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Effect of sectoral holdings on the flow-performance sensitivity of mutual funds

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ABSTRACT

We find that the flow-performance sensitivity (FPS) of mutual funds depends on the composition of their sectoral holdings. We use the Morningstar classification of fund holdings into the following three Super Sectors: Defensive, Sensitive, and Cyclical. On average, the FPS decreases as the fraction of defensive or sensitive stocks increases in the fund's portfolio. The FPS increases as the fraction of cyclical stocks increases. During high sentiment periods, the sensitivity of new sales as well as redemptions increases, resulting in overall higher FPS for all funds. However, in both the low and the high sentiment periods, the FPS is lower for funds with a higher fraction of defensive or sensitive stocks and higher for funds with a higher fraction of cyclical stocks. Investors with a long investment horizon may wish to avoid mutual funds that invest primarily in cyclical stocks as funds with high FPS tend to have high liquidity costs.

1. Introduction

Fund performance is not persistent (Carhart, 1997) and yet investors consistently allocate more money to funds with superior past performance (Sirri & Tufano, 1998). This finding suggests that investors try to infer the skill of fund managers from their past performance in the absence of any other credible signal of managerial skill. In Berk and Green (2004)' rational expectation model of mutual fund performance and flows, the flow-performance sensitivity depends not only on the magnitude of fund returns but also on the informativeness of these returns for the fund manager's ability. Higher past performance generates even higher flows from investors if they believe that the performance is attributable to the skill of the fund manager rather than luck.

Since flow-performance sensitivity (FPS) depends on the weight that investors put on the informativeness of the past performance for managerial ability, our first objective is to identify fund characteristics that may affect the perceived informativeness of past performance of funds. Notably, Berk and Green (2004) and Huang et al. (2022) have identified fund age (track record) as one such characteristic, with longer histories of past performance making recent past performance less informative. Furthermore, the latter authors also identify highly volatile past returns as less informative of managerial skill. We identify the portfolio composition of funds as another important determinant of FPS. This characteristic is readily available to investors, and its role in the decision making of investors is widely documented in literature. Agarwal, Gay, and Ling (2014) show that investors examine the proportion of winner and loser stocks in the disclosed portfolios and allocate more flows to funds with a higher proportion of winner stocks. Furthermore, portfolio composition is a fundamental driver of fund performance. We make use of the Morningstar classification of fund holdings into

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three major Super Sectors, namely, Defensive, Sensitive, and Cyclical. We study the effect of percentages of fund holdings in these three sectors on the FPS in the cross-section of mutual funds.

Mutual funds report their complete holdings to the Securities and Exchange Commission (SEC) every quarter. However, these holdings are available with a significant lag. Moreover, a typical actively managed equity fund holds around 80 stocks in its portfolio, and it may be too cumbersome for investors to analyze the complete portfolios of funds in a meaningful way. Therefore, we use the sectoral holdings of funds in our study which are a simpler and more easily understandable description of portfolio holdings. More importantly, the data on sectoral holdings of funds are available on the Morningstar website and it can be easily accessed free of cost by investors.

We find that the FPS of funds depends on their sectoral holdings. Funds that hold more defensive stocks in their portfolios experience lower FPS and funds that hold more cyclical stocks experience higher FPS. In other words, for the same level of performance, funds that hold more cyclical stocks will receive higher flows from investors compared to those that hold more defensive stocks. We explain this phenomenon in terms of the informativeness of performance about managerial skills. For funds holding more defensive stocks, investors attribute cross-sectional differences in fund performance to luck rather than skill, and therefore FPS is lower. For funds holding more cyclical stocks, investors attribute cross-sectional differences in fund performance to skill, and therefore FPS is higher.

We also examine the FPS in calm and extreme markets as defined by Franzoni and Schmalz (2017). They find that the FPS is about twice as large in calm markets (i.e., when the market excess return of the previous quarter is between −5% and 5%) compared to extreme markets (i.e., when the market excess return of the previous quarter is either less than −5% or more than 5%). First, we estimate the FPS separately in low, mid, and high market excess return sub-periods. We also find that the FPS in calm markets is higher than that in extreme markets. Next, we investigate the effect of fund holdings on FPS in the low, mid, and high market excess return sub-periods. We find that the funds with higher percentage of defensive stocks in their portfolios have comparatively lower FPS in all sub-periods. During moderate market return periods, the FPS of new sales as well as redemptions is lower for funds with a higher fraction of defensive stocks. During extremely low and extremely high market return periods, the defensive portfolios reduce FPS mainly through the channel of new sales.

In addition, we examine whether market sentiment affects how investors allocate capital across different funds. We use the Baker and Wurgler (2006) measure of monthly sentiment[1] to divide our sample into low and high sentiment periods. We find that the FPS of all funds is higher in high sentiment months. However, in the cross-section of funds, the FPS is lower for funds with a higher fraction of defensive stocks in both low sentiment and high sentiment periods. More importantly, the role of defensive stocks in reducing FPS is comparatively stronger in high sentiment periods. The key finding from this analysis is that defensive stocks control the FPS from increasing in high sentiment periods by moderating the sensitivity of not only new sales but also that of redemptions to performance.

Finally, we study the impact of the risk-free rate on FPS using the rate measure of De Jesus (2021). We confirm the author's main result that FPS is comparatively lower during periods of low risk-free rates. We show that an increase in the fraction of defensive stocks in a fund's portfolio mitigates the sensitivity of the fund's flows to past performance almost exclusively during high rate periods. Importantly, defensive stocks weaken the sensitivity of new sales but not redemptions when the risk-free rate is high.

2. Literature review

Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) examine the relation between mutual fund flows and various measures of fund performance. They find that fund flows are better explained by CAPM alphas than by alphas based on other competing models. Therefore, in this paper, we prefer to use CAPM alpha as our measure of fund performance to explain fund flows. In our empirical analysis, we report results based on the CAPM alpha of funds.

Franzoni and Schmalz (2017) show that the FPS is roughly twice as large in mild market conditions (i.e., when the excess return of the market in the previous quarter is between −5% and 5%) compared to turbulent markets (i.e., when the excess return of the market in the previous quarter is either less than −5% or more than 5%). We use the same thresholds in our analysis for consistency.

Baker and Wurgler (2006), Baker and Wurgler (2007) show that the capital allocation decisions of investors across different classes of stocks may depend on the aggregate investor sentiment in the market. Therefore, it is plausible that the effect of investor sentiment on the FPS of mutual funds depends on the portfolio composition of the funds. We use the monthly sentiment index developed by Baker and Wurgler (2006). We divide the sample period into low sentiment months and high sentiment months and estimate FPS separately for the two sub-periods.

De Jesus (2021) develops a theoretical model of portfolio allocation which states that the risk-free rate is a key driver of FPS through its effect on the acquisition of private information by investors. More precisely, a decrease in the risk-free rate reduces the opportunity cost, in terms of foregone interest on cash, of acquiring private information about mutual funds. Therefore, the author argues that investors are enticed by low risk-free rates to purchase private information and rely less on public information, such as past performance, in their capital allocation decisions. This results in fund flows that are less sensitive to past performance. We split the sample of our study into below and above average risk-free rate months to confirm this result and investigate how the level of the risk-free rate mediates the impact of portfolio composition on FPS.

Berk and Green (2004) argue that the capital allocation decisions of investors are rational. More specifically, the past performance

[1] Available at: https://people.stern.nyu.edu/jwurgler/.

chasing of investors is not wasteful, according to the authors' model, since past performance is informative of managerial skill. Likewise, it is conceivable that the portfolio composition of a fund has an actual impact on this informativeness, and investors are rationally using this variable in their mutual fund selection decisions. Conversely, the effect of fund holdings on FPS in our study could be driven by the behavioural biases of investors. Frazzini and Lamont (2008) find empirical evidence that the allocation decisions of mutual fund investors are in fact irrational and destructive to their wealth.

3. Data

The main source for our data on mutual funds is Morningstar Direct. We download observations for all surviving as well as non-surviving funds from Morningstar Direct, therefore, the data is survivorship bias free. Our sample consists of monthly observations on fund flows and performance for the period 2001–2017. We include only actively managed U.S. domestic equity mutual funds in our analysis. In particular, a fund is included if it is domiciled in the United States, its US_Broad_Asset_Class is "U.S. Stock", and its Morningstar Category is one of the following: "Large Blend", "Large Growth", "Large Value", "Mid Blend", "Mid Growth", "Mid Value", "Small Blend", "Small Growth", and "Small Value". We focus on actively managed funds, therefore we exclude index funds. We also exclude funds that have total net assets under $10 million and funds that are younger than one year.

The number of unique funds in our sample is 2,621. The total number of observations is 218,285 for 204 months from January 2001 to December 2017. That is, there are a little more than 1,070 mutual funds per month on average in our sample. It is an unbalanced panel because the number of funds keeps changing from month to month. The average fund size in our sample is USD 1.7 billion dollars. Therefore, the total assets under management for funds in our sample is around USD 1.8 trillion dollars per month on average. According to the 2018 Investment Company Fact Book of the Investment Company Institute (2018), total net assets of the US mutual fund industry was USD 18.7 trillion at the end of December 2017, of which USD 10.8 trillion was held by equity mutual funds. Our sample includes a small fraction, around 16% on average, of the total assets managed by all equity mutual funds. This is because we include only actively managed equity funds that satisfy all the criteria specified in the previous paragraph.

A fund may have multiple share classes. We combine the different share classes of a fund in a month to create a unique fund observation. For this observation, total net assets (TNA) of the fund is defined as the sum of the assets under management of all share classes of the fund. Fund age (AGE) is the number of years since the inception of the fund's oldest share class. The fund level variables expense ratio (EXPRATIO), turnover ratio (TURNOVER), and monthly return (RETURN) are calculated as the lagged asset-weighted averages of the respective share class level variables. The total family size (FAMTOTAL) of a fund is the sum of TNAs of all funds belonging to the same management company as the fund. The family size (FAMSIZE) of a fund is FAMTOTAL minus the TNA of the fund. We use log of one plus FAMSIZE in the regressions. We use the 1-year Treasury constant maturity rate[2] as a proxy for the risk-free rate as in De Jesus (2021). We provide comprehensive variable definitions in Appendix A.

Investment companies in the U.S. report their monthly sales and purchases of shares to the U.S. Securities and Exchange Commission (SEC) in their Form N-SAR filings. Morningstar Direct contains the New Sales (total Net Asset Value (NAV) of shares sold) and Redemptions (total NAV of shares redeemed) of funds on a monthly basis as per their N-SAR filings. Net Cash Flow is defined as New Sales minus Redemptions.

We define New Sales Flow and Redemptions Flow for fund *i* in month *t* as the dollar amounts of new sales and redemptions, respectively, divided by the total net assets (TNA) of the fund at the end of month/t:

$$NEWSALES\_FLOW_{i,t} = \frac{NewSales_{i,t}}{TNA_{i,t-1}} \tag{1}$$

$$REDEMPTIONS\_FLOW_{i,t} = \frac{Redemptions_{i,t}}{TNA_{i,t-1}} \tag{2}$$

where $\text{NewSales}_{i,t}$ and $\text{Redemptions}_{i,t}$ are the dollar amounts of new sales and redemptions for fund *i* in month *t* and $\text{TNA}_{i,t-1}$ is the size of fund *i* at the end of month/t.

Net Cash Flow is the difference between New Sales Flow and Redemptions Flow:

$$NET\_CASHFLOW_{i,t} = NEWSALES\_FLOW_{i,t} - REDEMPTIONS\_FLOW_{i,t} \tag{3}$$

Morningstar splits stocks into 11 sectors according to their main business. The 11 sectors are further bundled into the following Super Sectors: Defensive, Cyclical, and Sensitive.[3] The Defensive Super Sector includes the following sectors: Healthcare, Consumer Defensive, and Utilities. The Cyclical Super Sector includes the following sectors: Basic Materials, Consumer Cyclical, Financial Services, and Real Estate. The Sensitive Super Sector includes the following sectors: Communication Services, Energy, Industrials, and Technology. In Appendix B, we provide the list of all sectors and examples of companies in each sector.

In general, Defensive Super Sector industries are only slightly affected by economic cycles, whereas Cyclical Super Sector industries are most affected by economic shifts. Sensitive Super Sector industries are affected by economic cycles to some extent but not as much as the industries in the Cyclical Super Sector. We perform all our analysis at the Super Sector level for tractability.

[2] Available at: https://fred.stlouisfed.org/series/GS1.

[3] https://www.morningstar.com/InvGlossary/sector_definition_what_is.aspx.

We report summary statistics of the main variables of our analysis in Table 1. More specifically, we show the mean, median, standard deviation, and 1st and 99th percentiles. The funds have a mean holding of the relatively moderate sensitive stocks of 41.08%, while their mean holdings of cyclical and defensive stocks are 32.88% and 21.85%, respectively. The funds in our sample have mean monthly new sales and redemptions of 2.16% and 2.45%, respectively, resulting in a net cash outflow of 0.29% per month. Clearly, the funds as a whole were struggling to retain the money of investors. Furthermore, they underperformed the market on average since their mean CAPM, 3-factor, 4-factor, and 6-factor alphas are −0.09%, −0.12%, −0.13%, and −0.12% per month, respectively.[4] The mean TNA of the funds is USD 1,688.19 million, whereas their median TNA is just USD 364.13 million. It is apparent that the fund size distribution is positively skewed, i.e., there are many small funds and a few very large funds. The mean family size is USD 47.19 billion. The mean annual net expense ratio is 1.20%, whereas the mean annual turnover ratio, defined as the minimum of the securities purchased and the securities sold, divided by the average TNA over the previous year, is 74.25%. The mean age of the funds is 16.54 years. We winsorize the variables at the 0.5% and 99.5% levels in each month separately.

4. Fund flows and past performance

4.1. Portfolio holdings and flow-performance sensitivity

An investor who wants to invest in stocks with certain characteristics is likely to choose mutual funds that invest in stocks with those characteristics. In particular, investors with preference for defensive stocks may prefer to invest in funds that hold defensive stocks. Similarly, investors with preference for sensitive or cyclical stocks may prefer to invest in funds that hold sensitive or cyclical stocks, respectively. The investors' revealed preferences for certain types of stocks may also affect how they interpret the performance of funds.

Brown et al. (2018) define sensation seeking as "a personality trait clinically defined as the seeking of varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experience". We use the term "sensation-seeking investors" in the same spirit in the context of mutual fund investors.

Grinblatt and Keloharzu (2009) find a positive relationship between sensation seeking and trading activity. This implies that sensation-seeking investors believe in the existence of skilled investing in general, since frequent trading is costly, and therefore can only be justified under the belief that consistently superior returns can be achieved by superior investors. Thus, they will likely interpret superior returns as evidence of skill. On the other hand, sensation-avoiding investors trade less frequently, implying that they are more cautious and believe less strongly in skilled investing. Thus, they will be more cautious in attributing superior past performance to skill.

In our empirical setting, investors in cyclical funds are the sensation-seeking investors whereas those in defensive mutual funds are the sensation-avoiding investors. Investors in sensitive funds fall in the middle of the sensation-seeking spectrum.

Sensation-avoiding investors will invest in funds that hold more defensive stocks and will attribute any superior performance to luck. Therefore, the flow-performance sensitivity will be lower for funds that hold more defensive stocks. On the other hand, sensation-seeking investors will invest in funds that hold more cyclical stocks and will attribute any superior performance to the fund manager's skill. Therefore, the flow-performance sensitivity will be higher for funds that hold more cyclical stocks.

Hypothesis 1: The flow-performance sensitivity of mutual funds will decrease with the fraction of defensive stocks and increase with the fraction of cyclical stocks in the fund portfolios.

In our empirical setting, the fund holdings are categorized into three types: defensive stocks, sensitive stocks, and cyclical stocks. First, we run separate regressions for the three types of holdings and report the results in Table 2. We rank funds in each Morningstar Category each month based on their performance in the 12 trailing months. We use CAPM alpha as the fund performance measure. The Alpha_rank varies from 0 to 1. We include the following control variables in all regressions: lagged values of fund size, family size, annual turnover ratio, expense ratio and fund age. We also include category net cash flows, category new sales and category redemptions as control variables in the regressions for net cash flows, new sales and redemptions respectively. Appendix A provides precise definitions of these variables. We include all control variables in all regressions but report only the coefficients of the main variables of interest for brevity. In Panel A, column (1) reports the results of a regression of net cash flow on the fund's performance rank, the fraction of defensive holdings in the fund's portfolio, and the interaction between the fund's performance rank and the fraction of defensive holdings. The coefficient of the interaction term is negative and statistically significant. This means that the flow-performance sensitivity decreases as the fraction of defensive stocks in the fund portfolio increases.

We perform similar regressions for the fraction of sensitive stocks (Panel B) and the fraction of cyclical stocks (Panel C). The interaction term in the case of fraction of sensitive stocks (Panel B) is negative and significant. On the other hand, the interaction term in the case of fraction of cyclical stocks (Panel C) is positive and significant. Looking together at the results from the three panels in Table 2, we conclude that flow-performance sensitivity decreases strongly as the fraction of defensive stocks increases, decreases moderately as the fraction of sensitive stocks increases, and increases strongly as the fraction of cyclical stocks increases.

In Panels A, B, and C, we presented results for the fraction of defensive stocks, sensitive stocks, and cyclical stocks, respectively. In Panel D, we analyse these three components of fund holdings together in the same regression. Since the sum of the three fractions in the data set is not always 100 percent, we first scale the three fractions as follows:

[4] The factors data was obtained from the Kenneth French online data library, available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1
Summary statistics.

	Mean	Median	Standard Deviation	P1	P99
Defensive Holdings (%)	21.85	21.75	7.65	4.71	43.24
Sensitive Holdings (%)	41.08	40.90	8.91	19.44	63.22
Cyclical Holdings (%)	32.88	32.40	9.93	10.52	57.25
New Sales (% of TNA)	2.16	1.31	2.75	0.00	14.67
Redemptions (% of TNA)	2.45	1.89	2.23	0.00	12.39
Net Cash Flow (% of TNA)	−0.29	−0.49	3.00	−9.17	10.96
Market-Adjusted Return (% per month)	−0.05	−0.07	1.89	−5.25	5.26
CAPM Alpha (% per month)	−0.09	−0.11	1.89	−5.16	5.29
3-Factor Alpha (% per month)	−0.12	−0.10	1.49	−4.23	3.85
4-Factor Alpha (% per month)	−0.13	−0.11	1.48	−4.23	3.80
6-Factor Alpha (% per month)	−0.12	−0.12	1.51	−4.19	3.95
Fund Size ($ million)	1688.19	364.13	6166.93	12.52	20834.49
Family Size ($ billion)	47.19	11.17	142.03	0.00	703.72
Log Fund Size	19.75	19.71	1.68	16.34	23.75
Log Family Size	21.42	23.14	5.81	0.00	27.28
Expense Ratio (% per year)	1.20	1.15	0.46	0.25	2.48
Turnover Ratio (% per year)	74.25	59.00	62.40	3.00	311.00
Age (years)	16.54	13.00	13.30	4.00	76.00
Category New Sales (% of TNA)	0.02	0.02	0.02	0.01	0.07
Category Redemptions (% of TNA)	0.02	0.02	0.04	0.01	0.13
Category Net Cash Flow (% of TNA)	0.00	0.00	0.02	−0.05	0.02

We report summary statistics for the mutual funds in our sample. The sample covers monthly observations from January 2001 to December 2017. The number of observations is 218,285. For definitions of variables, please refer to Appendix A.

Pct_defensive_s = Pct_defensive * 100/(Pct_defensive + Pct_sensitive + Pct_cyclical).
Pct_sensitive_s = Pct_sensitive * 100/(Pct_defensive + Pct_sensitive + Pct_cyclical).
Pct_cyclical_s = Pct_cyclical * 100/(Pct_defensive + Pct_sensitive + Pct_cyclical).

The sum of pct_defensive_s, pct_sensitive_s, and pct_cyclical_s, as defined above, is always equal to 100. We include pct_defensive_s and pct_sensitive_s in the regressions, while keeping pct_cyclical_s as the base level. The results are reported in Panel D. In column (1), for net cash flow, the highly significant interaction terms show that FPS decreases as the fractions of defensive or sensitive stocks increase in the portfolio. It also follows that FPS increases as the fraction of cyclical stocks increases in the portfolio. Furthermore, the results are economically significant. The mean values of pct_defensive_s and pct_sensitive_s are 22.8032% and 42.8657%, respectively, which implies a mean FPS of 3.9705–0.0248 × 22.8032–0.0125 × 42.8657 = 2.8692. The standard deviations of pct_defensive_s and pct_sensitive_s are 7.9998% and 9.1463%, respectively, which implies that FPS decreases as a result of a one standard deviation increase in the fraction of defensive (sensitive) stocks by 0.0248×7.9998 = 0.1984 (0.0125×9.1463 = 0.1143). Therefore, an increase of defensive (sensitive) stocks from the mean by one standard deviation reduces FPS by 0.1984/2.8692 = 6.91% (0.1143/2.8692 = 3.98%). This magnitude is similar to that of the effect of return dispersion on FPS in Harvey and Liu (2019) when control variables are considered. The results in Panel D are consistent with the separate results in Panels A, B, and C.

In each panel of Table 2, we also report results of regressions in which the dependent variable is new sales (column (2)) or redemptions (column (3)). In each panel, the coefficient of the interaction term in the case of new sales (column (2)) is statistically significant and comparable to the coefficient of the interaction term for net cash flow in column (1). The coefficient of the interaction term in the case of redemptions is not statistically significant at the 5% level of significance in any panel with the exception of Panel B. We conclude that the cross-sectional variation in the flow-performance relation is driven mainly by new sales and not redemptions.

Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) show that investor flows respond most significantly to CAPM alpha. Therefore, we have presented our results using ranks based on the CAPM alpha of funds. We also run similar regressions using ranks of funds based on raw returns and find results that are qualitatively similar.

4.2. Aggregate risk

Franzoni and Schmalz (2017) find that flow-performance sensitivity is a hump-shaped function of the realizations of aggregate risk. Their main measure of risk is the excess return on the market factor. They define as moderate the quarters during which the excess return on the CRSP value-weighted index is between −5% and 5% and the other quarters as extreme. They conclude that the FPS is significantly higher in moderate quarters than in extreme ones.

We divide all months of our sample into three groups: those with excess market return less than −5%, between −5% and 5%, and more than 5%. We run separate regressions of fund flows on the past performance ranks for each sub-sample. Columns (1)-(3) of Table 3 show that the past performance rank is highly significant for net flows in each sub-sample. The coefficients of Alpha_rank in low, moderate and high excess market return months are 2.5804, 2.7813 and 2.6924 respectively. This is consistent with Franzoni and Schmalz (2017), who also find that FPS is lower in both the lowest and the highest excess market return months and higher during moderate excess market return months.

We further examine the components of net cash flow—new sales and redemptions—in the three sub-periods. The coefficients of

Table 2
Effect of holdings on FPS.

Panel A: Defensive holdings and FPS	(1)	(2)	(3)
	Net	New	Red
Alpha_rank	3.3429***	2.3779***	−0.9187***
	(0.000)	(0.000)	(0.000)
pct_defensive	0.0117***	0.0028	−0.0091***
	(0.000)	(0.369)	(0.000)
Alpha_rank*pct_defensive	−0.0254***	−0.0187***	0.0059
	(0.000)	(0.001)	(0.148)
Constant	−1.6538***	−0.3183	1.1954***
	(0.000)	(0.170)	(0.000)
Observations	201,397	201,397	201,397
R^2	0.10	0.09	0.06
Panel B: Sensitive holdings and FPS	(1)	(2)	(3)
	Net	New	Red
Alpha_rank	3.2862***	2.8666***	−0.2948
	(0.000)	(0.000)	(0.185)
pct_sensitive	−0.0042*	0.0046	0.0086***
	(0.087)	(0.209)	(0.007)
Alpha_rank*pct_sensitive	−0.0124***	−0.0227***	−0.0126**
	(0.001)	(0.000)	(0.013)
Constant	−1.1844***	−0.4396	0.6230***
	(0.000)	(0.126)	(0.000)
Observations	201,397	201,397	201,397
R^2	0.10	0.09	0.06
Panel C: Cyclical holdings and FPS	(1)	(2)	(3)
	Net	New	Red
Alpha_rank	2.2950***	1.4899***	−0.8481***
	(0.000)	(0.000)	(0.000)
pct_cyclical	−0.0107***	−0.0113**	0.0003
	(0.000)	(0.012)	(0.939)
Alpha_rank*pct_cyclical	0.0151***	0.0171**	0.0035
	(0.000)	(0.011)	(0.483)
Constant	−1.0507***	−0.0219	0.9410***
	(0.000)	(0.935)	(0.000)
Observations	201,397	201,397	201,397
R^2	0.10	0.09	0.06
Panel D: Sectoral holdings and FPS	(1)	(2)	(3)
	Net	New	Red
Alpha_rank	3.9705***	3.4440***	−0.4026
	(0.000)	(0.000)	(0.250)
pct_defensive_s	0.0148***	0.0091**	−0.0064**
	(0.000)	(0.044)	(0.040)
pct_sensitive_s	0.0034	0.0099**	0.0058
	(0.189)	(0.035)	(0.121)
Alpha_rank*pct_defensive_s	−0.0248***	−0.0208***	0.0029
	(0.000)	(0.003)	(0.559)
Alpha_rank*pct_sensitive_s	−0.0125***	−0.0208***	−0.0103*
	(0.003)	(0.003)	(0.062)
Constant	−1.9420***	−1.0165***	0.9116***
	(0.000)	(0.009)	(0.000)
Observations	201,397	201,397	201,397
R2	0.10	0.09	0.06

We estimate the sensitivity of fund flows to the past performance of funds and the sensitivity of their holdings. Net Cash Flow (column (1)) is defined as NET_CASHFLOW_PCT = 100* (new sales – redemptions)/(lag fund size). New Sales Flow (column (2)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (column (3)) is defined as REDEMPTIONS_FLOW_PCT = 100*redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The variables pct_defensive (Panel A), pct_sensitive (Panel B), and pct_cyclical (Panel C) are the percentages of the fund portfolio invested in defensive, sensitive, and cyclical stocks, respectively, according to Morningstar Direct. The interaction variable is equal to the product of Alpha_rank and pct_defensive in Panel A, pct_sensitive in Panel B, and pct_cyclical in Panel C. The variables in Panel D are the combined variables of Panels A and B. We regress each of the three fund flow variables on the performance variable, the holdings sensitivity variables, the corresponding interaction variables, and control variables. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The standard errors are adjusted for serial correlation using Newey-West lags of order three. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3
FPS in low, mid, and high markets.

	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	Net	Net	New	New	New	Red	Red	Red
Alpha_rank	2.5804***	2.7813***	2.6924***	1.9029***	1.8790***	1.9774***	−0.6342***	−0.8644***	−0.7009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−1.7339***	−1.0603***	−1.5232***	−0.9693***	−0.1249	−0.0532	0.5574*	0.7870***	1.3381***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.534)	(0.835)	(0.061)	(0.000)	(0.000)
Observations	34,968	94,669	71,760	34,968	94,669	71,760	34,968	94,669	71,760
R^2	0.08	0.10	0.10	0.08	0.08	0.09	0.06	0.05	0.06

We estimate the sensitivity of fund flows to the past performance of funds in different market conditions. Net Cash Flow (columns (1)-(3)) is defined as NET_CASHFLOW_PCT = 100* (new sales – redemptions)/(lag fund size). New Sales Flow (columns (4)-(6)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (columns (7)-(9)) is defined as REDEMPTIONS_FLOW_PCT = 100*redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The sample is split into periods of low (columns (1), (4), and (7)), moderate (columns (2), (5), and (8)), and high (columns (3), (6), and (9)) market excess return in the previous quarter. The threshold values are −5% and 5% as in Franzoni and Schmalz (2017). We regress each of the three fund flow variables on the performance variable and control variables in each subperiod separately. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Alpha_rank in the case of new sales are 1.9029, 1.8790, and 1.9774 in low, moderate, and high market excess return periods. These coefficients are statistically significant in each regression. However, the coefficients in each sub-period are of similar magnitude. In the case of redemptions, the coefficients of Alpha_rank are −0.6342, −0.8644, and −0.7009 in low, moderate, and high market excess return periods. It seems that redemptions are more sensitive to performance in moderate periods. Overall, we find that new sales are comparatively less sensitive to performance during calm markets and redemptions are comparatively more sensitive during calm markets.

Next, we investigate the effect of fund holdings on FPS in the three sub-periods. In Table 4, Panel A, we include Alpha_rank, pct_defensive and the interaction term Alpha_rank * pct_defensive, and control variables in the regressions. In columns (1)-(3), for net cash flow, the interaction terms are negative and statistically significant. That is, the funds with a higher percentage of defensive stocks in their portfolios have comparatively lower FPS in all sub-periods. The coefficients of the interaction term are of similar magnitude in the three sub-periods. In columns (4)-(6), for new sales, the interaction terms are negative and statistically significant. In columns (7)-(9), for redemptions, the interaction term is significant only in moderate markets. This means that the sensitivity of redemptions to performance (−1.0938 + 0.0095*pct_defensive) is of lower magnitude for funds with more defensive stocks in moderate periods.

We may conclude that during extremely low and extremely high market return periods, the defensive portfolios reduce FPS mainly by reducing the performance sensitivity of new sales. However, during periods of moderate returns, the defensive portfolios reduce overall FPS by reducing the sensitivity of new sales as well as redemptions. Investors do not disproportionately reward good performance nor punish bad performance during periods of moderate market returns in the case of funds that have a high fraction of defensive stocks.

In Panel B, the main dependent variable of interest is the interaction term Alpha_rank*pct_sensitive. In columns (1)-(3), the coefficient of the interaction term is negative and significant for net cash flow in low and moderate periods but insignificant in high market excess returns periods. However, in columns (4)-(6), the interaction term is negative and significant for new sales in all periods. In columns (7)-(9), the interaction term is negative and significant for redemptions in all periods. That is, the sensitivity of new sales to performance decreases but the sensitivity of redemptions to performance increases as the fraction of sensitive stocks in the portfolio increases.

In Panel C, the main dependent variable of interest is the interaction term Alpha_rank*pct_cyclical. In columns (1)-(3), the coefficient of the interaction term is positive and significant for net cash flow in all sub-periods. In columns (4)-(6), for new sales, the interaction term is positive and significant in low and moderate periods but insignificant in high periods. In columns (7)-(9), for redemptions, the interaction term is positive and significant only in low market excess return periods. That is, in low market excess return periods, the sensitivity of new sales to performance increases and the sensitivity of redemptions to performance decreases as the fraction of cyclical stocks in the portfolio increases.

In Panel D, we include pct_defensive_s and pct_sensitive_s in the regressions, while keeping pct_cyclical_s as the base level. The results are broadly in agreement with the results in Panels A, B, and C. In particular, the interaction term Alpha_rank*pct_defensive_s is statistically significant in all sub-periods for net cash flow. Also, the interaction term Alpha_rank*pct_sensitive_s is strongly statistically significant in the moderate period but less statistically significant in the low period for net cash flow. The overall conclusion is that, in general, FPS decreases significantly as the fraction of defensive stocks increases in all sub-periods. The FPS also decreases as the fraction of sensitive stocks increases, although the effect of sensitive stocks is not as strong as that of defensive stocks. A corollary of these results is that FPS increases as the fraction of cyclical stocks in the fund portfolio increases.

Table 4
Effect of holdings on FPS in low, moderate, and high market excess return quarters.

Panel A: Defensive holdings and FPS in low, moderate, and high market excess return quarters	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	Net	Net	New	New	New	Red	Red	Red
Alpha_rank	3.2236***	3.4525***	3.2478***	2.5211***	2.3051***	2.4078***	−0.6013**	−1.0938***	−0.8332***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)	(0.000)
pct_defensive	0.0214***	0.0086***	0.0112***	0.0112**	−0.0007	0.0034	−0.0093**	−0.0095***	−0.0084***
	(0.000)	(0.006)	(0.003)	(0.014)	(0.809)	(0.376)	(0.038)	(0.000)	(0.004)
Alpha_rank*pct_defensive	−0.0256**	−0.0279***	−0.0216***	−0.0253**	−0.0174***	−0.0171***	−0.0021	0.0095**	0.0049
	(0.015)	(0.000)	(0.000)	(0.012)	(0.001)	(0.008)	(0.801)	(0.012)	(0.280)
Constant	−2.3068***	−1.2717***	−1.8614***	−1.3025***	−0.0753	−0.1534	0.8908***	1.0274***	1.5952***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.724)	(0.537)	(0.010)	(0.000)	(0.000)
Observations	34,968	94,669	71,760	34,968	94,669	71,760	34,968	94,669	71,760
R^2	0.09	0.10	0.10	0.08	0.09	0.09	0.07	0.06	0.06

Panel B: Sensitive holdings and FPS in low, moderate, and high market excess return quarters	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	Net	Net	New	New	New	Red	Red	Red
Alpha_rank	3.2550***	3.5792***	2.8821***	3.3275***	2.9631***	2.4879***	0.1974	−0.4972**	−0.2611
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.559)	(0.020)	(0.119)
pct_sensitive	−0.0026	−0.0042	−0.0049*	0.0104	0.0042	0.0023	0.0134***	0.0076***	0.0075**
	(0.566)	(0.102)	(0.094)	(0.157)	(0.165)	(0.492)	(0.005)	(0.010)	(0.010)
Alpha_rank*pct_sensitive	−0.0135**	−0.0181***	−0.0038	−0.0338***	−0.0264***	−0.0116*	−0.0230**	−0.0102**	−0.0106**
	(0.010)	(0.000)	(0.470)	(0.001)	(0.000)	(0.057)	(0.011)	(0.025)	(0.014)
Constant	−1.6392***	−0.9182***	−1.3291***	−1.3497***	−0.3052	−0.1576	0.0301	0.5296***	1.0662***
	(0.005)	(0.000)	(0.000)	(0.006)	(0.180)	(0.607)	(0.918)	(0.003)	(0.000)
Observations	34,968	94,669	71,760	34,968	94,669	71,760	34,968	94,669	71,760
R^2	0.09	0.10	0.10	0.08	0.09	0.09	0.07	0.06	0.06

Panel C: Cyclical holdings and FPS in low, moderate, and high market excess return quarters	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	Net	Net	New	New	New	Red	Red	Red
Alpha_rank	2.2229***	2.2380***	2.4144***	1.0800***	1.4465***	1.7661***	−1.2060***	−0.8250***	−0.6945***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pct_cyclical	−0.0172***	−0.0077***	−0.0115***	−0.0247***	−0.0066*	−0.0111***	−0.0069	0.0024	0.0009
	(0.001)	(0.002)	(0.000)	(0.005)	(0.052)	(0.002)	(0.222)	(0.366)	(0.763)
Alpha_rank*pct_cyclical	0.0163**	0.0188***	0.0091*	0.0335***	0.0169***	0.0087	0.0203**	−0.0007	0.0010
	(0.038)	(0.000)	(0.061)	(0.008)	(0.001)	(0.148)	(0.025)	(0.857)	(0.814)
Constant	−1.3132***	−0.8417***	−1.2136***	−0.4951*	0.0405	0.1354	0.8063**	0.7275***	1.3178***
	(0.002)	(0.000)	(0.000)	(0.085)	(0.861)	(0.645)	(0.016)	(0.000)	(0.000)
Observations	34,968	94,669	71,760	34,968	94,669	71,760	34,968	94,669	71,760
R^2	0.09	0.10	0.10	0.09	0.09	0.09	0.07	0.06	0.06

Panel D: Sectoral holdings and FPS	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	Net	Net	New	New	New	Red	Red	Red

(*continued on next page*)

Table 4 (*continued*)

Panel D: Sectoral holdings and FPS	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	Net	Net	New	New	New	Red	Red	Red
Alpha_rank	4.0173***	4.3252***	3.4373***	4.5156***	3.4465***	2.8813***	0.7456	−0.7770***	−0.4643*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.211)	(0.008)	(0.089)
pct_defensive_s	0.0267***	0.0108***	0.0143***	0.0250***	0.0037	0.0087**	−0.0013	−0.0081***	−0.0066**
	(0.000)	(0.001)	(0.000)	(0.003)	(0.305)	(0.034)	(0.826)	(0.002)	(0.049)
pct_sensitive_s	0.0064	0.0019	0.0041	0.0198**	0.0072**	0.0086**	0.0131**	0.0041	0.0043
	(0.227)	(0.498)	(0.153)	(0.033)	(0.049)	(0.025)	(0.028)	(0.187)	(0.213)
Alpha_rank*pct_defensive_s	−0.0279**	−0.0278***	−0.0188***	−0.0373***	−0.0189***	−0.0150**	−0.0125	0.0080*	0.0038
	(0.015)	(0.000)	(0.002)	(0.006)	(0.001)	(0.035)	(0.201)	(0.053)	(0.464)
Alpha_rank*pct_sensitive_s	−0.0126*	−0.0178***	−0.0049	−0.0347***	−0.0232***	−0.0100	−0.0256**	−0.0070	−0.0072
	(0.052)	(0.000)	(0.372)	(0.006)	(0.000)	(0.125)	(0.012)	(0.137)	(0.105)
Constant	−2.8176***	−1.4700***	−2.1625***	−2.6802***	−0.5708*	−0.7879**	0.1246	0.8683***	1.3842***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.052)	(0.016)	(0.784)	(0.000)	(0.000)
Observations	34,968	94,669	71,760	34,968	94,669	71,760	34,968	94,669	71,760
R^2	0.09	0.11	0.10	0.09	0.09	0.10	0.07	0.06	0.06

We estimate the sensitivity of fund flows to the past performance of funds and the sensitivity of their holdings in different market conditions. Net Cash Flow (columns (1)-(3)) is defined as NET_-CASHFLOW_PCT = 100*(new sales – redemptions)/(lag fund size). New Sales Flow (columns (4)-(6)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (columns (7)-(9)) is defined as REDEMPTIONS_FLOW_PCT = 100* redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The variables pct_defensive (Panel A), pct_sensitive (Panel B), and pct_cyclical (Panel C) are the percentages of the fund portfolio invested in defensive, sensitive, and cyclical stocks, respectively, according to Morningstar Direct. The interaction variable is equal to the product of Alpha_rank and pct_defensive in Panel A, pct_sensitive in Panel B, and pct_cyclical in Panel C. The variables in Panel D are the combined variables of Panels A and B. The sample is split into periods of low (columns (1), (4), and (7)), moderate (columns (2), (5), and (8)), and high (columns (3), (6), and (9)) market excess return in the previous quarter. The threshold values are −5% and 5% as in Franzoni and Schmalz (2017). We regress each of the three fund flow variables on the performance variable, the holdings sensitivity variables, the corresponding interaction variables, and control variables in each subperiod separately. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5
FPS and sectoral holdings in low and high investor sentiment periods.

Panel A: FPS in low and high investor sentiment periods	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	Net	New	New	Red	Red
Alpha_rank	2.3244***	3.1072***	1.7472***	2.0857***	−0.6057***	−0.9312***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.9847***	−1.6868***	−0.0930	−0.4063***	0.8274***	1.0384***
	(0.000)	(0.000)	(0.692)	(0.008)	(0.000)	(0.000)
Observations	107,586	93,811	107,586	93,811	107,586	93,811
R^2	0.08	0.11	0.07	0.10	0.05	0.06

Panel B: Sectoral holdings in low and high sentiment periods	Low sentiment periods			High sentiment periods		
	Mean	N	Standard Deviation	Mean	N	Standard Deviation
Defensive Holdings (%)	22.20	112,874	7.74	21.47	105,411	7.54
Sensitive Holdings (%)	40.79	112,874	8.69	41.38	105,411	9.13
Cyclical Holdings (%)	33.02	112,874	9.91	32.72	105,411	9.94

In Panel A, we estimate the sensitivity of fund flows to the past performance of funds in low and high sentiment periods. In Panel B, we report the distributions of sectoral holdings of funds in low and high sentiment periods. Net Cash Flow (columns (1)-(2)) is defined as NET_CASHFLOW_PCT = 100*(new sales – redemptions)/(lag fund size). New Sales Flow (columns (3)-(4)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (columns (5)-(6)) is defined as REDEMPTIONS_FLOW_PCT = 100*redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The sample is split into periods of low (columns (1), (3), and (5)) and high (columns (2), (4), and (6)) investor sentiment in the previous month. The threshold value is 0 and investor sentiment is the updated version of the orthogonalized sentiment index of Baker and Wurgler (2006). We regress each of the three fund flow variables on the performance variable and control variables in each subperiod separately. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3. The effect of sentiment

We estimate FPS separately for low sentiment and high sentiment periods and report the results in Table 5 Panel A. Comparing columns (1) and (2), we find that the FPS of net cash flows is higher in high sentiment periods. Columns (3)-(6) suggest that both new sales and redemptions have higher sensitivity in high sentiment months.

In Table 5 Panel B, we tabulate the distributions of the fractions of defensive stocks, sensitive stocks and cyclical stocks in fund portfolios in low and high sentiment periods. We find that the sectoral holdings of funds do not materially change with investor sentiment. This is consistent with mutual funds specializing in certain types of stocks, resulting in greater cross-sectional variation in our sectoral holdings variables relative to their time-series variation. We conclude that mutual funds do not significantly change their portfolio holdings from one sector to another in response to changes in investor sentiment.

In Table 6, we estimate how the portfolio composition affects the FPS in low and high sentiment periods. In Panel A, the coefficient of the interaction term for net cash flows (columns (1) and (4)) is negative and significant in low as well as high sentiment periods. This means that FPS is lower for funds with a higher fraction of defensive stocks in low as well as high sentiment periods. However, the coefficient of the interaction term is −0.0212 in low sentiment periods and −0.0295 in high sentiment periods. That is, FPS decreases with the fraction of defensive stocks at a considerably higher rate in high sentiment periods. The coefficients of the interaction term for new sales in low and high sentiment periods (columns (2) and (5)) are not very different from each other. However, in the case of redemptions (columns (3) and (6)), the coefficient of the interaction term is insignificant in low sentiment months but significant in high sentiment months. This means that the sensitivity of redemptions to performance does not depend on the fraction of defensive stocks in low sentiment months but decreases with the fraction of defensive stocks in high sentiment months.

In Panel B, we examine the effect of the fraction of sensitive stocks on FPS. We find that as the fraction of sensitive stocks increases, the sensitivity of new sales decreases, whereas the sensitivity of redemptions increases in both low and high sentiment periods. Overall, the sensitivity of net cash flow decreases as the fraction of sensitive stocks increases in both low and high sentiment periods, and the effect is of almost equal magnitude in both sub-periods (the coefficient of the interaction term is equal to −0.0124 and −0.0125 in low and high sentiment periods, respectively).

In Panel C, we examine the effect of the fraction of cyclical stocks on FPS. As expected, the effect of cyclical stocks is in the opposite direction to that of defensive stocks. The sensitivity of net cash flow increases as the fraction of cyclical stocks increases in both low and high sentiment periods. The coefficient of the interaction term is 0.0150 and 0.0151 in low and high sentiment periods, respectively, which means that the effect of cyclical stocks on FPS is the same across the two sub-periods. This effect is mainly due to the higher sensitivity of new sales for funds with a higher fraction of cyclical stocks.

In Panel D, we include both pct_defensive_s and pct_sensitive_s in the regressions, thus setting pct_cyclical_s as the base level. In the case of net cash flow, the interaction terms Alpha_rank*pct_defensive_s and Alpha_rank*pct_sensitive_s are statistically significant in low as well as high sentiment periods (columns (1) and (4)). The coefficient of Alpha_rank*pct_defensive_s is much higher in magnitude

Table 6
Effect of holdings on FPS in low and high investor sentiment periods.

Panel A: Defensive holdings and FPS	Low Sentiment			High Sentiment		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	2.8797***	2.2210***	−0.6650***	3.8061***	2.5348***	−1.1725***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pct_defensive	0.0137***	0.0065**	−0.0071***	0.0098***	−0.0009	−0.0111***
	(0.000)	(0.028)	(0.001)	(0.001)	(0.757)	(0.000)
Alpha_rank*pct_defensive	−0.0212***	−0.0182***	0.0019	−0.0295***	−0.0192***	0.0098**
	(0.000)	(0.000)	(0.589)	(0.000)	(0.001)	(0.023)
Constant	−1.3765***	−0.3082	1.0413***	−1.9311***	−0.3283*	1.3494***
	(0.000)	(0.189)	(0.000)	(0.000)	(0.069)	(0.000)
Observations	107,586	107,586	107,586	93,811	93,811	93,811
R^2	0.08	0.08	0.05	0.12	0.10	0.07
Panel B: Sensitive holdings and FPS	**Low Sentiment**			**High Sentiment**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	2.8605***	2.5181***	−0.3291**	3.7119***	3.2152***	−0.2605
	(0.000)	(0.000)	(0.029)	(0.000)	(0.000)	(0.230)
pct_sensitive	−0.0073***	−0.0012	0.0060**	−0.0010	0.0105***	0.0112***
	(0.006)	(0.634)	(0.012)	(0.661)	(0.004)	(0.000)
Alpha_rank*pct_sensitive	−0.0124***	−0.0189***	−0.0072**	−0.0125***	−0.0264***	−0.0181***
	(0.004)	(0.000)	(0.042)	(0.006)	(0.000)	(0.000)
Constant	−0.7006***	−0.0472	0.6540***	−1.6683***	−0.8320***	0.5919***
	(0.004)	(0.850)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	107,586	107,586	107,586	93,811	93,811	93,811
R^2	0.08	0.08	0.05	0.12	0.10	0.07
Panel C: Cyclical holdings and FPS	**Low Sentiment**			**High Sentiment**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	1.8652***	1.3533***	−0.5679***	2.7248***	1.6265***	−1.1284***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pct_cyclical	−0.0093***	−0.0075***	0.0026	−0.0120***	−0.0152***	−0.0021
	(0.000)	(0.004)	(0.162)	(0.000)	(0.001)	(0.531)
Alpha_rank*pct_cyclical	0.0150***	0.0138***	−0.0003	0.0151***	0.0203***	0.0074
	(0.000)	(0.002)	(0.919)	(0.001)	(0.002)	(0.148)
Constant	−0.7105***	0.0373	0.8375***	−1.3909***	−0.0812	1.0446***
	(0.000)	(0.889)	(0.000)	(0.000)	(0.631)	(0.000)
Observations	107,586	107,586	107,586	93,811	93,811	93,811
R^2	0.08	0.08	0.05	0.12	0.10	0.07
Panel D: Sectoral holdings and FPS	**Low Sentiment**			**High Sentiment**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	3.4523***	2.9240***	−0.4781**	4.4888***	3.9640***	−0.3270
	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)	(0.341)
pct_defensive_s	0.0146***	0.0083***	−0.0067***	0.0150***	0.0099**	−0.0061*
	(0.000)	(0.009)	(0.003)	(0.000)	(0.023)	(0.068)
pct_sensitive_s	0.0002	0.0034	0.0028	0.0066**	0.0164***	0.0087**
	(0.936)	(0.230)	(0.251)	(0.012)	(0.000)	(0.015)
Alpha_rank*pct_defensive_s	−0.0200***	−0.0163***	0.0025	−0.0295***	−0.0253***	0.0034
	(0.000)	(0.001)	(0.498)	(0.000)	(0.000)	(0.512)
Alpha_rank*pct_sensitive_s	−0.0129***	−0.0164***	−0.0043	−0.0121**	−0.0252***	−0.0163***
	(0.004)	(0.001)	(0.212)	(0.011)	(0.000)	(0.003)
Constant	−1.4456***	−0.5931**	1.0078***	−2.4385***	−1.4399***	0.8153***
	(0.000)	(0.025)	(0.000)	(0.000)	(0.000)	(0.002)
Observations	107,586	107,586	107,586	93,811	93,811	93,811
R^2	0.08	0.08	0.05	0.12	0.11	0.08

We estimate the sensitivity of fund flows to the past performance of funds and the sensitivity of their holdings in different sentiment periods. Net Cash Flow (columns (1) and (4)) is defined as NET_CASHFLOW_PCT = 100*(new sales – redemptions)/(lag fund size). New Sales Flow (columns (2) and (5)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (columns (3) and (6)) is defined as REDEMPTIONS_FLOW_PCT = 100*redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The variables pct_defensive (Panel A), pct_sensitive (Panel B), and pct_cyclical (Panel C), are the percentages of the fund portfolio invested in defensive, sensitive, and cyclical stocks, respectively, according to Morningstar Direct. The interaction variable is equal to the product of Alpha_rank and pct_defensive in Panel A, pct_sensitive in Panel B, and pct_cyclical in Panel C. The variables in Panel D are the combined variables of Panels A and B. The sample is split into periods of low (columns (1)- (3)) and high (columns (4)-(6)) investor sentiment in the previous month. The threshold value is 0 and investor sentiment is the updated version of the orthogonalized sentiment index of Baker and Wurgler (2006). We regress each of the three fund flow variables on the performance variable, the holdings sensitivity variables, the corresponding interaction variables, and control variables in each subperiod separately. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

than that of Alpha_rank*pct_sensitive_s in both sub-periods. It follows that FPS decreases significantly as the fraction of defensive or sensitive stocks increases in all sub-periods. The flip side of this conclusion is that FPS increases as the fraction of cyclical stocks increases in the fund portfolio.

4.4. The effect of the risk-free rate

The sensitivity of fund flows to past performance goes down during periods of low risk-free rates due to the acquisition of private information, according to De Jesus (2021). We investigate this claim further by splitting our sample into periods of below (low) and above median (high) risk-free rates and estimating FPS separately in each sub-sample. We report our results in Table 7. We confirm that the sensitivity of flows to past performance is lower in months with lower risk-free rates and show that both new sales and redemptions drive this effect.

We estimate the impact of fund holdings on FPS for periods of low and high risk-free rates and report the results in Table 8. The low magnitude and weak statistical significance of the coefficients of the interaction terms in columns (1)-(3) of Panel A show that the fraction of defensive stocks does not notably affect FPS when the risk-free rate is low. Conversely, the inclusion of defensive stocks in a fund portfolio strongly lowers the sensitivity of flows to past performance during periods of above average risk-free rates. More precisely, the interaction term coefficients are strongly statistically significant in columns (4) and (5) but not in column (6). The implication is that defensive holdings lower the sensitivity of net flows to performance in months of high risk-free rates primarily through the new sales channel.

Panel B contains the results obtained when the fraction of sensitive stocks is the holdings variable included in the estimations. The interaction term coefficients in columns (1) and (4) indicate that the effect of sensitive holdings on the sensitivity of net flows to past performance is negative and approximately twice as large in periods of high risk-free rates. The coefficients in the remaining columns show that the effect is primarily driven by new sales as in the case of the fraction of defensive stocks in Panel A. However, sensitive stocks actually increase the sensitivity of redemption to past performance during high risk-free rate months as conveyed by the coefficient of the interaction term in column (6).

We study the effect of the fraction of cyclical stocks on FPS in Panel C. The fraction does not have a strong effect on FPS in low risk-free rate environments as according to the coefficients in columns (1)-(3). Nonetheless, the addition of cyclical stocks to a fund portfolio increases the sensitivity of redemptions to performance according to the negative and statistically significant interaction term coefficient in column (3). In contract, an increase in the fraction of cyclical stocks increases (decreases) the sensitivity of new sales (redemptions) to performance during high risk-free rate periods as according to columns (5) and (6). The net effect is an increase in FPS (column (4)).

Table 7
FPS in low and high risk-free rate periods.

	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	Net	New	New	Red	Red
Alpha_rank	2.5151***	2.9165***	1.7947***	2.0382***	−0.7178***	−0.8191***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−1.4111***	−1.2603***	−0.6798***	0.1805	0.6726***	1.1932***
	(0.000)	(0.000)	(0.000)	(0.461)	(0.000)	(0.000)
Observations	123,090	78,307	123,090	78,307	123,090	78,307
R^2	0.08	0.11	0.07	0.10	0.04	0.07

We estimate the sensitivity of fund flows to the past performance of funds in different sentiment periods. Net Cash Flow (columns (1)-(2)) is defined as NET_CASHFLOW_PCT = 100*(new sales – redemptions)/(lag fund size). New Sales Flow (columns (3)-(4)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (columns (5)-(6)) is defined as REDEMPTIONS_FLOW_PCT = 100*redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The sample is split into periods of low (columns (1), (3), and (5)) and high (columns (2), (4), and (6)) risk-free rate in the previous month. The threshold value is the sample median, and the risk-free rate is the 1-year Treasury constant maturity rate as in De Jesus (2021). We regress each of the three fund flow variables on the performance variable and control variables in each subperiod separately. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Effect of holdings on FPS in low and high risk-free rate periods.

Panel A: Defensive holdings and FPS	Low Rate			High Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	2.8133***	1.9392***	−0.8581***	3.8725***	2.8167***	−0.9793***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pct_defensive	0.0031	−0.0046*	−0.0079***	0.0204***	0.0102***	−0.0103***
	(0.316)	(0.066)	(0.000)	(0.000)	(0.001)	(0.000)
Alpha_rank*pct_defensive	−0.0094**	−0.0026	0.0059*	−0.0414***	−0.0348***	0.0058
	(0.042)	(0.531)	(0.086)	(0.000)	(0.000)	(0.190)
Constant	−1.5904***	−0.6520***	0.9084***	−1.7172***	0.0154	1.4823***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.953)	(0.000)
Observations	123,090	123,090	123,090	78,307	78,307	78,307
R^2	0.08	0.07	0.04	0.11	0.10	0.07

Panel B: Sensitive holdings and FPS	Low Rate			High Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	2.9134***	2.1494***	−0.6870***	3.6591***	3.5838***	0.0974
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.674)
pct_sensitive	−0.0020	−0.0026	−0.0002	−0.0063**	0.0119***	0.0174***
	(0.329)	(0.219)	(0.875)	(0.029)	(0.003)	(0.000)
Alpha_rank*pct_sensitive	−0.0084**	−0.0076**	−0.0012	−0.0165***	−0.0378***	−0.0240***
	(0.021)	(0.034)	(0.647)	(0.001)	(0.000)	(0.000)
Constant	−1.3282***	−0.5588***	0.6993***	−1.0406***	−0.3203	0.5466***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.293)	(0.006)
Observations	123,090	123,090	123,090	78,307	78,307	78,307
R^2	0.08	0.07	0.04	0.12	0.11	0.08

Panel C: Cyclical holdings and FPS	Low Rate			High Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	2.4667***	2.0137***	−0.5049***	2.1233***	0.9661***	−1.1913***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pct_cyclical	−0.0054***	0.0017	0.0070***	−0.0159***	−0.0243***	−0.0065*
	(0.006)	(0.330)	(0.000)	(0.000)	(0.000)	(0.062)
Alpha_rank*pct_cyclical	0.0020	−0.0060*	−0.0064***	0.0282***	0.0401***	0.0135***
	(0.530)	(0.078)	(0.010)	(0.000)	(0.000)	(0.009)
Constant	−1.2870***	−0.8168***	0.5101***	−0.8143***	0.7729***	1.3720***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
Observations	123,090	123,090	123,090	78,307	78,307	78,307
R^2	0.08	0.07	0.04	0.11	0.11	0.08

Panel D: Sectoral holdings and FPS	Low Rate			High Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	New	Red	Net	New	Red
Alpha_rank	2.9082***	1.7710***	−1.0364***	5.0328***	5.1169***	0.2313
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.510)
pct_defensive_s	0.0049	−0.0047*	−0.0097***	0.0247***	0.0230***	−0.0031
	(0.105)	(0.055)	(0.000)	(0.000)	(0.000)	(0.347)
pct_sensitive_s	0.0024	−0.0017	−0.0039**	0.0044	0.0215***	0.0155***
	(0.253)	(0.408)	(0.013)	(0.157)	(0.000)	(0.000)
Alpha_rank*pct_defensive_s	−0.0053	0.0042	0.0083**	−0.0442***	−0.0459***	−0.0024
	(0.231)	(0.327)	(0.017)	(0.000)	(0.000)	(0.647)
Alpha_rank*pct_sensitive_s	−0.0037	0.0009	0.0026	−0.0213***	−0.0424***	−0.0233***
	(0.311)	(0.816)	(0.348)	(0.000)	(0.000)	(0.000)
Constant	−1.7546***	−0.6190***	1.1595***	−2.1295***	−1.4140***	0.6636**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.019)
Observations	123,090	123,090	123,090	78,307	78,307	78,307
R^2	0.08	0.08	0.05	0.12	0.11	0.08

We estimate the sensitivity of fund flows to the past performance of funds and the sensitivity of their holdings in different sentiment periods. Net Cash Flow (columns (1) and (4)) is defined as NET_CASHFLOW_PCT = 100*(new sales – redemptions)/(lag fund size). New Sales Flow (columns (2) and (5)) is defined as NEWSALES_FLOW_PCT = 100*new sales/(lag fund size). Redemptions Flow (columns (3) and (6)) is defined as REDEMPTIONS_FLOW_PCT = 100*redemptions/(lag fund size). We define a fund's performance rank variable as the fractional rank of the fund in the cross-section of its Morningstar style category in a given month on a scale of 0 to 1. Alpha_rank is the performance rank based on the cumulative CAPM alpha earned over the trailing 12 months. The variables pct_defensive (Panel A), pct_sensitive (Panel B), and pct_cyclical (Panel C) are the percentages of the fund portfolio invested in defensive, sensitive, and cyclical stocks, respectively, according to Morningstar Direct. The interaction variable is equal to the product of Alpha_rank and pct_defensive in Panel A, pct_sensitive in Panel B, and pct_cyclical in Panel C. The variables in Panel D are the combined variables of Panels A and B. The sample is split into periods of low (columns (1), (3), and (5)) and high (columns (2), (4), and (6)) risk-free rate in the previous month. The threshold value is the sample median, and the risk-free rate is the 1-year Treasury constant maturity rate as in De Jesus (2021). We regress each of the three fund flow variables on the performance variable, the holdings sensitivity variables, the corresponding interaction variables, and control variables in each subperiod separately. We use Fama-Macbeth regressions – cross-sectional regressions are run every month. The sample consists of monthly observations from January 2001 to December 2017, a total of 204 months. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

We combine pct_defensive_s and pct_sensitive_s in the same regressions in Panel D. The two variables have a very low estimated impact on flows sensitivity in low risk-free rate conditions. However, an increase in pct_defensive_s slightly lowers the sensitivity of redemptions to past performance as according to the low magnitude but strong statistical significance of the interaction term coefficient in column (3). On the other hand, columns (4)-(6) confirm the main insight from Panels A,B, and C that portfolio composition affects FPS most strongly during high risk-free rates. Rising rates deter the costly private information acquisition of investors of all funds in favour of past performance chasing as in De Jesus (2021). However, investors of funds holding mostly cyclical stocks shift towards chasing past performance more aggressively when private information becomes scarce. Furthermore, the substitution of cyclical stocks with defensive stocks has a larger dampening effect on FPS than with sensitive stocks. Finally, the effect of holdings on FPS is predominantly arising from their effect on new sales sensitivity.

5. Conclusion

Mutual fund investors choose funds with certain expectations about the risk-return characteristics of their chosen funds. Their reaction to the performance of funds is reflected in their subsequent flows into or out of funds. We find that investors attribute superior performance more to luck and less to managerial skill in the case of funds holding predominantly defensive stocks. On the other hand, in the case of funds holding predominantly cyclical stocks, investors attribute superior performance more to managerial skill and less to luck. Therefore, flow-performance sensitivity is higher in the case of funds with more cyclical holdings. These results are mainly driven by new sales rather than redemptions.

Mutual fund flows are intrinsically related to investor sentiment. We show that, on average, flow-performance sensitivity is higher in high sentiment months for all funds. This is also true for new sales and redemptions measured separately. However, in both low sentiment months and high sentiment months, flow-performance sensitivity decreases as the fraction of defensive stocks in a fund's portfolio increases. Furthermore, in high sentiment periods, a higher fraction of defensive stocks reduces the sensitivity of new sales as well as redemptions to performance, resulting overall in lower flow-performance sensitivity. By contrast, the sensitivity of redemptions to performance does not change with the fraction of defensive stocks in low sentiment months, and the fraction's overall effect on flow-performance sensitivity arises exclusively from its dampening effect on new sales sensitivity.

There is evidence that flow-performance sensitivity is affected by the risk-free rate (De Jesus, 2021). We confirm that FPS is lower during low risk-free rate environments. Notably, this effect is driven by both new sales and redemptions. We also show that an increase in defensive stocks results in a decrease in FPS primarily during high risk-free rate months when the new sales channel dominates.

Our results have important implications for mutual fund investors. Mutual funds with high FPS driven by cyclical holdings may not be suitable for long-term investors due to the high liquidity costs that are passed on to them when flows are uncertain, as in Chordia (1996) and Johnson (2004). High FPS implies uncertain flows, which results in funds holding more liquid assets with high opportunity costs, such as cash, or incurring higher transaction costs to satisfy the liquidity demands of short-term investors. While the short-term investors that frequently switch between funds are predominantly responsible for these liquidity costs, the long-term investors disproportionately bear them.

Our results add to the body of evidence that mutual fund investors are not a homogeneous group. We show that they are individual agents with diverse preferences dictating their investment choices and reactions to fund performance. Therefore, mutual fund managers would do well to adopt portfolio management strategies that cater to the observed preferences of their investors. For example, since the FPS increases as the fraction of cyclical stocks increases, the fund managers with high fraction of cyclical stocks should take extra precaution to ensure that their funds with higher FPS do not underperform. This can be coordinated at the fund family level. There is already some evidence that large mutual fund families use their internal markets (i.e., cross-trading among funds of the family) to engage in risk-shifting and liquidity management to enhance the performance of strategically chosen funds (Goncalves-Pinto et al (2018)). A fund family may also use its internal markets to support the performance of funds with a high fraction of cyclical stocks. The facility of cross-trading will ensure that they can sell some of their stocks to other funds in the family at market prices when they face redemptions. As a result, they can receive high flows when their performance is good and do not suffer big losses due to redemptions when their performance is bad. Moreover, the portfolio composition of funds may affect the types of investors in the funds, thus determining the sensitivity of flows to past performance. Therefore, fund managers may wish to strategically alter their investment portfolios in order to have some control over flows sensitivity, which is an important factor in fund liquidity management.[5] The investment choices of portfolio managers driven by liquidity considerations arising from flow-performance sensitivity variability may be an interesting avenue for future research.

[5] Flow-induced price pressure effects are a significant cost in the mutual fund industry as in Coval and Stafford (2007).

CRediT authorship contribution statement

Svetoslav Covachev: Conceptualization, Data curation, Writing – original draft, Software, Formal analysis. **Vijay Yadav:** Methodology, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A

Variable definitions.

Defensive Holdings (%)	The percentage of the fund portfolio invested in defensive stocks, according to Morningstar Direct data.
Sensitive Holdings (%)	The percentage of the fund portfolio invested in sensitive stocks, according to Morningstar Direct data.
Cyclical Holdings (%)	The percentage of the fund portfolio invested in cyclical stocks, according to Morningstar Direct data.
New Sales (% of TNA)	The new sales of the fund as a percentage of its TNA on the previous month end.
Redemptions (% of TNA)	The redemptions of the fund as a percentage of its TNA on the previous month end.
Net Cash Flow (% of TNA)	The net cash flows (new sales – redemptions) of the fund as a percentage of its TNA on the previous month end.
Market-Adjusted Return (% per month)	The net of fees monthly excess return of the fund minus the market excess return.
CAPM Alpha (% per month)	The net of fees monthly CAPM alpha of the fund. The fund's market factor beta was estimated with a time series regression over the trailing 36 months.
3-Factor Alpha (% per month)	The net of fees monthly Fama and French (1993) 3-Factor alpha of the fund. The fund's factor betas were estimated with a time series regression over the trailing 36 months.
4-Factor Alpha (% per month)	The net of fees monthly Carhart (1997) 4-Factor alpha of the fund. The fund's factor betas were estimated with a time series regression over the trailing 36 months.
6-Factor Alpha (% per month)	The net of fees monthly Fama and French (2015) 6-Factor alpha of the fund, where the sixth factor is momentum. The fund's factor betas were estimated with a time series regression over the trailing 36 months.
Fund Size ($ million)	The combined TNA of all share classes belonging to the fund.
Family Size ($ billion)	The combined TNA of all funds overseen by the management company of the fund, excluding the TNA of the fund itself.
Log Fund Size	The natural logarithm of Fund Size.
Log Family Size	The natural logarithm of (one plus Family Size).
Expense Ratio (% per year)	The percentage of the fund's assets that are used to cover the expenses of the fund, including operating expenses and management fees, but excluding brokerage costs.
Turnover Ratio (% per year)	The minimum of the fund's total purchases and total sales of securities in a year, divided by the fund's average month end TNA in the previous year.
Age (years)	The age of the oldest share class of the fund.
Category New Sales (% of TNA)	The total new sales of all funds in a given Morningstar style category as a percentage of their total TNA on the previous month end.
Category Redemptions (% of TNA)	The total redemptions of all funds in a given Morningstar style category as a percentage of their total TNA on the previous month end.
Category Net Cash Flow (% of TNA)	The total net cash flow (new sales – redemptions) of all funds in a given Morningstar style category as a percentage of their total TNA on the previous month end.
Investor Sentiment	The updated version of the sentiment index of Baker and Wurgler (2006). It was constructed by the authors based on the first principal component of five sentiment measures, which had been orthogonalized relative to six macroeconomic variables.
Risk-Free Rate	The 1-year Treasury constant maturity rate obtained from the FRED website of the Federal Reserve Bank of St. Louis.

Appendix B

Morningstar classification of companies into three super sectors.

Morningstar classifies the universe of all companies into 148 industries. Each company is mapped into the industry which most accurately reflects the underlying business of that company. Then, the 148 industries are grouped into 69 industry groups. The 69 industry groups are further grouped into 11 sectors. Finally, the 11 sectors are grouped into 3 super sectors. We report the three super sectors and their constituent sectors in the table below. We also report examples of companies in each sector.

1. Defensive Sectors

Sector Name	Examples of Companies
Healthcare	Astra Zeneca PLC, Pfizer Inc, Roche Holding AG
Consumer Defensive	Philip Morris International Inc, Procter & Gamble Company, Wal-Mart Stores
Utilities	Electricite de France, Exelon Corporation, PG&E Corporation

2. Sensitive Sectors

Sector Name	Examples of Companies
Communication Services	AT&T Inc, France Telecom, Verizon Communications Inc
Energy	BP PLA, ExxonMobil Corporation, Royal Dutch Shell PLC
Industrials	3 M Company, Boeing Company, Siemens AG
Technology	Apple Inc, Google Inc, Microsoft Corp

3. Cyclical Sectors

Sector Name	Examples of Companies
Basic Materials	ArcelorMittal, BHL Billiton Limited, Rio Tinto PLC
Consumer Cyclical	Ford Motor Company, McDonald's Corporation, News Corporation
Financial Services	Allianz SE, J.P. Morgan Chase & Co, Legg Mason Inc
Real Estate	Kimco Realty Corporation, Vornado Realty Trust, Westfield Group

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