher measure of anticipatory trading has a 0.9% higher annualized four-factor alpha. Meanwhile, a one standard deviation higher measure of anticipation of a mutual fund’s trades by institutions is associated with a 0.07–0.15% lower annualized four-factor alpha.

When studying the negative relationship between corporate investments and future returns, one can distinguish between rational and sentiment-based explanations. The rational camp argues that the negative relationships are explained by time-varying discount rates, assuming that stock prices are efficient. Short-term market mispricing is irrelevant to investment decisions because rational corporate managers optimize long-term firm value (e.g., Cochrane 1991; Lamont 2000; Hirshleifer et al. 2009). More recently, Hou et al.’s (2015) findings support the view that firms’ investment decisions are aligned with the discount rate. Aggressive firms with lower discount rates invest more, whereas conservative firms with higher discount rates face higher investment hurdles and thus invest less. Behavioral explanations support the notion that corporate investments are influenced by waves of investor optimism and pessimism. Periods of higher corporate investment correspond to periods of investor optimism and are followed by lower (aggregate) stock returns. Investor sentiment can be assumed to influence real managerial decisions, either because managers rationally exploit market mispricing

(“managerial catering”) or because they are caught up in market euphoria (“expectation bias”) and increase capital investment (e.g. Baker et al. 2003; Polk and Sapienza 2004; Arif and Lee 2014). As a result, corporate investments are likely to increase when firms are more overvalued by issuing more equity (Baker and Wurgler 2000) or because of a firm mispricing channel (Polk and Sapienza 2004, 2009).

Huang et al. (2020) showed that a large set of asset pricing factors (anomalies) is significantly vulnerable to noise trader risk, which arises from uninformative demand shifts among mutual fund investors. When allocating capital to mutual funds, mutual fund investors are largely unaware of systematic factors and rely on simple signals. They aggregate flow-induced trades of individual stocks underlying the factors to measure uninformed demand for factors. Moreover, they find that mutual funds’ flow-induced trading significantly determines average returns, volatility, and co-movements among the well-studied factors, implying the vulnerability of these factors to noise trader risk. Importantly, they show that arbitrageurs and other investors have significantly priced this flow-driven noise trader risk. Zou (2016) suggested that trading noise has a significant impact on default risk estimation. Adjusting for trading noise significantly affects firms’ estimation of distance-to-default, in terms of magnitude and relative ranking among firms. As a result, default probabilities adjusted for trading noise are more powerful predictors of corporate default events. Moreover, Kou et al. (2021) proposed a bankruptcy prediction model for small- and medium-sized firms in the absence of financial statements. The authors emphasize the significance of transactional data and payment network-based variables in predicting bankruptcy.

Barber et al. (2016) argued that sophisticated investors will consider all factors (priced and unpriced) that explain cross-sectional variation in fund performance when evaluating a fund manager’s skill. They examined the factors that investors pay attention to by analyzing mutual fund flows as a function of recent returns decomposed into alpha and factor-related returns. Surprisingly, when evaluating funds, investors pay the most attention to market risk (beta) and regard returns attributable to size, value, momentum, and industry factors as alpha. Using proxies for investor sophistication (wealth, distribution channels, and periods of high investor sentiment), the authors determined that more sophisticated investors use more sophisticated benchmarks when evaluating fund performance.

Data and descriptive statistics

Fund flows

I employ a subset of the flow data examined in a recent study by Ben-Rephael et al. (2012) of the ICI. Although their research relies on ICI data from 1984 to 2008, I use aggregate mutual fund flows from January 1984 to December 2015. Over our sample period, the aggregate data contain 33 categories: 5 for domestic equity funds, 4 for international equity funds, 4 for mixed funds (both equity and bonds), and 20 for bond funds. The aggregate data are published monthly. The emphasis is on equity funds that include domestic equity, international equity, and mixed funds. Domestic equity is the most important asset class in terms of asset values and flows, and it includes the following asset classes: growth, aggressive growth, growth and income, income equity, and sector. Following Warther (1995) and Ben-Rephael et al. (2012) calculated monthly net flows as

Table 1 Summary statistics

	Mean	Median	SD	Min	Max
<i>NFLOWS</i> (%)	0.59	0.50	0.85	− 2.94	3.85
<i>NSR</i> (%)	0.64	0.56	0.67	− 1.18	3.61
<i>NEIO</i> (%)	− 0.05	− 0.02	0.33	− 2.41	2.23
<i>FTS</i>	0.03	0.00	0.09	0.00	0.59
<i>Mkt-RF</i>	0.65	1.16	4.45	− 23.24	12.47
<i>CMA_LO</i>	1.12	1.63	4.81	− 25.44	14.27
<i>CMA</i>	0.26	0.10	2.02	− 6.88	9.58
<i>R_IA</i>	0.31	0.29	1.94	− 7.16	9.24
<i>CMA_HI</i>	0.86	1.39	5.52	− 27.83	14.12

The table presents the summary statistics of the equity fund flows, the market excess return and the other factor portfolio returns used in the study. The sample period ranges from February 1984 to December 2015, covering a total of 383 months. Fund flows are calculated based on data from the Investment Company Institute (ICI). The following fund categories are included: domestic equity, international equity, and mixed funds. The equity market returns are value-weighted returns of NYSE, Amex, and Nasdaq stocks from the Center for Research in Security Prices (CRSP). The net flows of the equity funds and their components are normalized each month by the previous month's fund assets value: *NFLOWS* is the normalized net flows (in %). *NSR* is the normalized net sales ("new sales" minus "redemptions") in %. *NEIO* is the normalized "net exchanges" ("exchanges in" minus "exchanges out") in %. *FTS* is based on the daily flight-to-safety dummy of Bekaert et al. (2019) and transformed to derive a monthly indicator, which provides information about the fraction of *FTS* days within the month. *Mkt-RF* is the excess market return, the value-weighted returns of NYSE, Amex, and Nasdaq stocks from the Center for Research in Security Prices (CRSP) over 30-day T-bill return in %. *CMA_LO* is the average return on the two conservative investment portfolios. *CMA_HI* is the average return on the two aggressive investment portfolios. Conservative Minus Aggressive (*CMA*) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. *R_IA* is the investment factor of Hou et al. (2015)

the sum of the following components: "new sales" plus "exchanges in" minus "redemption" and "exchanges out." The fund assets at the beginning of the month are used to normalize the monthly flow components. Moreover, the flows are divided into two categories: *NEIO* and *NSR*. *NEIO* is the normalized aggregate net exchanges of equity funds ("exchanges in" minus "exchanges out" flows from bond to equity funds), and *NSR* is the normalized aggregate net sales of equity funds ("new sales" minus "redemptions"). I concentrate on *NEIO* in my analysis, which is motivated by the findings of Ben-Rephael et al. (2012). The reason for this is that net exchanges reflect mutual fund investors' asset allocation decisions to shift their holdings between bond and equity funds, whereas net sales and redemption are influenced more by long-term savings and withdrawals.

I focus on two investment factors: the Conservative Minus Aggressive (*CMA*) factor, which includes a conservative and aggressive investment portfolio, and the *R_IA* investment factor developed by Hou et al. (2015). The data are obtained from the websites of Kenneth French and Chen Xue. I also use *FTS*, a market stress indicator based on Baele et al.'s (2020) flight-to-safety dummy, which is available daily. I convert the daily dummies into a monthly indicator that shows the fraction of *FTS* days in a given month. I identified 11% of the months as having *FTS* of varying intensity. Table 1 presents the summary statistics of the equity fund flows, the market stress indicator, and the factor portfolio returns.

Net exchanges and the investment factor returns

My primary research question concerns the relationship between mutual fund flows (normalized net sales (NSR) or normalized net exchanges (NEIO)) and investment factor returns.² The analysis is structured as follows: First, I use a regression analysis to determine whether a relationship exists between flows and contemporaneous and subsequent investment factor returns. Second, I estimate the accumulated dynamic effects using a vector autoregression (VAR) methodology. Third, I examine the economic significance using trading strategies based on signals from previous flows. Finally, I relate the trading exercise results to sentiment measures.

Relationship between the investment factor and contemporaneous and lagged flows

In this section, I examine the relationship between factor returns and all US equity fund flows (NFLOWS net flows) and the two separate components, namely, NEIO (normalized net exchanges) and NSR (normalized net sales). The two flow components, NEIO and NSR, correlate positively with an average value of 0.32, which is statistically significant at the 1% level. Previous research indicates that flows between bond and equity funds within the same fund family are particularly interesting. When using normalized net exchanges, one deliberately ignores flows between equity funds that do not contain the same information. Furthermore, unlike net exchanges, flows into bond and equity funds that are not part of the same fund family do not contain the same information because they strictly refer to very different investors. Therefore, "net exchanges" is the most accurate proxy for flows from bond funds to equity funds.³ Table 2 shows the coefficients from time-series regressions with factor portfolio returns as the dependent variable on both contemporaneous and lag flows.

For each Table, specifications (1), (2), and (4) use NFLOWS, NSR, and NEIO concurrently in the regressions, which, for example, are all extremely important market factors (Panel A). The adjusted-R2 between Mkt-RF and NSR is lowest with 4.9%, whereas the adjusted-R2 between Mkt-RF and NEIO is highest with 32.0%. This could imply that the positive relationship between Mkt-RF and NFLOWS, as well as Mkt-RF and NSR, is primarily due to NEIO. This is a plausible explanation given that NEIO and NSR are positively and significantly correlated, with a correlation value of 0.32. Assuming that fund flows are uninformed, nonfundamental investment decisions, a positive coefficient indicates that stocks are overpriced (underpriced) and market prices temporarily deviate from fundamental value during periods of flows from the bond to equity funds (from equity to bond funds). This pricing error is later corrected. Table 2 Panel A also includes

² A limitation of my study is that given the timing of my analysis relying on monthly data, data availability does not allow me to directly test for a relation of e.g. manager' optimism or aggregate investment and net exchanges. However, building on the Arif and Lee (2014) results, I find that net exchanges are related to their sentiment measures. Using annual data, they show that aggregate investment is more likely to increase during periods of high consumer confidence, high net inflows into equity markets, and high sentiment as measured by the Baker-Wurgler sentiment index. Net inflows into equity markets is the single most important explanatory variable for changes in aggregate investment. My monthly flow variable can be interpreted similarly to net inflows into equity markets as a measure of price "noise" that is due to investor demand/supply shock stemming from sentiment. I find that it is significantly (below 1%) correlated with monthly changes in the "Consumer Sentiment Index" of the Michigan University Survey Center (0.16) or the monthly changes of the (seasonally adjusted) OECD consumer confidence indicator (0.11). Hence, I conclude that it captures dimensions of investor sentiment and can be assumed to be related to aggregate investments in line with the Arif and Lee (2014) results.

³ Fant (1999) also makes use of all four components of the fund flows ("new sales," "redemptions," "exchanges in," and "exchanges out"), but uses "exchanges in" and "exchanges out" separately, which results in different flow measures.

Table 2 Regression of factor portfolio returns on flows and FTS

Panel A: Mkt-RF	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>INTERCEPT</i>	-0.35	-0.11	0.76	0.99***	0.55**	0.43	0.98***
<i>NFLOWS_t</i>	2.18***						
<i>NSR_t</i>		1.53***					
<i>NEIO_t</i>				8.57***			
<i>FTS</i>							-13.14***
<i>Mean_{NSR2-4}</i>			-0.15			0.21	
<i>Mean_{NEIO2-4}</i>					-3.53***	-3.78***	
<i>Adj. R2</i>	15.3%	4.9%	0.0%	32.0%	1.6%	1.4%	6.5%
Panel B: CMA	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>INTERCEPT</i>	0.37***	0.28**	0.16	0.20*	0.31***	0.27**	0.23**
<i>NFLOWS_t</i>	-0.23**						
<i>NSR_t</i>		-0.04					
<i>NEIO_t</i>				-1.53***			
<i>FTS</i>							1.20
<i>Mean_{NSR2-4}</i>			0.20			0.06	
<i>Mean_{NEIO2-4}</i>					1.48**	1.40**	
<i>Adj. R2</i>	0.6%	0.0%	0.1%	4.7%	1.3%	1.1%	0.0%
Panel C: R_IA	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>INTERCEPT</i>	0.41***	0.32***	0.18	0.25**	0.37***	0.30**	0.27***
<i>NFLOWS_t</i>	-0.21*						
<i>NSR_t</i>		-0.02					
<i>NEIO_t</i>				-1.46***			
<i>FTS</i>							1.45
<i>Mean_{NSR2-4}</i>			0.26**			0.12	
<i>Mean_{NEIO2-4}</i>					1.62***	1.47***	
<i>Adj. R2</i>	0.5%	0.0%	0.4%	4.7%	1.9%	1.7%	0.2%

The table presents the coefficients from the time-series regressions of NFLOWS, NSR and NEIO, and the flight-to-safety (FTS) indicator on the respective factor portfolio returns. The sample period the sample period ranges from February 1984 to December 2015, covering a total of 383 months. Fund flows are calculated based on data from the Investment Company Institute (ICI). The following fund categories are included: domestic equity, international equity, and mixed funds. The net flows of the equity funds and their components are normalized each month by the previous month's fund assets value: NFLOWS is the normalized net flows (in %). NSR is the normalized net sales ("new sales" minus "redemptions") in %. NEIO is the normalized "net exchanges" ("exchanges in" minus "exchanges out") in %. $MEAN_{NEIO2-4}$ ($MEAN_{NSR2-4}$) is the average of NEIO (NSR) lags from period $t-2$ to $t-4$. FTS is based on the daily flight-to-safety dummy of Baele et al. (2020) and transformed to derive a monthly indicator, which provides information about the fraction of FTS days within the month. Mkt-RF is the excess market return, the value-weighted returns of NYSE, Amex, and Nasdaq stocks from the Center for Research in Security Prices (CRSP) over 30-day T-bill return in %. Conservative Minus Aggressive (CMA) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios R_IA is the investment factor of Hou et al. (2015). Coefficients are corrected for any persistence of the single regressor according to Amihud and Hurvich (2004) or Amihud et al. (2008) for multiple persistent regressors. Simulated p -values are computed as in Boudoukh et al. (2007), via 10,000 simulations under the null of zero predictability, but accounting for the regressors' auto-correlation, cross-correlations and the cross-correlation of the errors

***, **, *Statistical significance at the 1%, 5% and 10% level, respectively

the coefficients of Mkt-RF from time-series regressions on lagged NEIO and NSR. In keeping with previous research (Warther 1995; Fant 1999; Ben-Rephael et al. 2012), I focus on NSR and NEIO. Specifications (3), (5), and (6) are based on NSR, NEIO, and joint lags, respectively. Unreported findings suggest that NSR lags from $t-2$ to $t-4$ are insignificant both individually and collectively (based on Wald statistics). In contrast, for NEIO lags, each coefficient is negative and only partially significant, and the p -value of the Wald statistic is below 1%. Interestingly, the coefficients for longer lags ($t-2$ to

$t - 4$) are all significant and significantly smaller than the coefficient for the first lag. Ben-Rephael et al. (2012) attributed the one-month delay in reversal to ICI's delayed release of flow information. Apparently, investors only learn about new flow information with a month lag. However, this difference is unimportant for my analysis because the results are qualitatively similar when the first lag is included. Hence, the explanatory variable in specifications (3), (5), and (6) is the mean of NEIO lags 2–4, with the first lag omitted due to the one-month lag in ICI's reporting. I find the relationship between NEIO (NSR) and Mkt-RF highly significant (insignificant), with an adjusted-R2 that is much higher for specification (5) than specification (3). When using both lagged flows as regressors (specification (6)), I found that the NEIO lags take precedence.

The same analysis is replicated for the CMA (R IA) factor and yield similar reversal patterns. When investors are optimistic (pessimistic), the negative coefficient for $NEIO_t$ in Panels B and C of Table 2 suggests that the CMA (R_IA) factor portfolio is temporarily mispriced and undervalued (overvalued). My findings suggest that during periods when retail investors, for example, shift their holdings from bonds to equity mutual funds, aggressive investment stocks substantially outperform conservative investment stocks. The initial mispricing in both portfolios is then corrected, resulting in $Mean_{NEIO_{2-4}}$ coefficients with the opposite sign of $NEIO_t$ coefficients. I find a strong (significant) reversal effect for both the market and investment factors.

The magnitude of the significant “reversal” effect for the investment factors is comparable to the magnitude of the initial mispricing. In Table 3, I focus on the CMA factor and separately replicate the analysis for stocks with conservative and aggressive investments. The CMA is the average return on the two conservative investment portfolios (CMA_LO) minus the average return on the two aggressive investment portfolios (CMA_HI). The mispricing in t is stronger for stocks with aggressive investments (short leg) compared to the conservative investment portfolio (long leg). A time-series regression of the long (short) leg on NEIO yielded a coefficient of 8.69 (10.22), which is significant at the 1% level. The reversal relationship is also distinct; the relationship between the short leg and past net exchanges is significantly stronger than that between the long leg and past net exchanges. The coefficient from a time-series regression of the long (short) leg on the average NEIO from $t - 2$ to $t - 4$ is -3.32 (-4.80), and it is significant at the 1% level. Baker et al. (2003) suggested that negative investment-future return sensitivity varies across firms and becomes increasingly negative as equity dependence increases. They contend that equity-dependent firms offer excellent investment opportunities. My findings suggest that the observed effect for the CMA factor is caused by the difference in the reversal effects of conservative and aggressive investment portfolios.

To gain a better understanding of the dynamics, I use a vector autoregression (VAR) methodology to estimate the accumulated dynamic effect of NEIO on the factor portfolios. The equation system is a three-variable VAR involving NSR, NEIO, and the respective factor portfolio. I am interested in the accumulated impulse response to one-standard-deviation shock to NEIO on the factor portfolio returns.

The Cholesky order is NSR, NEIO, CMA factor portfolio based on the lagged interrelationships between the variables. However, I find that changing the order has no effect on the quality of the results. Figure 1 depicts the results of the impulse response simulation. It shows the point estimates and the bootstrap 90% confidence interval

Table 3 Regression of the long and short leg of the CMA factor portfolio on flows

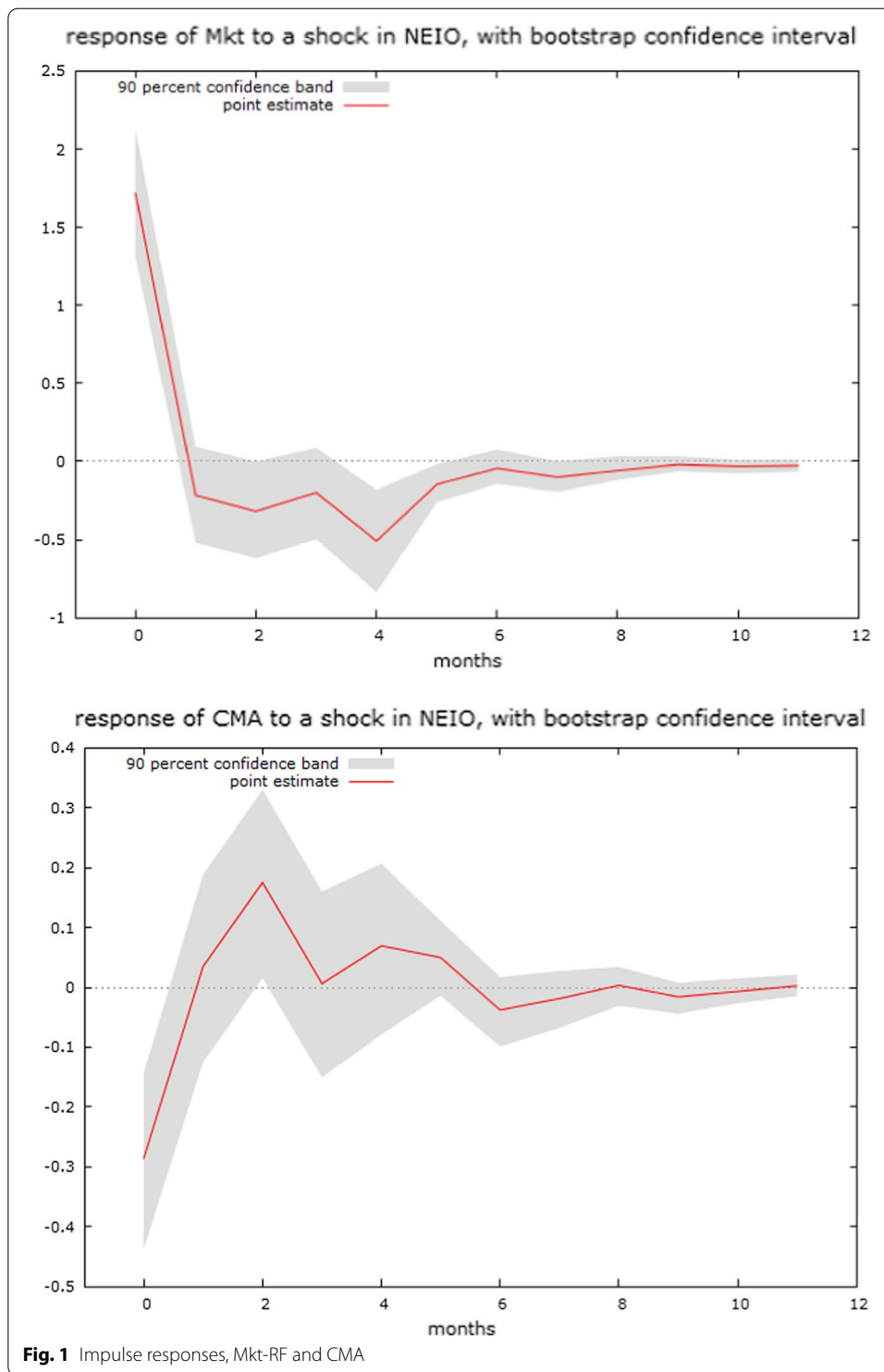
Panel A: CMA_LO	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INTERCEPT	0.01	0.19	1.22***	1.46***	1.02***	0.92**	1.50***
NFLOWS _t	2.42***						
NSR _t		1.86***					
NEIO _t				8.69***			
FTS							-15.08***
Mean _{NSR2-4}			-0.15			0.19	
Mean _{NEIO2-4}					-3.32***	-3.56***	
Adj. R2	16.2%	6.3%	0.0%	28.1%	1.2%	1.0%	7.3%
Panel B: CMA_HI	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INTERCEPT	-0.36	-0.09	1.06***	1.26***	0.71**	0.64*	1.27***
NFLOWS _t	2.65***						
NSR _t		1.90***					
NEIO _t				10.22***			
FTS							-16.28***
Mean _{NSR2-4}			-0.34			0.13	
Mean _{NEIO2-4}					-4.80***	-4.96***	
Adj. R2	14.8%	4.9%	0.0%	29.6%	2.0%	1.8%	6.5%

The table presents the coefficients from the time-series regressions of NFLOWS, NSR and NEIO, and the flight-to-safety (FTS) indicator on the respective factor portfolio returns. The sample period the sample period ranges from February 1984 to December 2015, covering a total of 383 months. Fund flows are calculated based on data from the Investment Company Institute (ICI). The following fund categories are included: domestic equity, international equity, and mixed funds. The net flows of the equity funds and their components are normalized each month by the previous month's fund assets value: NFLOWS is the normalized net flows (in %). NSR is the normalized net sales ("new sales" minus "redemptions") in %. NEIO is the normalized "net exchanges" ("exchanges in" minus "exchanges out") in %. MEAN_{NEIO2-4} (MEAN_{NSR2-4}) is the average of NEIO (NSR) lags from period t - 2 to t - 4. FTS is based on the daily flight-to-safety dummy of Baele et al. (2020) and transformed to derive a monthly indicator, which provides information about the fraction of FTS days within the month. Conservative Minus Aggressive (CMA) is the average return on the two conservative investment portfolios (CMA_LO) minus the average return on the two aggressive investment portfolios (CMA_HI). Coefficients are corrected for any persistence of the single regressor according to Amihud and Hurvich (2004) or Amihud et al. (2008) for multiple persistent regressors. Simulated p-values are computed as in Boudoukh et al. (2007), via 10,000 simulations under the null of zero predictability, but accounting for the regressors' auto-correlation, cross-correlations and the cross-correlation of the errors

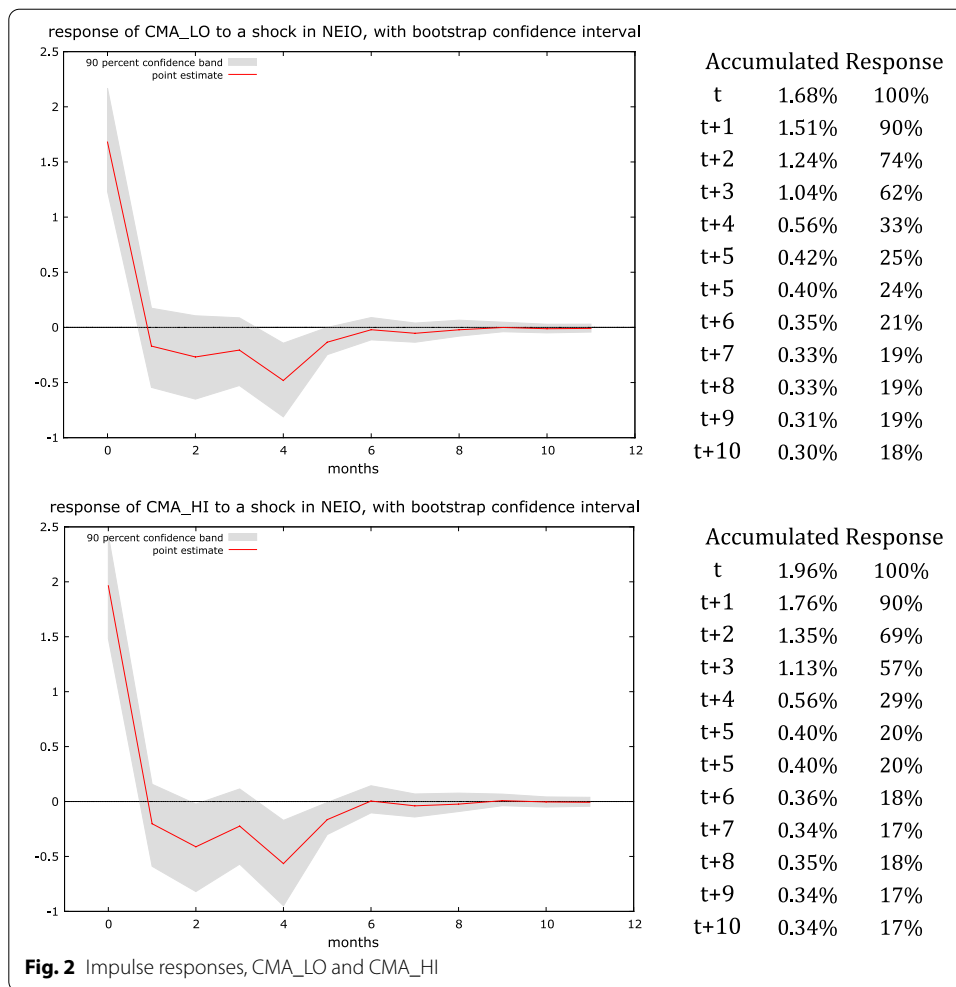
***, **, *Statistical significance at the 1%, 5% and 10% level, respectively

of a one-standard-deviation shock to NEIO (normalized net exchanges) on factor portfolio returns. The estimation of the impulse response is based on a three-variable VAR system with four lags for each variable.⁴ The shock's contemporaneous period is denoted by period t. These findings follow the previous findings. Both graphs are in line with the mispricing-reversal pattern that I mentioned earlier. Surprisingly, the CMA portfolio undergoes a complete reversal between periods t + 1 and t + 5. I replicated the analysis for the conservative and aggressive investment portfolios separately to understand the differences in the CMA factor. Figure 2 depicts the point estimates, bootstrap 90% confidence intervals, and impulse response function results of a one-standard-deviation shock to NEIO (normalized net exchanges) on both portfolios.

⁴ The augmented Dickey-Fuller test was used to test stationarity. The null hypothesis is that the time series is non-stationary and the alternative is that the series is stationary. Results suggest that the stationarity of the flow and return data that I use can be confirmed. In line with Ben-Rephael et al. (2012), I verified that there is no structural break in the VAR equations. The test of Andrews (1993) for structural breaks in any of the three equations for unknown change points was estimated. The test indicated that there is no structural break. Next to stationarity of the variables, which is critical to development of a VAR model, the VAR is covariance-stationary, if the eigenvalues of the coefficient matrix all lie inside the unit circle (Hamilton 1994). In this case, the consequences of any given shock must eventually die out. Results suggest that my VAR models are stable.



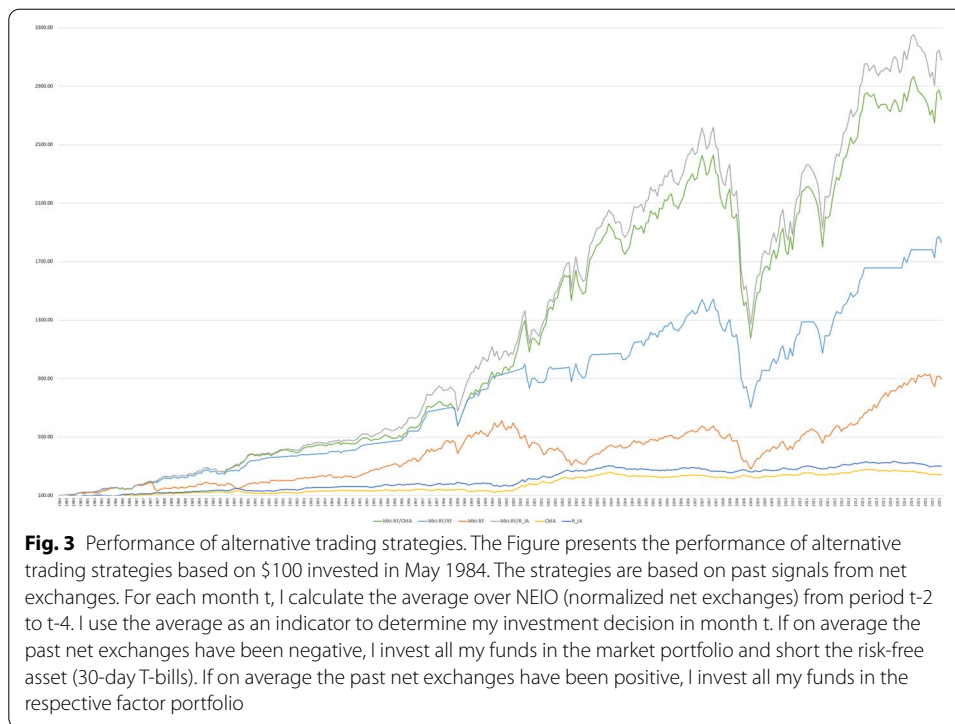
The accumulated responses show the cumulative periodic effect, and the reversal column shows the reversal effect in percent (%). The contemporaneous effects in period t differ, with 1.68% for stocks with conservative investments and 1.96% for stocks with aggressive investments, resulting in a contemporaneous effect of -0.29% in period



t for the CMA portfolio. Furthermore, the cumulative responses in the subsequent periods differ. For the first six months, the aggressive investment portfolio reverts much stronger than the conservative investment portfolio. Hence, the difference in the intensity of the reversal effect causes the CMA factor to reverse.⁵ As a result, the CMA factor portfolio performs especially well in the months following the inflow period. This observation is used in a trading exercise in the following.

My findings indicate a statistically significant reversal relationship between net exchanges and factor portfolio returns, but the economic significance of the effect is unclear. Hence, in the following, I investigate a trading strategy based on a previous signal from net exchanges. To make my investment decision in month t, I use the average over NEIO from period t−2 to period t−4 as an indicator. Because the flow information is released with a one-month lag, I do not use it in period t−1. Moreover, the strategy is to take a position in the market factor that contradicts what the indicator suggests because of the strong inverse relationship between net exchanges and the market factor.

⁵ I obtain very similar results for R_IA.



Hence, if the past net exchanges have been negative on average, I invest all of my funds in the market and short the risk-free rate. However, if the past net exchanges have been positive, I invest all of my funds in the risk-free rate or investment factor portfolio. I identified 213 of 379 months (56%) where the decision is to be in the market over the entire sample period. In these months, the average market return over the risk-free rate was 1.25%, with a standard deviation of 4.62%. In contrast, I identified 166 of 379 months (44%) where the decision was made to be long in the factor portfolio. The market factor's average return in these months is -0.05% , with a standard deviation of 4.13%. Meanwhile, the average market returns of the two subgroups differ statistically significantly (the p -value of the difference between the two subgroups' average market returns is less than 1%). However, the variances of the two subgroups are not statistically and significantly different from one another (the p -value of the F-test for the difference of variances is above 10%). Regarding the factor portfolios, the average return of the CMA factor in periods of previous negative (positive) net exchanges is 0.04% (0.58%), with a standard deviation of 2.11% (1.93). At the 1% level, the averages of the two subgroups are statistically significantly different. The R_IA factors' average return in periods of previous negative (positive) net exchanges is 0.05% (0.63%), with a standard deviation of 1.85% (2.02%). At the 1% level, the averages of the two subgroups are statistically significantly different. The performance of the investment strategies is depicted in Fig. 3.

In Fig. 3, I compare the performance of the various dynamic strategies with a simple static investment in the market factor. First, all dynamic strategies outperform the market factor portfolio. Second, the Mkt-RF/CMA and the Mkt-RF/R_IA strategies outperform the other strategies, suggesting a statistically and economically significant relationship between the investment factors and past net exchanges. Third, the investment

factor strategies significantly outperform the market factor portfolio. The average return of the Mkt-RF/R_IA strategy (the market factor portfolio) is 0.98% (0.65%), and the standard deviation is 3.72% (4.45%). The superior performance is generated during the months following positive net exchanges, in which the CMA factor (R_IA factor) significantly outperforms the market factor by 0.62% (0.68%). The outperformance was statistically significant at the 5% level.

Apparently, investors' optimism interacts with real managerial decisions. Although managers may rationally exploit market misvaluation given the short time frame that I assume for the contemporaneous mispricing effects, I find it less plausible that corporate managers "cater" to noise traders (the "managerial catering" hypothesis) by, for example, timing their stock issuances to take advantage of the lower-than-rational cost of capital. Hence, I find it more likely that the evidence can be interpreted in favor of the "expectation bias" hypothesis. When retail investors and managers are jointly caught up in the market euphoria, they are too optimistic. Therefore, retail investors shift their money from bonds to equity mutual funds, and equity-dependent firms invest more aggressively. Hence, the mispricing during these periods is particularly pronounced for the aggressive investment portfolio compared with the conservative investment portfolio. Subsequently, the reversal relation is also stronger, and therefore, returns are significantly lower for the aggressive investment portfolio than the conservative investment portfolio. Moreover, although the market performs poorly, investment factor returns are significantly positive and far less volatile.

The superior performance of the investment factor strategies is obtained during the months following the flows from the bond to equity funds, hence, in periods of negative price corrections. Flight-to-safety or market stress episodes can be thought of as specific instances of extreme negative price corrections. As a result, to understand the performance difference, I regress the difference between the monthly returns of the investment factor strategy and the market factor returns on a market stress indicator FTS, which is based on Baele et al.'s (2020) flight-to-safety dummy. I convert the daily dummies into a monthly indicator that shows the fraction of FTS days in a given month. Surprisingly, I discovered that FTS is negatively and highly significantly correlated with past positive flows, but not with past negative flows. Therefore, in line with my reasoning, observing an average positive flow in periods $t-2$ until $t-4$ makes it significantly more likely to experience flight-to-safety days in month t . The method independently identifies 11% of the months as having FTS of varying intensity. With a slope coefficient of 5.41 (5.97), the FTS beta for the Mkt-RF/CMA strategy (Mkt-RF/R_IA strategy) is highly significant. The average effect for the Mkt-RF/CMA strategy (Mkt-RF/R_IA strategy) implies that for a month with an FTS incidence equal to the average value among all FTS months (i.e., 0.23), a 1.38% (1.52%) return difference is observed. When I simply used a monthly dummy variable to classify an FTS month, I found that the Mkt-RF/CMA (Mkt-RF/R_IA) strategy outperforms the market factor by 1.85% (2.01%) during all FTS months (42 of 379 months).

Given the relationship between flows and market returns, a flow-based trading strategy could take advantage of the well-documented momentum anomaly. For example, Vayanos and Woolley (2013) proposed a theory of momentum and reversal based on flows between investment funds. Flows are triggered by changes in the efficiency of

fund managers, wherein investors can observe directly or infer from past performance. Momentum emerges when flows exhibit inertia and rational prices underreact to expected future flows. The flows push prices away from fundamental values, causing a reversal. Moreover, flows generate co-movement, lead-lag effects, and amplification, in addition to momentum and reversal, with these being more pronounced for high-idiosyncratic-risk assets. A calibration of their model based on mutual fund returns and flow yields sizable Sharpe ratios for momentum and value strategies. As a result, my flow-based portfolios' abnormal returns may produce large alphas, but these might be well explained by well-known equity risk factors. I employ the Fama–French plus momentum factors commonly used in the literature (the factors are from Kenneth French's data library). The results indicate that flow-based trading strategies continue to deliver significant risk-adjusted abnormal returns. The Mkt-RF/CMA (Mkt-RF/R IA) strategy has a risk-adjusted alpha of 0.57% (0.58%) and a robust t -stat of 3.34% (3.33%). Noticeably, both flow-based portfolios exhibit positive and statistically significant (at the 1% level) loadings on value and negative and statistically significant (at the 1% level) loadings on momentum. Hence, my results are not influenced by well-known equity risks.

As I previously demonstrated, the investment factors are negatively related to NEIO and positively related to lagged net exchanges. Accordingly, I investigate the joint relationships between NEIO, investment factor returns, and sentiment indicators that may explain NEIO.

As shown in Panels A and B of Table 4 in specifications (2), (5), and (8), the lagged relationship of the investment factors with the sentiment measures is not all positive, with only four of six sentiment betas being insignificant. I apply the Amihud et al. (2008) correction for multiple persistent regressors and calculate the p -value using a simulation, as Boudoukh et al. (2007) did. As a result, there is weak evidence that investment factor returns following periods of high sentiment (CSI) are typically positive. However, once I control for NEIO, the lagged relationships of these variables with the investment factor are all insignificant. These findings are interpreted as evidence in favor of price noise caused by uninformed trading, which captures different information compared with well-known sentiment measures.

Conclusions

According to the “expectation bias” hypothesis, managers make more (fewer) capital investments during periods of optimism (pessimism) because they overestimate (underestimate) this value of expected future cash flows. Periods of higher corporate investment correspond to periods of investor optimism and are followed by lower aggregate stock returns. Equivalently, when retail investors are optimistic (pessimistic), equity mutual funds experience inflows (outflows) that must be quickly equitized by fund managers. Consequently, the collective actions of fund managers generate short-term price pressure on aggregate stock prices. In addition, mutual fund investors' uninformative demand shifts negatively predict future market returns because investors are frequently too optimistic (too pessimistic). In this vein, I investigate the impact of flows between bond and equity funds on investment factor returns in the United States over the period 1984–2015. I find contemporaneous mispricing effects and a statistical reversal relationship between these flows and both legs of the investment factor. Meanwhile, the statistical reversal relationship between past net

Table 4 Regressions of the investment factors on CCI, CSI and BW_Sent

Panel A:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CMA									
<i>Expl. Var</i>	dCCI			dCSI			dSent		
<i>INTER-CEPT</i>	0.20*	0.26**	0.29***	0.20*	0.26**	0.28***	0.21**	0.26**	0.29***
<i>NEIO</i>	- 1.51***			- 1.55***			- 1.56***		
<i>Expl</i>	- 0.24			0.01			1.41		
<i>Expl-1</i>	- 0.90			0.02			1.07		
<i>Expl-2</i>	1.04			0.03			- 0.15		
<i>Expl-3</i>	1.16			0.07**			- 0.26		
<i>Expl-4</i>	- 1.30			0.02			- 0.05		
<i>MEAN-NEIO1-4</i>	1.69**			1.44**			1.75**		
<i>MEAN-Expl1-4</i>	0.00			0.09			- 0.46		
<i>CMA lags</i>	No	No	Yes	No	No	Yes	No	No	Yes
<i>R²</i>	5.0%	0.6%	4.8%	5.0%	2.2%	5.3%	7.1%	0.8%	4.8%
<i>Wald Stats</i>									
<i>Expl. lags</i>	0.85			0.14**			0.65		

Panel A:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R_IA									
<i>Expl. Var</i>	dCCI			dCSI			dSent		
<i>INTER-CEPT</i>	0.25***	0.31***	0.36***	0.25**	0.31***	0.34***	0.26***	0.31***	0.35***
<i>NEIO</i>	- 1.46***			- 1.47***			- 1.49***		
<i>Expl</i>	0.04			0.01			1.28		
<i>Expl-1</i>	- 0.17			0.19			0.74		
<i>Expl-2</i>	- 0.08			0.02			- 0.25		
<i>Expl-3</i>	1.48			0.04**			- 0.42		
<i>Expl-4</i>	- 1.43			0.03			- 0.25		
<i>MEAN-NEIO1-4</i>	1.89***			1.59**			2.00***		
<i>MEAN-Expl1-4</i>	- 0.29			0.10			- 0.89		
<i>CMA lags</i>	No	No	Yes	No	No	Yes	No	No	Yes
<i>R²</i>	4.9%	0.4%	4.8%	4.9%	1.8%	5.4%	7.0%	0.6%	5.0%
<i>Wald Stats</i>									
<i>Expl. lags</i>	- 0.20			0.13**			- 0.17		

The table presents the coefficients from the time-series regressions of CMA and R_IA portfolio returns on NEIO and selected market stress indicators. The sample period ranges from February 1984 to December 2015, covering a total of 383 months. Fund flows are calculated based on data from the Investment Company Institute (ICI). The excess equity market returns (ExRet) are the value-weighted returns of NYSE, Amex, and Nasdaq stocks from the Center for Research in Security Prices (CRSP) over the 30-day T-bill return. NSR is the normalized net sales ("new sales" minus "redemptions") in %. NEIO is the normalized "net exchanges" ("exchanges in" minus "exchanges out") in %. $MEAN_{NEIO1-4}$ is the average of NEIO lags from period $t - 1$ to $t - 4$. dCCI is the monthly change of the (seasonally adjusted) OECD consumer confidence indicator. dCSI is the monthly change of the University of Michigan consumer sentiment indicator. dSent is the monthly change of Baker and Wurgler's (2006) sentiment indicator. $MEAN_{Expl1-4}$ is the average of the explanatory variable lags from period $t - 1$ to $t - 4$. Coefficients and Wald statistics are corrected for any persistence of the single regressor according to Amihud and Hurvich (2004) or Amihud et al. (2008) for multiple persistent regressors. Simulated p -values are computed as in Boudoukh et al. (2007), via 10,000 simulations under the null of zero predictability, but accounting for the regressors' auto-correlation, cross-correlations and the cross-correlation of the errors

***, **, *Statistical significance at the 1%, 5% and 10% level, respectively

exchanges and the investment factor is economically significant. A one-standard-deviation shock to net exchanges causes a 0.29% decrease in investment factor returns, which are reversed within 5 months. A trading strategy based on signals from previous net exchanges and the investment factor outperforms the market by 0.68% in the months following positive net exchanges and produces significant alphas after accounting for well-known equity risk factors. I interpret my findings as evidence in favor of a behavioral explanation, in which sentiment influences actual managerial decisions. Given the timing of all my findings, I find it less plausible, but still possible, that managers (rationally) exploit market mispricing, such as by timing stock issuances (the “managerial catering” hypothesis). Moreover, I conjectured this study’s net exchanges serve as a proxy for market-level optimism/pessimism, and retail investors and managers are both caught up in market euphoria (the “expectation bias” hypothesis). Hence, retail investors shift their holdings from bond to equity mutual funds, and high-end investment firms invest more aggressively. As a result, high- and low-investment firms can be assumed to be differentially influenced by market-level euphoria, and thus, the investment factor can be influenced. During these periods, the mispricing is especially pronounced for a high-investment portfolio versus a low-investment portfolio. Subsequently, the reversal relationship is stronger, and therefore, returns for the high-investment portfolio are significantly lower than those for the low-investment portfolio. As a result, in line with my hypothesis, the investment factor outperforms the market factor during months following periods of positive flows. Interestingly, in the regressions, my measure of flows, which serves as a proxy for market-level euphoria, outperforms other indicators of investor sentiment.

Abbreviations

CMA: Conservative minus aggressive factor; R_IA: Investment factor of Hou et al. (2015); NFLOWs: Normalized net flows; NSR: Normalized net sales; NEIO: Normalized net exchanges; FTS: Flight-to-safety.

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Author contributions

This is a single-authored paper, hence, I contributed to all parts for this paper. Author read and approved the final manuscript.

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Availability of data and materials

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Declarations**Competing interests**

The authors declare that they have no competing interests.

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