A man's world? Consumption-based investment in the mutual fund industry[a]

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Abstract

We examine whether U.S. mutual fund managers invest in line with gender-specific consumption patterns. Male and female managers allocate investments differently across sectors, with consumption patterns closely linked to investment decisions. Portfolios with a stronger focus on consumption-related investments tend to be less risky, yield lower returns, and exhibit slightly weaker overall performance. Using a novel measure of portfolio masculinity, we find that more masculine portfolios underperform. A counterfactual analysis highlights potentially large shifts in some sector investments if women managed half the volume, compared to the current $< 5\%$ of US mutual fund assets, with corresponding implications for capital allocation.

Keywords: Mutual funds, capital allocation, consumption preferences, gender.

JEL Classification: G11, G21, G23

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1 Introduction

Professional investors allocate and manage a substantial part of global wealth. Among them are managers of banks, mutual funds, and family offices.[1] The investment decisions of these relatively few individuals affect the global allocation of physical capital, and thus eventually the direction of technological change and overall productive efficiency. Furthermore, these decisions have consequences for many people: 71.5 million households in the United States invest in US-registered funds, and median mutual fund assets of mutual fund-owning households amount to $125,000 (ICI, 2024). Thus, it is important to understand what exactly makes professional investors select a portfolio on behalf of their clients. In particular, it is important to find out whether personal characteristics or preferences distort professional decisions away from a purely professional choice. Ideally, a professional investor's personal characteristics should not have an impact on the direction of investments, since they invest on behalf of their clients. Modern portfolio theory suggests that investors should compose their portfolio on the basis of the joint distribution of returns of various assets. However, several studies have documented that even highly trained professional investors are subject to biased investment behavior (Frazzini (2006); Pool et al. (2012); Du et al. (2023)).

This paper empirically explores a novel factor that might affect investment choices of mutual fund managers: their consumption preferences. Specifically, we investigate whether male and female fund managers tend to allocate capital in line with the consumption patterns typically associated with their gender. Investing according to consumption preferences can occur through a specific form of familiarity bias (Massa and Simonov (2006); Pool et al. (2012); Chague et al. (2022)), where managers enjoy doing more business in sectors that produce goods they are familiar with as consumers. It can also be a profitable strategy when investors learn about aggregate consumer demand from the realization of their own consumption preferences to identify worthwhile investments. Recent theoretical research shows that this type of behavior can be the result of optimal play in equilibrium in Bayesian capital markets games with demand uncertainty (Grüner and Siemroth (2019); Strausz (2017)). While there is some evidence for this type of behavior for individual investors (Grüner and Siemroth (2019), Keloharju et al. (2012)), this is the first empirical paper to systematically analyze the link between consumption and investment for institutional investors, and to shed light on possible real economic implications.

[1]For example, the top 400 asset management firms manage more than 66 trillion US dollars of investments (`https://www.ipe.com/reports/special-reports/top-400-asset-managers/total-global-aum-2019/10031648.article`), and in 2018, US mutual fund managers alone allocate more than 17 trillion US dollars of investments, more than ten percent of global financial wealth (`https://www.statista.com/topics/1441/mutual-funds/`). The global mutual funds industry accounts for 20 trillion USD investment (`https://mutualfunds.com/education/how-big-is-the-mutual-fund-industry/`), and family offices manage another 4 trillion dollars of financial wealth (`https://www.forbes.com/sites/francoisbotha/2018/12/17/the-rise-of-the-family-office-where-do-they-go-beyond-2019/`).

Consumption-induced investment behavior of mutual fund managers can potentially affect fund performance and thus be relevant for fund investors, and it can also have broader market implications regarding relative sectoral growth in the real economy. A mismatch between available funds for consumer spending and control over investment may lead to excessive capacity in some sectors and too little capacity in others. Only 10% of US fund managers are female (Niessen-Ruenzi and Ruenzi (2019)), controlling an even smaller share of total net assets, which could lead to a stronger representation of male consumption preferences in investment decisions. This type of asymmetry can lead to an inefficient allocation of capital.

Our analysis draws on a panel dataset of single-managed US domestic equity funds obtained from the CRSP survivor-bias free mutual fund database. We link these data to fund managers' gender identities from Morningstar and the funds' portfolio holdings from Thomson Reuters. The sample runs from 2004 to 2019.[2]

We first investigate whether female and male fund managers differ in how they allocate investments across sectors and find that this is the case. We find that, for example, female fund managers are more likely to hold stocks from the healthcare sector, while male fund managers are more likely to hold stocks from the energy sector. Going beyond specific sectors, we test whether the allocation across sectors is the same for female and male fund managers. We can reject equal allocations at both the extensive and the intensive margin, and after controlling for fund characteristics and time trends.

In the next step, we examine whether fund managers' gender-specific consumption preferences can explain gender differences in investments. To address this question, we make use of consumption data that is collected by the US Consumer Expenditure Survey (CES).[3] In our analysis, we focus on the highest income category of the CES data, given that mutual fund managers are top earners with a median annual compensation of $400k (Cen et al. (2023)), separately for each gender. In several consumption categories, we observe significant gender differences in consumption spending, which—to the extent that prices for a given good are the same for male and female consumers—must reflect differences in consumption preferences. For example, women tend to consume more in the Personal Care and Apparel Pets/Toys categories, while men tend to consume more in the Gasoline/Fuels and Vehicle categories. Throughout the paper, we use consumption spending shares as our measure of consumption preferences, properly taking price changes into account where necessary by the use of fixed effects.

[2]The sample ends before the onset of the Covid-19 crisis to avoid that consumer preferences and investment choices during this particular time affect our results.

[3]In most of the article, we distinguish investments according to which sector the investment is made in. Our corresponding categorization into sectors is based on the Global Industry Classification Standard (GICS). When testing for the link between consumption and investment, we instead distinguish investments according to which CES consumption category they supply. Not every investment is part of a consumption category (e.g., investments in industrial machinery, defense, etc.), so these analyses consider a subset of the investments in the portfolio.

We then link consumption preferences to the fund holdings data to examine whether investments of mutual fund managers are related to gender-specific consumption preferences. We find a clear statistical link, i.e., both male and female managers invest relatively more in what their gender on average prefers to consume. We use a multivariate regression framework with fund-quarter fixed effects to control for time-varying fund characteristics and consumption category-quarter fixed effects to take care of time-varying investment patterns across mutual funds. Our results show that an increase in the consumption share of one percentage point is associated with a larger share in the fund portfolio in the sector supplying that consumption of about 0.115 percentage points. Not surprisingly, investment shares do not reflect consumption shares 1:1. Instead, changes in investment and changes in consumption are related with a ratio of 1:8 to 1:9. While this result is economically meaningful, we note that it is one of correlation, not causality, as natural experiments with consumer preferences are difficult to find.

Our results have potential implications for both individual funds and the market as a whole. With respect to the fund level, consumption-based investment decisions could either lead to higher fund performance if they are based on informational advantages of fund managers, or they could lead to lower fund performance if they are the result of a counterproductive behavioral bias. Relating the weight that a fund manager places on consumption-preferences when investing to the funds' alpha as a measure of market-outperformance, we find that a higher consumption weight in investments tends to be associated with lower performance. Thus, investing based on consumption-preferences seems to reflect bias rather than the use of superior information. Moreover, we find that fund managers who rely more on consumption-preferences take significantly less systematic risk and deliver lower returns.

We also investigate within gender heterogeneity in investment behavior. With a novel method to rank funds according to their masculinity (a "portfolio masculinity index" (PMI)), we observe considerable within-gender heterogeneity. A portfolio is considered more masculine (or more feminine) if it aligns more closely with the average investment choices of male (or female) fund managers.[4] Notably, male-managed funds can exhibit varying degrees of femininity, and vice versa. Our analysis reveals a significant negative relationship between portfolio masculinity and fund performance, suggesting that more masculine investment strategies tend to underperform.

This adverse effect of portfolio masculinity on returns is consistent with theoretical work suggesting that investors who allocate disproportionately to industries aligned with their personal consumption preferences may misallocate capital. In this context, male managers overweighting male-preferred industries tend to generate lower returns, while those investing more in female-preferred sectors may benefit from higher returns due to limited productive capacity in those

[4]Portfolio masculinity and femininity can also exceed gender averages when a portfolio lies beyond the average male or female allocation. A formal definition is provided in Section 2.5.

sectors. This suggests that male consumption signals are less valuable than female ones, and managers—regardless of gender—who rely more heavily on male consumption preferences are more likely to underperform.

By moving beyond a binary gender classification, our PMI provides a more nuanced measure of investment behavior, uncovering a clear link between femininity and performance. This methodology offers a novel way to assess heterogeneity at a granular level, extending beyond gender to other domains, such as within-party differences in two-party political systems.

Fund managers' consumption-based investment decisions do not only have the potential to affect fund performance. On a macroeconomic level, consumption-based investment decisions may have broader implications for capital flows to the real economy, because women make up roughly 50% of the population, but only 9% of fund managers in our sample. Moreover, women control an even smaller share of total net assets, around 3%. Both can lead to a mismatch between consumption and investment. If more female fund managers were present in the industry, their distinct consumption preferences and thus investments could redirect capital flows toward different sectors of the economy. Such a reallocation of funds has the potential to stimulate aggregate investment in some industries, for example by lowering the cost of capital, while other industries would receive comparatively less aggregate investment, potentially altering the overall landscape of the economy. To examine these changes, we compute hypothetical sector allocations for the case of gender parity in the mutual fund industry. Our results show that women managing 50% of all mutual fund assets would result in significantly lower portfolio shares for the energy, utilities and financials sectors, while there would be an increase in investment in the healthcare, materials and IT sectors. This reallocation of capital could drive innovation and growth in healthcare and tech industries, while potentially increasing financial constraints in the energy and finance sectors.

Our paper contributes to several strands of the literature. While gender differences in preferences more generally have been summarized in several overview articles (Croson and Gneezy (2009); Meyers-Levy and Loken (2015); Baudin and Hiller (2018)), there also is a smaller but growing literature on gender differences in consumption preferences specifically, which points out that individuals tend to prefer products that match with their self-perceived gender identity (Worth et al. (1992)). With respect to gender differences in investment choices, the previous literature documents that female investors are more risk averse (Charness and Gneezy (2007)), less overconfident (Barber and Odean (2001)), and differ from male investors in their ESG preferences (Assaf et al. (2024)). Furthermore, Bajo et al. (2024) suggest that mutual fund managers invest in brands popular among their own gender, and Keloharju et al. (2012) suggest that retail investors tend to invest more in companies they frequently visit as customers.

Our paper contributes to this literature by providing the first empirical evidence of a link between gender-specific consumption spending and mutual fund managers' investment decisions, particularly their sector allocations. The previous, mostly theoretical, literature on the link between consumption preferences and investment choices (Grüner and Siemroth (2019); Strausz (2017)) has argued that investors might use their preference for a product to conclude that others share this preference, buy more, and—at any given aggregate investment level—make any investment more profitable. In this signal extraction setup, managers would behave optimally in identifying profitable investments for their clients. We here document empirically that a link between investment choices and consumption preferences indeed exists among mutual fund managers.

We also contribute to the literature on biased investment behavior. The previous literature has already established various investment biases among institutional and retail investors. Some examples include familiarity bias, disposition effects (Frazzini (2006); Cici (2012)), overconfidence (Barber and Odean (2001, 2008); Puetz and Ruenzi (2011)), repurchasing bias (Du et al. (2023)), and herding and home bias (Wermers (1999); Pool et al. (2012). Keloharju et al. (2012) show that retail investors are more likely to purchase and less likely to sell shares of companies they frequent as customers. Our paper empirically establishes a novel link between institutional investors' consumption preferences and their investment behavior. We deem this link of particular importance, given that each investor is a consumer at the same point in time.

Importantly, this paper is the first to examine how greater gender balance in the financial industry would affect capital flows to the real economy. Achieving gender parity among fund managers as well as other measures to implement more feminine investment strategies has the potential to reshape the investment landscape, particularly in terms of consumption-driven investment decisions.

2 Data

2.1 Mutual fund data

We merge three major mutual fund databases to construct our dataset. The universe of domestic U.S. open-end equity funds is obtained from the CRSP Survivor-Bias-Free U.S. Mutual Fund database. We then merge the CRSP mutual fund database with all open-end equity funds that are included in the Morningstar Direct mutual fund database using TICKER and CUSIP as fund identifiers. The merging procedure follows the matching algorithm of Pastor et al. (2015). The databases are merged because CRSP contains high-quality data on fund characteristics and performance, while Morningstar is considered more precise with respect to manager identities and manager information (Massa et al., 2010). Finally, we obtain quarterly portfolio holdings from the Thomson Reuters database and merge them with the CRSP mutual fund database using MFLINKS by Wermers (2000). Share classes are aggregated to the portfolio level to avoid multiple counting. Following the previous literature, fund-quarters with total net assets of less than $15 million are excluded (Elton et al., 2001). Since portfolio data are available on a quarterly level only, the highest frequency we can use in the analyses is quarterly.

We only consider domestic U.S. open-end equity funds to make sure that fund performance is comparable across funds, and to rule out that differences in investment scope or the universe of stocks a fund manager can pick from affect our results. Therefore, index funds (where no active investment decision is made), fixed income funds, money market funds, balanced funds as well as funds investing in foreign stocks are excluded from the sample. We restrict the sample to single-managed funds to make sure that investment decisions can be clearly attributed to one individual rather than a team of managers who may be subject to group-specific decision biases as well (Baer et al., 2011). In addition, Evans et al. (2024) show that there is a strategic element in the disclosure of manager names for team-managed funds. Anonymously managed funds significantly underperform, and are less likely to deviate from their benchmark than funds with named managers. Even though this bias should be independent of manager gender, we focus on single managed funds as we deem this the cleanest setting for our analysis.

Manager gender is determined based on Morningstar's fund manager history. We first use the gender classifications from Niessen-Ruenzi and Ruenzi (2019), whose sample of funds and fund managers partially overlaps with ours. Next, for the remaining unclassified fund managers, we use a name-gender dictionary (Martínez et al., 2021) to automatically classify the gender of the fund managers based on their first name. The details of this approach are explained in appendix A.1. After this step, 96% of all fund manager names in the sample are classified. Finally, for the remaining managers (with uncommon or unisex names), we had two research assistants classify each fund manager independently. Their task was to search for these fund managers on the internet and classify them, for example, based on available information (such as a photo or a description using gender pronouns). The two research assistants agreed on their classifications for 97% of the remaining names. In the cases where they disagreed, we had a third research assistant break the tie. The details of this procedure are described in appendix A.2.

2.2 US consumption spending data

Ideally, we would like to observe consumption spending on different goods and services for every individual fund manager in our sample. However, such individual, private consumption data are not available. The next best publicly available data on consumption spending is from the US Consumer Expenditure Surveys (CE). The CE gives us the average spending amounts by gender and income group for every consumption category and year (as a two-year moving average). We use consumption data of female and male single households, where consumption by gender is easier to separate than in a family household, and from the top income group, as fund managers are top earners with median annual compensation of $400k for (Cen et al. (2023)).[5] These data are collected by the US Census Bureau for the Bureau of Labor Statistics. It is used to calculate the weights of goods and services in the market basket of the US Consumer Price Index, an important economic indicator, so a lot of care is taken to get these data right.

Our sample window starts in 2004, because the CES consumer survey switched its interview format in 2003 and the consumer data is a two-year moving average. Thus, to avoid a break during the sample window, we set 2004 as the starting year. Our sample window ends with the last quarter of 2019 in order to avoid the tumultuous changes brought about by the Covid-19 pandemic and the associated consumption restrictions in early 2020, which could severely bias the consumption spending data.

2.3 Industry classification

The Thomson Reuters portfolio data contain quarterly stock holdings of mutual funds. We use the Global Industry Classification Standard (GICS) to assign an industry or sector to all firm stocks included in mutual funds' portfolios. The literature recommends GICS as the best among industry classification systems along several dimensions, such as explaining return differences or classifying firms by industry (Bhojraj et al., 2003; Kile and Phillips, 2009; Hrazdil et al., 2013). GICS assigns an 8-digit number to a firm, where the first two digits identify the sector (which is the coarsest classification), the first four digits denote the industry group, the first six digits denote the industry, and all eight digits together denote the sub-industry (finest classification).[6] We used GICS classifications from three different data sources: The Compustat and CRSP stock datasets and the Thomson Reuters Eikon API. In addition to the existing 11 GICS sectors, we create a new 12th sector "unclassified" for the stocks for which we have no GICS classification.

Table 1: Summary statistics (all funds with one manager, fund-quarter level)

	Mean	Standard dev.	Bottom 1%	Median	Top 1%	Obs.
Male Manager (dummy)	0.91	0.28	0.00	1.00	1.00	26685
1-year Return	0.10	0.17	-0.40	0.11	0.44	25829
1-year 1-F alpha	-0.01	0.03	-0.09	-0.00	0.07	23052
1-year 4-F alpha	-0.00	0.02	-0.07	-0.00	0.05	23049
TR Portfolio Value (mill)	2009.86	9629.53	6.85	290.70	27506.85	26685
Fund Age (in y)	15.35	13.77	1.00	12.00	76.00	25759
Lag Expense Ratio (in %)	1.16	0.49	0.08	1.14	2.59	25022
Lag Log TNA	19.66	2.29	15.86	19.61	24.52	25605
Lag Fund Flow (in %)	10.28	37.06	-60.92	4.89	126.27	23300
PMI	0.91	2.24	-4.20	0.85	7.91	26685
Consumption weight	0.13	0.08	-0.04	0.13	0.34	20884
NumItems	151.59	328.49	14.00	77.00	2085.00	26685
NumSectors	10.44	1.74	3.00	11.00	12.00	26685
NumIndustries	34.45	13.13	4.00	33.00	69.00	26685
SectorShare Energy	7.50	5.46	0.00	6.71	24.31	26685
SectorShare Materials	3.99	3.79	0.00	3.28	17.02	26685
SectorShare Industrials	12.11	6.34	0.00	11.47	31.53	26685
SectorShare Consumer Discr.	11.18	6.04	0.00	10.53	28.69	26685
SectorShare Consumer Stap.	5.19	4.27	0.00	4.36	19.09	26685
SectorShare Health Care	12.48	6.22	0.00	12.40	29.54	26685
SectorShare Financials	13.51	8.75	0.00	12.71	35.24	26685
SectorShare IT	16.60	9.44	0.00	15.74	47.08	26685
SectorShare Communication	4.17	4.25	0.00	3.08	19.50	26685
SectorShare Utilities	2.04	4.23	0.00	0.52	12.87	26685
SectorShare Real Estate	1.75	3.03	0.00	0.58	11.43	26685
SectorShare Unclassified	9.47	11.19	0.00	7.92	46.74	26685

Note: This table presents summary statistics for all single-managed domestic equity mutual funds in our sample. The sample runs from 2004-2019. Means, standard deviations, medians, the top 99% and bottom 1%, as well as the number of observations are shown. Detailed variable definitions are provided in appendix C.

2.4 Descriptive statistics

Our final sample includes 1,526 single managed domestic equity funds and runs from 2004-2019. Table 1 provides descriptive statistics for the sample.[7] In our sample, 8.9% of fund managers are female. The average fund size is 8.412 billion USD, with an average annual return of 10%. On average, each fund's portfolio includes 152 stocks across 35 different GICS industries and 10 GICS sectors. The largest allocations are in IT (16.6%), financials (13.5%), and healthcare (12.5%).

In Table 2, we report summary statistics by gender. We find that female fund managers are in charge of significantly smaller funds in terms of total net assets. Furthermore, male fund mangers hold on average 153 stocks in their portfolios, while female managed funds are on average composed of 132 stocks. Sector and industry diversification are more pronounced for female managed funds, i.e., female managed portfolios comprise stocks from significantly more sectors and industries.[8] The fact that female fund managers are invested in more sectors and industries compared to male fund managers may help them better diversify some risks.

We also obtain a first indication on gender differences in sector allocation. Over the entire sample, male fund managers on average hold a larger share of stocks from the energy, financial, and communications sector, while female fund managers on average hold a larger share of stocks belonging to the healthcare, industrials, and IT sectors.

Table 3 shows consumption shares by gender in each sector, i.e., how much of total consumption spending goes into each sector, based on the CES data. It also shows the average share invested by mutual fund managers in each of these sectors by gender (InvShare).[9] The largest gender differences in consumption shares are observed for Personal Care, Apparel and Pets/Toys/Hobbies (with larger consumption shares of women compared to men), and for Food, Insurance, and Gasoline/Fuels (with larger consumption shares of men compared to women). When comparing consumption shares to investment shares, we observe that the largest gender differences in investment shares are Medical Supplies and Drugs (with larger investment shares of female compared to male fund managers), and Insurance and Gasoline/Fuels, (with larger investment shares of male fund managers). When averaging across consumption categories, the average investment gender difference in the direction of consumption gender differences is 0.081 percentage points. Thus, already in the raw data, we observe a partial overlap of gender specific

[5] These consumption spending data are available from `https://www.bls.gov/cex/tables/cross-tab/mean.htm#cu-singlesbyinc`.

[6] The full classification table can be found on the official GICS website. We use the version that was effective until 2023, https://www.msci.com/documents/1296102/11185224/Effective+until+March+17%2C+2023.xlsx.

[7] All variables are described in detail in Appendix Table C.

[8] For regressions with quarter fixed effects on this question, see Table 12 in the appendix.

[9] Table 11 in the appendix also displays summary statistics on whether funds invest in a sector at all, by gender, rather than the portfolio shares of each sector.

Table 2: Fund characteristics by manager gender

	Mean male (1)	Mean female (2)	Diff (M-F) (3)
1-year Return	0.10	0.11	-0.01*
1-year 1-F alpha	-0.01	-0.01	0.00
1-year 4-F alpha	0.00	0.00	0.00
TR Portfolio Value (mill)	2134.47	703.67	1430.80***
Fund Age (in y)	15.44	14.42	1.02***
Lag Expense Ratio (in %)	1.16	1.22	-0.07***
Lag Log TNA	19.71	19.14	0.57***
Lag Fund Flow (in %)	10.41	8.93	1.48*
PMI	1.00	0.00	1.00***
Consumption weight	0.13	0.13	0.01***
NumItems	153.45	132.10	21.36***
NumSectors	10.42	10.69	-0.27***
NumIndustries	34.29	36.10	-1.81***
SectorShare Energy	7.58	6.75	0.83***
SectorShare Materials	3.97	4.23	-0.26***
SectorShare Industrials	12.03	12.97	-0.94***
SectorShare Consumer Discretionary	11.20	10.96	0.24*
SectorShare Consumer Staples	5.19	5.22	-0.03
SectorShare Health Care	12.38	13.47	-1.09***
SectorShare Financials	13.64	12.15	1.49***
SectorShare IT	16.47	18.02	-1.56***
SectorShare Communication	4.22	3.67	0.55***
SectorShare Utilities	2.01	2.36	-0.35***
SectorShare Real Estate	1.76	1.68	0.08
SectorShare Unclassified	9.56	8.52	1.04***

Note: This table presents summary statistics by gender. Column (1) contains mean values for male fund managers, column (2) contains mean values for female fund managers. Differences between male and female fund managers are displayed in column (3). t-test for difference. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

consumption spending in the general population and gender specific investment decisions made by female and male fund managers.

Table 3: Gender differences in consumption and investment across consumption categories (in %), ordered by male-female difference

	Consumption-Share			InvShare		
	% Male	% Female	Diff. (M-F)	% Male	% Female	Diff. (M-F)
	(1)	(2)	(3)	(4)	(5)	(6)
Personal care	0.63	1.87	-1.25***	0.32	0.46	-0.13***
Apparel	2.13	3.20	-1.06***	0.56	0.55	0.01
Pets/toys/hobbies	0.72	1.66	-0.94***	0.28	0.38	-0.10***
Household furnishings	3.02	3.63	-0.61***	0.46	0.35	0.11***
Medical services	1.22	1.69	-0.47***	1.71	1.49	0.21***
Housekeeping supplies	0.74	1.17	-0.44***	0.92	0.88	0.04
Shelter	23.08	23.48	-0.41	0.14	0.24	-0.10***
Drugs	0.56	0.89	-0.34***	2.81	3.10	-0.29***
Transportation	1.24	1.53	-0.29***	1.45	1.49	-0.04
Footwear	0.39	0.60	-0.21***	0.35	0.31	0.03*
Medical supplies	0.19	0.30	-0.10***	0.35	0.66	-0.30***
Reading	0.24	0.32	-0.08***	0.15	0.19	-0.05***
Education	1.33	1.35	-0.02	0.26	0.32	-0.06***
Entertainment	1.40	1.32	0.08	0.14	0.17	-0.03***
Other apparel	2.06	1.74	0.32***	0.10	0.13	-0.04***
Tobacco	0.58	0.26	0.32***	0.61	0.45	0.16***
Other entertainment	0.88	0.46	0.42***	0.28	0.38	-0.10***
Alcohol	1.69	0.97	0.72***	0.28	0.28	-0.01
Vehicle	5.70	4.77	0.93***	0.31	0.18	0.13***
Gasoline/fuels	3.75	2.75	0.99***	2.26	1.69	0.57***
Food	10.53	9.51	1.02***	1.21	1.38	-0.17***
Insurance	17.49	16.46	1.04**	2.67	2.06	0.60***

Note: This table presents average consumption shares of the male (column (1)) and female (column (2)) population based on CES data ranging from 2004 to 2019. Columns (4) and (5) contain investment shares of male and female fund managers for each consumption category. Differences between male and female consumers and fund managers, respectively, are displayed in columns (3) and (6). Significance is determined based on a two-sided t-test. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

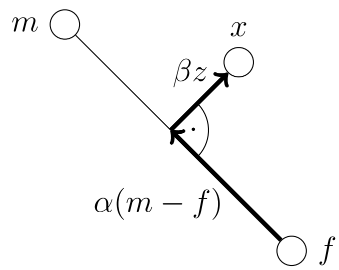


Figure 1: The portfolio masculinity index α is the distance of portfolio x along the line between representative male portfolio m and representative female portfolio f.

2.5 A "portfolio masculinity" index (PMI)

To determine if there are systematic differences in the portfolio compositions of male and female fund managers, we develop a "portfolio masculinity" index. This index allows us to compare each fund portfolio with a benchmark portfolio held by a representative male or female fund manager in a given quarter, respectively. Thus, we can classify funds according to the extent to which they follow gender-specific investment patterns.

Specifically, we define a measure α that maps the 12-dimensional portfolio shares of a fund by GICS sector into a single number that reflects how "male" or "female" the portfolio is:

$$\alpha : [0, 1]^{12} \to \mathbb{R}.$$

Every fund i at time t has a portfolio with a portfolio share of x_n^{it} in sector n. Thus, a fund has portfolio sector shares $x^{it} = (x_{n=1}^{it}, \ldots, x_{n=12}^{it})$.

We compute representative (mean) portfolios separately for all female and for all male managed funds, respectively, in a given quarter. Thus, the representative (mean) portfolio by female fund managers at time t is a vector $f^t = (f_1^t, \ldots, f_{12}^t)$, and the representative portfolio by male fund managers at time t is a vector $m^t = (m_1^t, \ldots, m_{12}^t)$.

Dropping i and t superscripts, consider any vector m and f in the 12-dimensional unit simplex, and any arbitrary fund portfolio x. We can then represent the position of x in the simplex as the sum of two vectors, one vector on the line passing through the male and the female representative portfolios, and one vector orthogonal to that line (see also Figure 1). Hence, the portfolio x can be expressed as

$$x = f + \alpha(m - f) + \beta z,$$

where $m - f$ is the vector from f to m, with its length scaled by $\alpha \in \mathbb{R}$, and z is a vector orthogonal to $m - f$ which reaches x, with its length scaled by $\beta \in \mathbb{R}$. α is our "portfolio masculinity" index, which measures the distance of a portfolio x from the female representative portfolio in the direction of the male portfolio.

To determine the unique solution for α, we first rearrange x to solve for z:

$$x = f + \alpha(m - f) + \beta z \iff z = \frac{x - (f + \alpha(m - f))}{\beta}.$$

Since $m - f$ and z are orthogonal, the dot-product of the two vectors must be zero, and this dot-product yields a linear equation in α:

$$\begin{aligned} (m - f) \cdot z &= 0 \\ \iff (m - f) \cdot \frac{x - (f + \alpha(m - f))}{\beta} &= 0 \\ \iff \sum_n (m_n - f_n)(x_n - f_n) &= \alpha \sum_n (m_n - f_n)^2 \\ \iff \alpha &= \frac{\sum_n (m_n - f_n)(x_n - f_n)}{\sum_n (m_n - f_n)^2}. \end{aligned} \tag{1}$$

Thus, we have a closed-form solution for the portfolio masculinity index α, based on vectors x, m, f.

To interpret the portfolio masculinity index α, consider a graphical example. The representative male portfolio m is a point in 12-dimensional space, just like the female representative portfolio f and any portfolio x. These 3 points span a plane in the 12-dimensional space. Figure 1 displays this plane. Even if x is not on the line between m and f, we can determine the distance of x from f in m-direction, by finding a vector (βz) passing through x, which is orthogonal to the line connecting m and f, and using the intersection. The portfolio masculinity index α is that distance of x from f in m direction. Portfolios in between the representative male and female portfolios m and f thus have $\alpha \in (0, 1)$. Portfolios that are "more male" than the representative male portfolio have $\alpha > 1$, and those that are more female than the representative female portfolio have $\alpha < 0$.

Table 4 displays regressions explaining the Portfolio Masculinity Index (PMI, α in (1) above) among funds with only one fund manager. The representative male and female portfolios are computed once per quarter. To make only comparisons between funds at the same time, we use quarter fixed effects to estimate within quarter. Column (1) uses fund manager gender as the main explanatory variable. In this case, the dummy variable indicating a male fund manager has a coefficient of one, by construction. In column (2), we add a set of dummy variables controlling for the fund objective, to investigate how much of the fund portfolio masculinity is driven by the fund objective. The coefficient reflecting male fund managers barely moves and amounts to 0.92, showing that the gender differences we observe are not largely driven by male

Table 4: Explaining the Portfolio Masculinity Index

	(1)	(2)
Dependent variable	PMI	PMI
Male Manager	1.000***	0.924***
	(0.179)	(0.175)
Control Quarter	Yes	Yes
Control Fund Objective	No	Yes
Adjusted R^2	0.013	0.070
Observations	26685	25017
Clusters	1526	1332

Note: PMI is the portfolio maleness index. The unit of observation is the fund-quarter. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

fund managers being in charge of funds with different investment objectives than female fund managers.

3 Results

3.1 Gender differences in sector allocations

Descriptive statistics in Table 2 already give a first indication that female and male fund managers differ in their portfolio allocation across sectors. However, it could be the case that fund managers are allocated to different types of funds conditional on their gender, or that they respond differently to temporal economic developments in different sectors. For example, Almazan et al. (2004) show that different types of fund managers are subject to different sets of mutual fund investment restrictions. Furthermore, Fang et al. (2014) show that fund families allocate their most skilled managers to market segments in which manager skill is rewarded best.

In addition, fund characteristics may determine portfolio allocations. For example, female fund managers are in charge of smaller funds (see Table 2). Large funds may focus on high-capitalization stocks and adopt passive or index-oriented strategies to maintain liquidity and minimize transaction costs, while small funds can exploit inefficiencies in less-liquid, small-cap stocks, enabling them to pursue more aggressive or niche strategies (Chen et al. (2004); Pollet and Wilson (2008). Finally, fund fees could potentially be associated with different sector allocation strategies. High-fee funds may adopt more active trading strategies to justify their costs, while low-fee funds often prioritize cost-efficient and more passive investment approaches to deliver value to investors (Barber et al., 2005). To capture these structural, and partially also gender-specific differences across funds, we now turn to a more formal analysis of fund managers' sector allocation conditional on manager gender and further fund controls and time and fund fixed effects.

Figure 2(a) plots the unadjusted gender difference in the probabilities whether a fund is invested in a specific GICS sector, holding the quarter constant. This difference is estimated from the following regression, which we run for each of the 12 sectors,

$$\text{SectorIndicator}_{iqs} = \alpha_s + \beta_s \text{Male Manager}_{iq} + \sum_t \gamma_{qs} \text{Quarter}_q + \varepsilon_{iqs}, \tag{2}$$

where $\text{SectorIndicator}_{iqs}$ is an indicator variable that equals 100 if fund i in quarter q is invested in sector s and equals 0 otherwise, and Quarter_q is a set of indicator variables for each quarter q in the sample. Figure 2(b) plots the adjusted gender difference in the probabilities whether a fund is invested in a specific sector, based on the following regression:

$$\text{SectorIndicator}_{iqs} = \alpha_s + \beta_s \text{Male Manager}_{iq} + \sum_t \gamma_{qs} \text{Quarter}_q + \delta \mathbf{X}_{iq} + \varepsilon_{iqs}, \tag{3}$$

where $\mathbf{X}_{iq}$ is a vector of controls for (1) the fund objective, (2) fund age in years, (3) expense ratio of the previous year, (4) the annual return of the previous year, (5) the log of the sum of total net assets from the previous year to capture fund size, and (6) fund flows from the previous year. Thus, the adjustment takes into account for example that female managers might be managing funds with different objectives (thus forcing them to invest in different sectors) or funds of lower volume (forcing them to deploy their funds differently).

If all managers were invested in all sectors in all quarters, then those differences would be zero for all sectors. However, Figure 2 reveals an interesting pattern: Male managers tend to be less invested in almost all sectors. The graph is not based on portfolio shares, which have to sum to 100% for every fund and quarter, but rather on an indicator whether a fund is invested in that sector at all in a given quarter. Thus, the negative differences illustrate that male managers are less diversified across sectors than female managers. The differences are significant both when unadjusted and when adjusted for fund characteristics in the energy sector (males 6 percentage points less likely to be invested), materials sector (males 8 percentage points less likely to be invested), industrials (males 2 percentage points less likely to be invested), consumer staples (males 6-8 percentage points less likely to be invested), and IT (males 2 percentage points less likely to be invested). The finance, consumer discretionary, communication services, and healthcare sectors only show a significant difference towards female fund managers when adjusting for fund characteristics.

Figure 3 repeats the exercise of Figure 2, but replaces the sector indicator in equation (2) with the percentage share of the portfolio invested in a sector. There are positive differences in favor of male managers in several sectors. In particular, when not adjusting for additional fund characteristics, male managers have a larger share of their portfolio invested in the energy (0.8 percentage points) and the finance sectors (1.5 percentage points), but these differences are not significantly different when adjusting for fund characteristics.[10] Whether adjusting or not, female fund managers have a significantly larger share of their portfolios invested in the IT sector (1.6 percentage points).

Hence, there is a pattern of male managers being less likely to be invested in several sectors, but still having about the same average portfolio shares in many of those sectors as female managers. This indicates that male managers are more extreme in their asset allocation across sectors, i.e., they are more likely to not invest in a given sector at all or to invest heavily with a large share of their portfolio, so that the average sector shares are roughly the same across genders.

Taken together, female and male managers seem to invest differently across sectors and industries. In the next step, rather than testing for each sector individually whether there is a significant difference in investments, we test whether the entire distribution of investments over sectors differs between the genders. To do this, we run unadjusted seemingly unrelated regressions, one for each sector s, such that

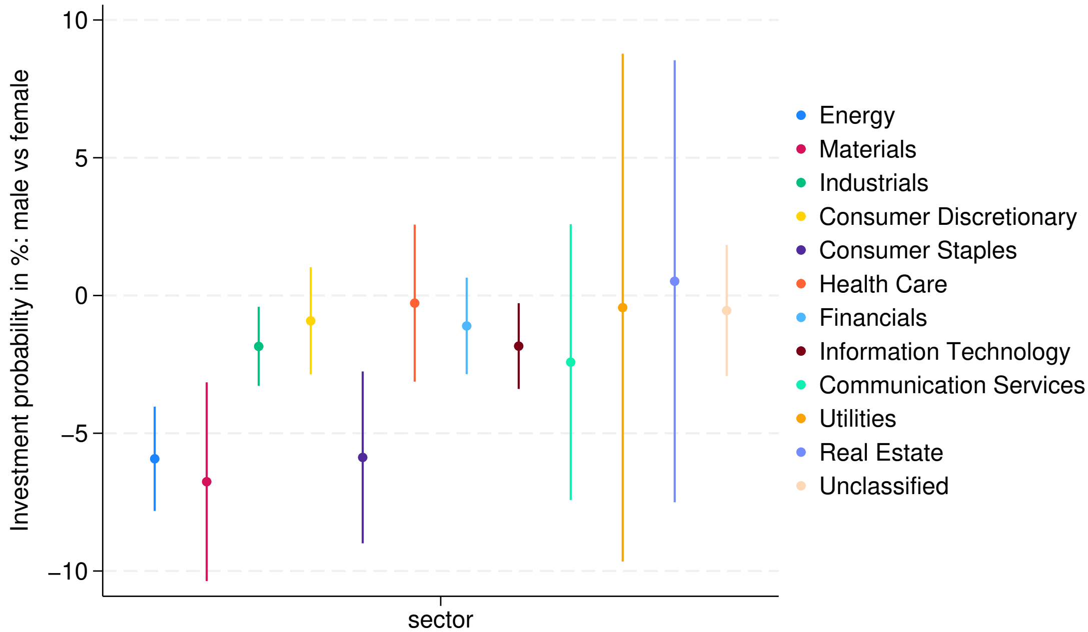
$$\text{SectorShare}_{iqs} = \alpha_s + \beta_s \text{Male Manager}_{iq} + \sum_t \gamma_{qs} \text{Quarter}_q + \varepsilon_{iqs}. \tag{4}$$

We can then test jointly whether $\beta_s = 0$ across $s = 1, \ldots, 12$, using a chi-square test. This test rejects that male and female fund managers allocate the same investment shares in their portfolio across sectors ($\chi^2(12) = 38.81$, $p = .0001$). The same test using indicators (as in equation (2)) also rejects the hypothesis that male and female fund managers are similarly likely to be invested in the sectors ($\chi^2(12) = 70.43$, $p < .0001$). Thus, going beyond specific sectors, male and female fund managers have a different distribution of investments across sectors. When adjusting the gender difference for time varying fund characteristics as above, we also reject the equality of distribution at conventional significance levels for sector shares ($\chi^2(12) = 23.61$, $p = .0145$) and for sector indicators ($\chi^2(12) = 83.57$, $p < .0001$). Such consistent evidence of a difference is remarkable at the very coarsest level of sector aggregation in GICS.

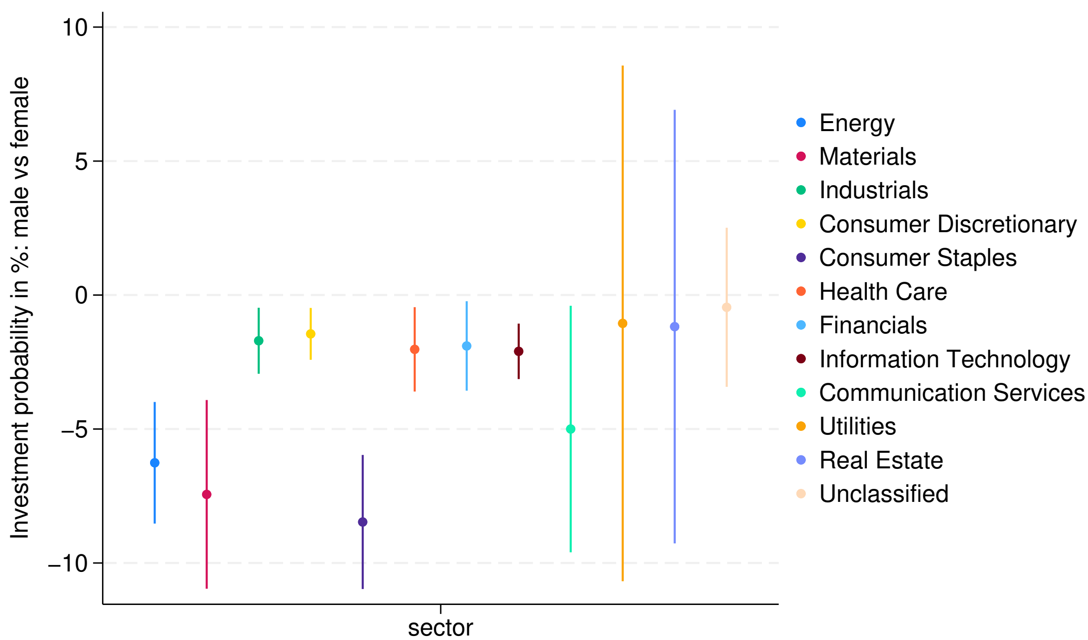
[10] Male managers also have a higher share invested in assets that we could not assign a GICS sector to.

Figure 2: Gender differences in sector allocations: Extensive margin

(a) Unadjusted gender difference



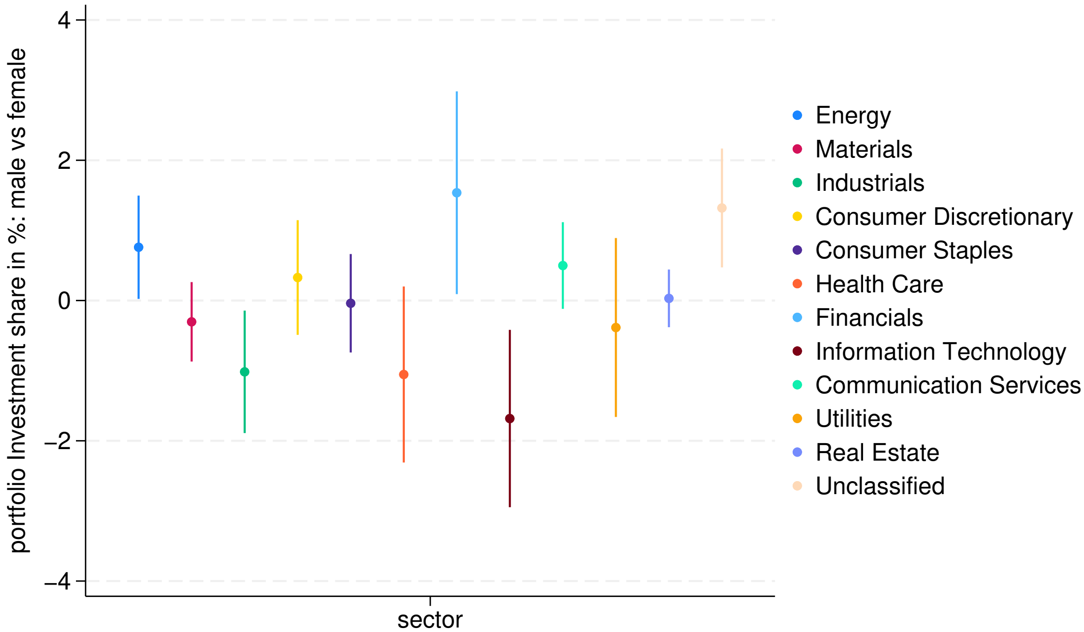
(b) Adjusted gender difference



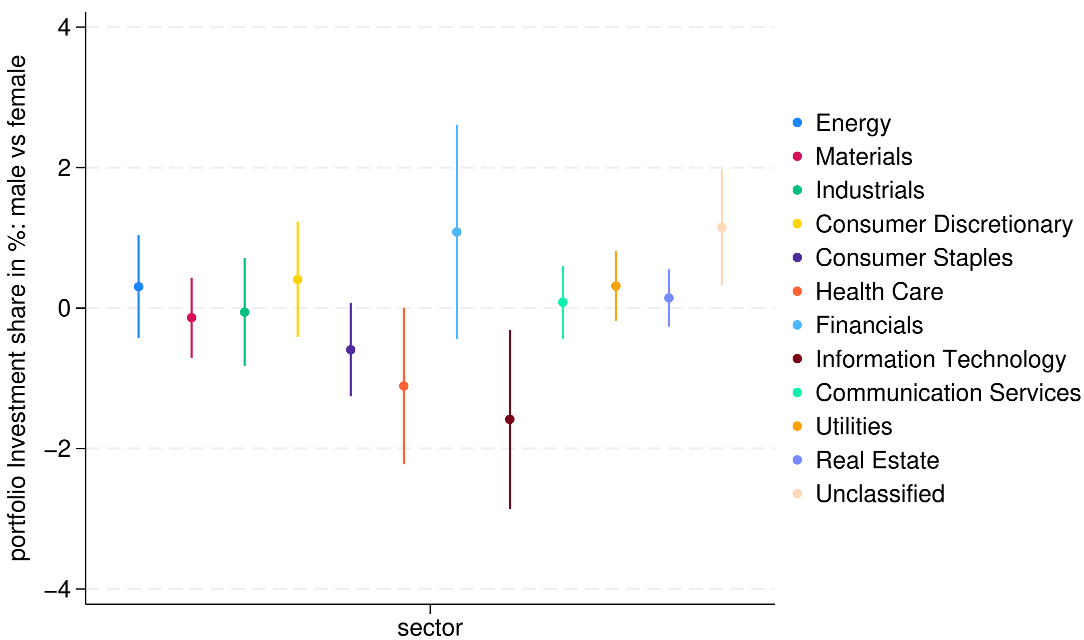
Note: Male vs female difference in probabilities that a fund is invested in a specific sector. Comparison within quarter. The lines represent 95% confidence intervals of the difference, standard error clustering on fund level.

Figure 3: Gender differences in sector allocations: Intensive margin

(a) Unadjusted gender difference



(b) Adjusted gender difference



Note: Male vs female difference in share of portfolio invested in a specific sector. Comparison within quarter. The lines represent 95% confidence intervals of the difference, standard error clustering on fund level.

In appendix B.4, we find a similar pattern for the finer aggregation level of GICS industries rather than sectors: Male managers are more extreme in their GICS industry allocation as well. When not adjusting, out of 70 industries, female managers are significantly more likely to be invested in eight, while male managers are significantly more likely to be invested in two. When it comes to portfolio shares, male managers have significantly larger shares in six industries. Female managers have a significantly larger portfolio share in five industries.

3.2 Consumption preferences as a driver of sector allocation

We now test one possible explanation for the gender differences in allocations across sectors and industries: different consumption preferences of men and women. For instance, if men devote more time and money to cars in their personal lives, this inclination may influence their professional investment decisions, making them more likely than female fund managers to allocate funds to the vehicle sector.

Consumption-based investment behavior could reflect a behavioral bias, i.e., personal likes and dislikes are uninformative for stock price movements and adversely affect investments that professional managers make on behalf of their clients. However, consumption-based investments could also be beneficial. Recent theoretical research on Bayesian investment games (Grüner and Siemroth, 2019; Strausz, 2017) suggests that there may be good reasons for investors to base investment decisions on individual consumption preferences. When preferences are correlated in society, investors can learn about the aggregate state of demand from their private preference signal. Consumers who like a product can conclude that others may like it too, which makes the company that produces it a potentially profitable investment. From society's perspective, this consumption-related behavior may not only constitute an equilibrium. It can also lead to an efficient allocation of investment funds when forward markets for consumer products are incomplete. Based on these theories, as a first step, we are interested in testing empirically whether investment decisions—here by professional fund managers—are influenced by individual consumption preferences.

To start, we examine whether more consumption in a consumption category is associated with more investments into firms producing in that consumption category. As explained in the data section 2, we do not observe individual consumption choices of managers, and instead use data from the US Consumer Expenditure Survey (CES), which is organized in consumption categories rather than GICS sector codes. Since one GICS code[11] can be related to more than one consumption category and vice versa, we had to bundle some consumption categories and GICS codes to create a 1:1 mapping from (small) groups of GICS codes to (small) groups of

[11] That is, a firm classification at the finest GICS level (sub-industry level).

consumption categories. The detailed matching procedure is described in appendix A.3. In what follows, we refer to the resulting bundled categories as consumption categories.

Since every fund is investing in multiple firms and associated consumption categories, we change the unit of observation to the fund-consumption category-quarter level (rather than the fund-quarter level as before). For fund i in quarter q and consumption category c, we estimate the following regression equation:

$$\begin{aligned} \text{InvShare}_{iqc} &= \alpha_{iq} + \beta \text{Consumption-Share}_{iqc} \\ &+ \gamma \mathbf{X}_{iqc} + \sum_{q} \sum_{c} \delta_{qc} \text{Quarter-Category}_{qc} + \varepsilon_{iqc}, \end{aligned} \tag{5}$$

where InvShare_{iqc} is the share of the portfolio invested in sectors or industries supplying consumption category c, and α_{iq} is the constant or fund-quarter fixed effect (depending on specification). Note that fund-quarter fixed effects absorb time-varying fund characteristics such as fund size or fund flows, which have been documented to differ between female and male fund managers (Niessen-Ruenzi and Ruenzi (2019)), and which are relevant for fund managers' investment behavior (Morris et al. (2017); Edelen (1999)). $\text{Quarter-Category}_{qc}$ are a set of dummy variables denoting quarter-years q and consumption categories c. That is, we allow quarter-year effects to differ by consumption-category, as different categories change size differently over time.[12] These fixed effects control for factors constant within quarter and consumption category, such as the size of the sectors associated with this consumption category in this quarter. Consequently, the estimate of the consumption effect is based on a comparison between male and female fund managers, in the same quarter and within the same consumption category, rather than across quarters or across consumption categories. These category-quarter fixed effects also address the problem that prices of different consumption categories may change differently over time, as we compare consumption between genders but within quarter. $\mathbf{X}_{iqc}$ is a vector of control variables (such as fund objective). The coefficient of interest is β, which shows whether the own gender's consumption patterns explain investment behavior.

Table 5 displays the results. Column (1) only uses the quarter-category fixed effects as further controls besides the consumption share. On average, an increase in the consumption share of one percentage point leads to a larger share in the fund portfolio invested in the sector supplying that consumption of about 0.11 percentage points. This estimate is significantly different from zero at the 1% level.

In column (2), we add dummies for the fund objective as additional controls, and the point estimate increases slightly to 0.118 percentage points, again statistically significantly

[12]Separate quarter-year and consumption category fixed effects would be less flexible, as they would constrain the time effect to be constant across consumption categories, and the category fixed effect to be constant across time. Our specification is more flexible, because it allows the consumption category effect to vary across time.

Table 5: Test of consumption-investment link

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Dependent variable	InvShare	InvShare	InvShare	InvInd	InvInd	InvInd
Consumption-Share	0.109***	0.118***	0.113***	2.004**	2.380**	2.100**
	(0.033)	(0.034)	(0.034)	(0.966)	(0.996)	(0.965)
Fund objective control	No	Yes	No	No	Yes	No
Fund-Quarter FE	No	No	Yes	No	No	Yes
Category-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.222	0.229	0.228	0.156	0.169	0.312
Observations	587070	550374	587070	587070	550374	587070
Clusters	1526	1332	1526	1526	1332	1526

Note: InvShare is the percentage of the portfolio invested in stocks with a GICS code mapped to the corresponding consumption category. InvInd is an indicator equal to 100 if and only if the portfolio invested in stocks with a GICS code mapped to the corresponding consumption category, and 0 otherwise. Consumption-Share is the percentage of expenditures in the current consumption category by members of the same gender. The unit of observation is the fund-quarter-category. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

different from zero at the 1% level. Column (3) replaces the fund objective control with a fund-quarter fixed effect that controls for any variables fixed across consumption categories by a fund in a quarter (including fund objective). The coefficient is again similar and statistically different from zero at 0.113. These estimates imply that the pass-through from consumption to investment is between 1/8 and 1/9.

Columns (4)-(6) repeat these regressions, but use as outcome variable an indicator whether the fund invested at all into the sector that supplies the consumption category (rather than the portfolio share of that sector as in columns 1-3).[13] Thus, increasing the spending in a consumption category by one percentage point increases the probability to invest in the associated sector by 2-2.4 percentage points, depending on the specification. The magnitude of the effect is much larger at the extensive margin than for the investment shares (columns 1-3), because the investment shares are rather small (on average 2% conditional on being positive) compared to the investment indicators (100% conditional on being positive). A majority of observations has a zero investment share, so a big part of the effect of consumption on investment comes from investing in a relevant sector firm at all, rather than increasing a positive investment

[13]This outcome variable ignores the information of the intensive margin, only using the extensive margin. But an advantage is that this outcome variable is completely determined by the fund manager choice—whether or not to invest in the sector—whereas a portfolio share is in part determined by price swings after the investment choice.

share more. That is, the consumption effect on investments to a large degree comes from the extensive margin.

Taken together, we provide evidence consistent with the hypothesis that consumption preferences affect investment behavior, even for professional investors. Since men and women tend to have different consumption preferences, it follows that consumption preferences can explain part of the gender difference in sector allocations.

An alternative way to test for a consumption related gender-differences in investment behavior is to take into account the relative importance of a consumption category for male and female investors. To do so, we replace the consumption share as main explanatory variable by a consumption ratio:

$$\text{Consumption-Share-Ratio}_{iqc} = \frac{i \text{ manager's own gender consumption share in } c \text{ in quarter } q}{i \text{ manager's other gender consumption share in } c \text{ in quarter } q}.$$

Thus, if hypothetically men spend 20% of income on cars and women 10% in a quarter, then the ratio is 2 for all men and 0.5 for all women in that quarter, which would indicate it to be a predominantly male consumption category. The larger the ratio, the more skewed that consumption category towards that gender.

Table 6 repeats the regressions with the consumption share ratio, to see if the genders invest more in sectors supplying consumption that is more important to their own gender. And indeed, across all regressions, there is a significantly positive effect of the consumption share ratio on the investment share. To interpret the estimate, on average, if men change spending from 5% to 10% in a consumption category, whereas women stay at 5% spending on that category, then the ratio increases from 1 to 2. And in this case the investment share of sectors supplying that consumption category increases by about 0.05-0.06 percentage points on average. The effect of the consumption share ratio is robustly significant across all specifications in Table 6.

Thus, in addition to managers investing more in firms whose products and services they consume more, they also invest more in firms whose products and services their own gender consumes more relative to the opposite gender.

4 Individual-level implications: Fund performance

4.1 Investments based on consumption preferences: Bias or valuable information?

A natural question is whether it is beneficial for fund managers to incorporate their personal consumption preferences into investment decisions. On the one hand, personal consumption

Table 6: Test of consumption-investment link: gender specific consumption categories

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Dependent variable	InvShare	InvShare	InvShare	InvInd	InvInd	InvInd
Consumption-Share-Ratio	0.049***	0.059***	0.056***	1.787***	1.915***	1.547***
	(0.012)	(0.013)	(0.013)	(0.578)	(0.578)	(0.501)
Fund objective control	No	Yes	No	No	Yes	No
Fund-Quarter FE	No	No	Yes	No	No	Yes
Category-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.222	0.229	0.227	0.156	0.169	0.312
Observations	587070	550374	587070	587070	550374	587070
Clusters	1526	1332	1526	1526	1332	1526

Note: InvShare is the percentage of the portfolio invested in stocks with a GICS code mapped to the corresponding consumption category. InvInd is an indicator equal to 100 if and only if the portfolio invested in stocks with a GICS code mapped to the corresponding consumption category, and 0 otherwise. Consumption-Share-Ratio is the percentage of expenditures in the current consumption category by members of the same gender, divided by the percentage of expenditures in the current consumption category by members of the opposite gender. The unit of observation is the fund-quarter-category. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

preferences may provide valuable information, such as insights into a firm's product quality, service offerings, attractiveness to consumers, or a sector's overall performance. More generally, a manager may have better information about sectors or firms whose goods and services they personally use. If this was the case, we would expect fund managers who rely more on their consumption preferences when investing to outperform.

On the other hand, using personal consumption preferences could introduce bias. An idiosyncratic liking of a firm's or sector's products does not necessarily translate into financial success. In the competitive mutual fund industry, managers who focus solely on financial aspects and avoid such biases may outperform those who invest based on personal preferences rather than financial prospects. Thus, if following personal preferences results from a bias, we would expect a negative relationship between fund performance and the extent to which managers rely on their consumption preferences when making investment decisions.

In order to test these hypotheses and to determine the weight that a fund puts on consumption preferences when making investment decisions, we adapt the regression approach used above to estimate the effect of consumption on investment shares. Specifically, we adapt

Table 7: Is more weight on consumption associated with better fund performance?

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Return	Return	1-F alpha	1-F alpha	4-F alpha	4-F alpha
Consumption Weight	-0.084***	-0.075***	-0.006	-0.026**	0.008	-0.019**
	(0.017)	(0.029)	(0.006)	(0.012)	(0.005)	(0.009)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.843	0.851	0.097	0.141	0.081	0.161
Observations	5596	5362	5056	4840	5055	4839
Clusters	1116	882	1030	814	1030	814

Note: Fund controls: (1) the fund objective, (2) fund age in years, (3) expense ratio of the previous year, (4) the log of the sum of total net assets from last year, and (5) the fund flow from last year. The unit of observation is the fund-year. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

equation (5) to allow for fund-year specific consumption-share coefficients:

$$\begin{aligned} \text{InvShare}_{iqc} &= \alpha + \sum_{iy} \beta_{iy} \text{Consumption-Share}_{iqc} \\ &+ \gamma \mathbf{X}_{iqc} + \sum_{q} \sum_{c} \delta_{qc} \text{Quarter-Category}_{qc} + \varepsilon_{iqc}, \end{aligned} \tag{6}$$

where β_{iy} is fund i's coefficient in year y on the consumption share of i's manager's gender in predicting i's investment share in quarter q across all consumption categories c. We interpret coefficients β_{iy} as the weight managers place on own-gender consumption preferences when investing: A larger coefficient means that managers increase (in absolute terms) their investment into a sector the more they consume that sector's goods and services themselves. We will refer to the β_{iy}-coefficients as *consumption weights*.

Further, $\mathbf{X}_{iqc}$ is a vector of fund controls, where we either use fund objective only, or the full set of fund controls, (a) the fund objective, (b) fund age in years, (c) expense ratio of the previous year, (d) the annual return last year, (e) the log of the sum of total net assets from last year, and (f) the fund flow from last year. Finally, the regression equation includes quarter-consumption category fixed effects. The average consumption weight is 0.13 (see Table 1), which matches closely the pooled estimate of the consumption effect on investment shares of 0.11 in Table 5.

Table 8: Is more weight on consumption associated with lower risk?

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	1-F beta	1-F beta	1-F beta	4-F beta	4-F beta	4-F beta
Consumption Weight	-40.808***	-48.406***	-11.787	-30.523***	-29.622***	6.980
	(11.318)	(12.252)	(7.890)	(10.992)	(10.569)	(5.082)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	No	Yes	Yes	No	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.084	0.208	0.585	0.058	0.102	0.591
Observations	5059	5059	4844	5059	5059	4844
Clusters	1030	1030	815	1030	1030	815

Note: Fund controls: (1) the fund objective, (2) fund age in years, (3) expense ratio of the previous year, (4) the log of the sum of total net assets from last year, and (5) the fund flow from last year. The unit of observation is the fund-year. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Next, we use the estimated consumption weights β_{iy} for each fund and year to analyze their relationship with fund performance. A positive coefficient on the consumption weight suggests that managers perform better when they invest more in sectors whose products or services same sex individuals personally consume, supporting the *preferences as beneficial information* view. Conversely, a negative coefficient indicates that managers perform worse when they invest more in such sectors, consistent with the *preferences as investment bias* view.

Table 7 presents the results of how the consumption weight affects returns. The two regressions in columns (1) and (2) show that a larger weight on consumption when investing is associated with a significantly lower return. This does not yet imply a poor performance because it may come along with lower risk.

Our dataset covers 22 consumption categories. Most funds make some of their investments outside these 22 consumption categories, i.e., they also make investments that are unrelated to consumption (e.g., in the defense industry). To the extent that consumption related investments are conservative (i.e., low-risk-low-return) ones, one should expect funds that invest more in firms with products in these consumption categories to exhibit both a lower return and a lower risk. This is what we observe. In Table 8, our measure of risk is beta either in the CAPM or the 4-factor model, representing how much daily fund returns move with the market return. In four of six regressions, a larger consumption weight is associated with lower risk. Thus, funds investing more in line with own-gender consumption preferences tend to be less risky.

To control for this effect, we use alpha as risk-adjusted measure of fund manager's performance. Columns (3) to (6) in Table 7 report regressions with alphas from a 1-factor and Carhart (1997) 4-factor model, respectively.[14] In the regression specifications with fund fixed effects (columns (4) and (6)), the coefficients on the consumption weight are significantly negative. Thus, overall, the regressions tend to provide some support for the *consumption as investment bias* hypothesis.

Next we look at the specific effects of the use of female consumption signals by female fund managers on their performance. Note that, while both male and female managers invest in line with gender specific consumption patterns, male investments on average correlate slightly more with own-gender consumption patterns than female investments.[15] In appendix Table 13, we allow the effect of the consumption weight on performance to differ by gender, but there is no significant gender difference for performance as measured by alpha. Hence, female managers who make more use of their consumption preferences in investing are neither more nor less successful than their male counterparts who also make more use of their consumption preferences. Moreover, in appendix section B.5, we compare the returns of hypothetical investment strategies that either invest proportional to male consumption shares, or proportional to female consumption shares. That is, the male consumption strategy invests more in a sector the more men consume their products and services, and similarly for the female consumption strategy with female consumption. Otherwise these strategies diversify within the sectors. We find that there is no significant difference in the returns of these two strategies. Hence, both of these analyses indicate that female consumption preferences are not a measurably better signal for investment than male consumption preferences (and similarly the other way around).However, the analyses of performance differences by gender ignore that there can be a lot of within-gender heterogeneity in how masculine or feminine the portfolio is. Thus, in the next section we will look at the effect of the portfolio masculinity index on performance.

4.2 Portfolio masculinity and fund performance

To investigate whether more feminine or more masculine portfolios perform better, we can use our Portfolio Masculinity Index (PMI) to explain fund performance. For all performance measures, we run regressions with, first, quarter fixed effects, thus comparing funds in the same quarter. We then repeat this regression, but additionally include common fund controls such as

[14] Annual performance alphas are estimated based on daily excess fund returns. We require a minimum of 100 daily return observations for the alpha to be estimated. The risk-free rate as well as the market, hml, smb and umd factors are obtained from Kenneth French's data library at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[15] See Table 2 where men have a slightly larger average consumption weight. Moreover, interacting Consumption-Share with a gender dummy in equation (5) shows that male managers on average have a 0.007 percentage points larger weight on consumption than female managers.

fund objective, fund size, fund age and expense ratio, as well as fund flows, to make funds more comparable. Finally, we estimate regressions with fund fixed effects, which use the variation over time of the same fund for estimation. Results are presented in Table 9. We have two main explanatory variables, a gender dummy indicating a male manager, and the PMI.

The portfolio masculinity index has a significantly negative coefficient in all regressions. The negative effect is even visible in the fund fixed effects regressions, where the estimates are based on the same fund that changed portfolio masculinity over time, holding other time-invariant fund-specific factors constant. Thus, the more masculine the portfolio, the lower the return and risk-adjusted return. The continuous variable PMI captures heterogeneity within genders that the binary gender dummy variable does not. In Table 9, PMI is a more significant predictor of performance than gender, indicating that heterogeneity within genders may be more important than heterogeneity across genders.[16] Thus, according to our estimates, men who hold more feminine portfolios earn on average slightly higher returns than men with more masculine portfolios.[17]

[16]Gender itself is only significant in regression specifications with fund fixed effects, which condition on manager gender changes, and are insignificant in all other specifications.

[17]The negative effect of PMI on returns is driven mostly by male managers, which are the vast majority of managers in our sample, see Table 1.

Table 9: Gender differences in fund performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Return	Return	Return	1-F alpha	1-F alpha	1-F alpha	4-F alpha	4-F alpha	4-F alpha
Male Manager	0.000	-0.002	0.023***	0.001	0.001	0.006**	0.001	0.001	0.004**
	(0.003)	(0.003)	(0.008)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
PMI	-0.003***	-0.002***	-0.001*	-0.000**	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.788	0.841	0.850	0.098	0.119	0.159	0.076	0.087	0.169
Observations	7362	5768	5541	6276	5217	5003	6275	5216	5002
Clusters	1470	1125	898	1239	1041	827	1239	1041	827

Note: Fund controls: (1) the fund objective, (2) fund age in years, (3) expense ratio of the previous year, (4) the log of the sum of total net assets from last year, and (5) the fund flow from last year. The unit of observation is the fund-year. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

The observed adverse role of portfolio masculinity on fund performance is broadly in line with previous theoretical work, according to which investors who allocate a disproportionally high amount of funds relative to their demand as consumers may misallocate funds when they rely on their own consumption signals.[18] In the present context, this would imply that male managers investing too much in 'male preferred' industries realize lower returns, whereas the returns of men investing in 'female preferred' industries would be higher, as the lower aggregate investments by female fund managers imply that there is less productive capacity in female sectors relative to demand. Note that this theory would imply that male consumption signals are less valuable than female ones. To the extent that more masculine managers (both male and female) rely more heavily on male consumption signals, they would tend to underperform.

If performance differences are due to the different value of consumption preferences, then all managers, male and female, should benefit by relying more strongly on information about female preferences than about male preferences. In this context, the observation that women on average invest slightly less in line with their same-gender consumption than men would be compatible with women relying too little on their consumption preferences or men relying too much on theirs.

While in line with our own previous theoretical work, other factors associated with masculinity may contribute to the observed adverse effect of portfolio masculinity on funds' risk-adjusted performance. This includes the lower sectoral diversification amongst male portfolios and the slightly stronger correlation of investment with gender specific consumption among male managers.

5 Market-level implications

Our finding that sectoral investments differ by gender is likely to be significant in a broader economic context. For more than 20 years, the fraction of female fund managers in the U.S. hovers around a stable 10% (Niessen-Ruenzi and Ruenzi (2019); Bajo et al. (2024)). This under-proportional representation of female fund managers may imply that the sectors they favor receive less investment than they might otherwise. If more female fund managers were present in mutual funds, their distinct consumption and thus investment preferences could potentially redirect capital flows toward different sectors of the economy. This reallocation of funds has the potential to stimulate growth in some industries, while other industries would receive comparatively less investment, potentially altering the overall landscape of sector growth.

[18] It is straightforward to see that in a simple version of the two-group model of Grüner and Siemroth (2019), where one group has no wealth to invest, a member of the other group has a more valuable signal and can allocate any funds with a higher expected return.

To highlight the importance of such possible market-level implications, we now examine how investment shares across sectors would change if there was gender parity in the mutual fund industry. Indeed, policy proposals aimed at addressing a gender imbalance in asset management could be informed by such counterfactual calculations. Which sectors would gain investments, and which lose, if women controlled the same fund volumes as men?

Exactly evaluating the aggregate portfolio held by the fund industry after a shift in the gender composition of the group of fund managers is a difficult exercise. Any major shift in the demand of mutual funds for "female" shares would be likely to affect absolute and relative share prices in the short-term. Some of the excess demand or supply would be taken up by the rest of the market. In the longer term, productive capacity may adjust to those stock market price signals and capacity adjustments may at least partly offset short-term stock price changes. In this exercise, we abstract from such effects.[19]

We focus on a single quarter instead of calculating the counterfactual portfolio shares across all quarters in our sample, since sectors become bigger or smaller over time. For this exercise, we focus on March 2019 as one of the most recent quarters in our sample (which ends in 2019).[20] In March 2019, male fund managers hold 97% of the invested volume, so men control an over-proportional share of the volume.

In this section, our measure of volume is Thomson Reuter's Portfolio Value, i.e., the value of the portfolio based on end of quarter stock prices. This number can be different from the funds available to the manager, but in these counterfactuals we care about the changes in the invested volume by sector due to the investment decisions and due to potential gender differences.

Table 10 displays which sectors would gain and which would lose investments by mutual funds if there was gender parity among fund managers, in the sense that both genders control the same volume, rather than men controlling 97% of it.

Figure 4 displays these numbers graphically. When switching to gender parity in terms of volume, the sector with the biggest loss of portfolio share is energy, dropping by about 27% followed by utilities dropping by almost 17% and the financial sectors dropping by about 9%. The biggest winners of our price-unadjusted counterfactual change are the IT sector with an increase of about 10% and materials and healthcare sectors with increases of about 7% each. In the case of the information technology sector and at given prices, the change of investment

[19]While the following calculations assume no stock price changes in case of reallocation as part of the counterfactual, the direction of quantities may indicate the direction of likely short term stock price changes. This is the case when individual stock demand is non-increasing in stock prices. In this case, increased demand at given prices would induce higher prices. Generally, the direction and extent of price changes cannot be as easily determined and would require a lot more assumptions about the shape of the aggregate demand function, or a fully fledged structural model, which is beyond the scope of this article.

[20]We do not pick the last quarter in our sample to avoid that our results are influenced by mutual fund window dressing or other strategic end-of-the-year behavior (Ng and Wang (2004); Agarwal et al. (2014)).

Table 10: Counterfactual investments by the mutual fund sector if both genders controlled the same volume of funds, March 2019

Sector	Male investment %	Female investment %	Investment % (factual)	Investment % (counterfactual)	Change %
Energy	3.1	1.3	3	2.2	-27.1
Utilities	1.5	1	1.5	1.3	-16.7
Financials	9.8	7.9	9.8	8.9	-9.3
Consumer Discretionary	13.5	11.7	13.4	12.6	-6.1
Communication Services	11.1	9.9	11.1	10.5	-4.8
Real Estate	2	2	2	2	-0.8
Consumer Staples	4.6	4.6	4.6	4.6	0.9
Industrials	9.7	10.2	9.7	9.9	2.4
Health Care	15.8	18.4	15.9	17.1	7.3
Materials	2.4	2.8	2.4	2.6	7.4
Information Technology	24.6	30	24.9	27.3	9.9
Female Volume %	3.3				

Note: This table displays the weighted average investment share—weighted by fund volume—into each sector by male and female fund managers in the first quarter of 2019. The factual investment is the weighted average investment share—weighted by fund volume—over all mutual funds with one manager in the sample by sector. The counterfactual investment is the estimated investment share by mutual funds into each sector, rescaling the weights such that male managers as a whole and female managers as a whole control the same fund volume, but keeping their relative weights within gender. That is, let the volume of fund i with manager of gender g be w_i^g and the investment share be s_i^g. The factual investment share is the weighted average $\sum_i w_i s_i / \sum_i w_i$. The counterfactual investment share is

$$\frac{\sum_{i|g=m} w_i^g s_i^g}{2\sum_{i|g=m} w_i^g} + \frac{\sum_{i|g=f} w_i^g s_i^g}{2\sum_{i|g=f} w_i^g},$$

where $\sum_{i|g=f} w_i^g$ is the sum of fund volumes over all funds with manager gender f. The "unclassified" sector shows the largest percentage change but is second smallest sector based on investment volume (not displayed).

would correspond to a 2.4 percentage point change of investment relative to the value of the entire US mutual fund market portfolio. The current (January 2025) market valuation of US mutual funds is about \$22 trillion.[21] Thus, the extra demand for information technology stocks associated with an increase of the share of female fund managers would at given prices be valued at about \$528 billion.

As we have argued above, our results should not be taken as a prediction of actual market outcomes, since we abstract from price changes and do not take into account possible capacity adjustments. Still, considering the importance of the mutual fund industry for the US stock market, our results clearly indicate that increasing the fraction of women in the mutual fund in-

[21] `https://fred.stlouisfed.org/series/BOGZ1LM654090000Q`

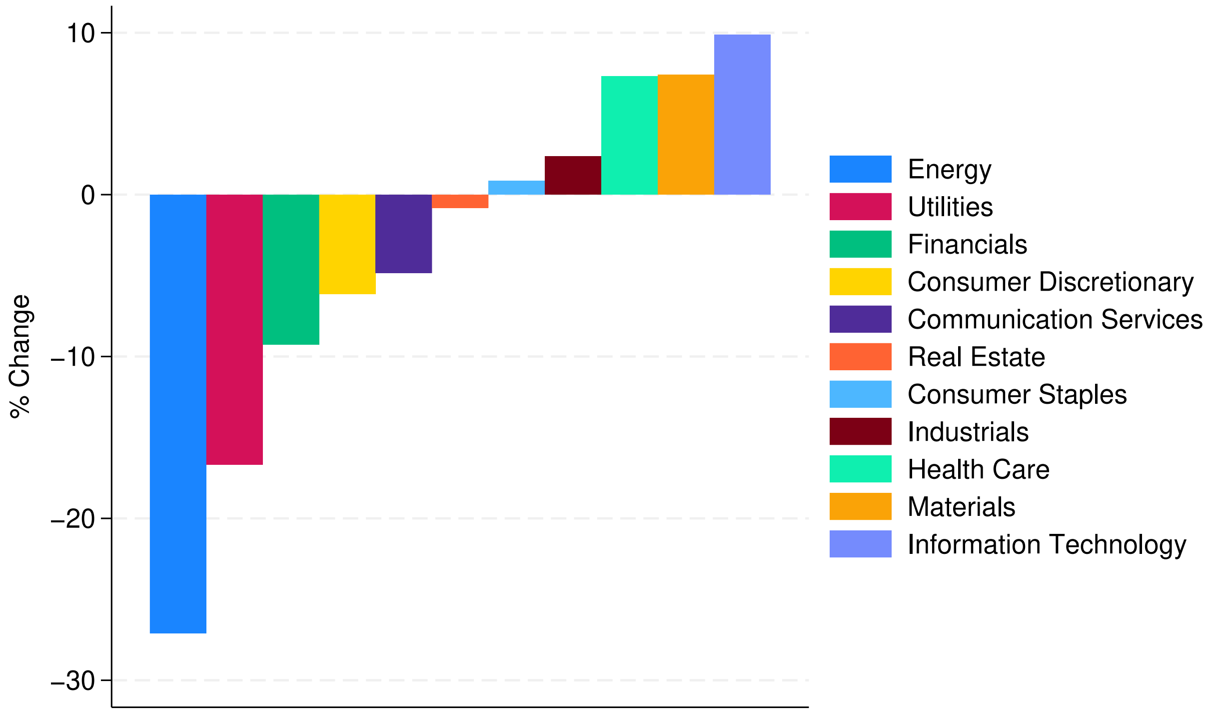


Figure 4: Change in investment shares share of the mutual fund sector in the counterfactual scenario where men and women manage the same volumes

dustry (or the volumes they manage) could have notable implications for the real economy. The significant reduction in portfolio shares for the energy, utilities and financials sectors suggests a potential decline in investment in these industries. Conversely, the increase in investment in healthcare, materials and the information technology sectors highlights a possible shift towards these three sectors. This reallocation of capital could drive innovation and growth in these sectors while potentially increasing financial restrictions in the energy, utilities and financials sectors.

6 Discussion and Conclusion

The consumption-related investment behavior of male and female portfolio managers that we identify has macro- and microeconomic consequences. On the macro-level, it may affect the overall allocation of capital. Compared to the population, male portfolio managers are more than proportionally represented in the US mutual fund industry, and, on average, they are controlling larger portfolios. In our sample, men control 96.842% of the overall asset volume. In such an environment, gender-specific investment behavior of portfolio managers can significantly affect the overall allocation of capital in the economy. US-registered investment company total net assets in 2023 amounted to $33.9 trillion USD (ICI, 2024), and according to BCG (2024), this represents more than 25% of US financial wealth. In theory, consumption-based investment behavior can be useful to achieve an efficient capital allocation, as it can direct funds to where they are needed, creating productive capacity in line with demand. However, this mechanism only works properly when those who consume are similar to those who invest. A mismatch between investment and consumption capacity can lead to a misallocation of capital.

On the micro-level, we find that masculine investment behavior adversely affects fund performance. Our analysis also shows that the performance effect arises not from gender as such, as even within the group of male fund managers, those with less masculine portfolios perform better. Our findings indicate that corrective measures may be in some fund's own best interest. Moreover, achieving gender parity among fund managers could lead to more balanced and diversified investment portfolios. On the macro-level, this diversification could reduce systemic risk by spreading investments across a wider array of sectors. Increased investment in sectors such as healthcare, materials and information technology could spur innovation and growth in these areas, potentially better aligning the sectoral investment with aggregate consumer demand.

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Online Appendix

A Data preparation

A.1 Dictionary-based gender classification

We used the World Gender Name Dictionary 2.0 (Raffo, 2021) for classification of gender given the fund manager's name, specifically the file

`wgnd_2_0_name-gender_nocode.tab`

This dataset assigns a gender to about 3.5 million first names, based on a collection of name-gender records from various data sources and countries (see Martínez et al., 2021 for details). The dictionary we use omits all names that have a gender conflict across data sources or geography. For example, if a name is predominantly male in one country but predominantly female in another, then it is dropped due to the conflict, which is important since the fund industry is rather international. Hence, we can be very confident the gender classification is made only for typical male and female names, independent of the origin of the fund manager.

The formatting of fund manager names is very clean and uniform in Morningstar, with the first word always being the first name. Our classification algorithm works as follows. First, it assigns the first name a gender if that name is listed in the dictionary. In a few cases, the first name is only given as initial, which cannot be classified by the dictionary. In most of these cases, a middle name is listed. Hence, second, if the first word of the name string is only an initial, and if there are at least three words in the name string, then we use the second (middle) name for gender classification instead of the first.

After using the classification from Niessen-Ruenzi and Ruenzi (2019) and using this algorithm on the remaining names, we successfully gender-classified 96% of fund manager names (5279 out of 5504). We do not expect this algorithm to be able to classify 100% of names, since some names are used by both genders, and some names are too uncommon to be included in the dictionary. Hence, the remaining names were classified manually be research assistants, as explained next.

A.2 Gender classification of remaining cases

We had two research assistants independently go through the remaining 225 unclassified names to make a gender classification. In addition to the manager name from Morningstar, they had the Morningstar name of the fund where the manager worked at the time. We limited the search time per name to 2 min in order to keep the workload manageable. We gave both RAs the following instructions:

> Please go through the following list of fund manager names and, based on a web search, assign a gender to each name if possible. A photo on the fund website or on LinkedIn, or the text (with she/he or her/him) in a fund prospectus, might reveal the gender. Write F in the gender column for women, and M for men. Copy the URL of the information source into the source column if possible. If you cannot determine the gender after 2 minutes of searching, then leave the column empty and move on to the next name. Note: The table also provides the name of the fund that the manager worked for. This fund might not be the current employer of that manager, as these are historical records. Consequently, a manager might work elsewhere now.

If both RAs made a classification, then they agreed in 206 out of 212 cases (97%).

A.3 Matching of consumption categories and GICS sub-industries

The Consumer Expenditure Survey, which we use for our our consumption data, groups household expenditures into 29 distinct consumption categories. The GICS sector classification to assign sectors to investments distinguishes a large number of distinct 8-digit sectoral classifications (called sub-industries). In order to compare the fund managers' investments to male and female consumption, we constructed a 1-to-1 mapping from the elements of a partitioning of the set of 8-digit GICS codes to the elements of a partitioning of the set of the 29 consumption categories. This means that in some cases we had to group the consumption categories in order to obtain a bijective mapping. Our final mapping between GICS codes and consumption categories is mostly based on the input from two research assistants. In the cases where the two research assistants did not agree, we made use of the input of a third research assistant that worked earlier on the matching of GICS codes to consumption categories. We also took a few additional decisions ourselves that we consider particularly plausible. Here is how we proceeded in detail to construct the GICS-consumption category mapping.

Step 1: Input A

In a first early attempt in 2021, we asked two student RAs to perform the following task in order to assign 8-digit GICS codes to the consumption categories:

> Your task is to assign the most plausible GICS categories (at the lowest level of aggregation) to the consumption categories that you are already familiar with. Specifically, you should answer the following question:
>
> In which GICS category do we find firms that produce goods that fall into this consumption category? If there are multiple categories that fit, then you should rank your results according to plausibility:
>
> - Most plausible category
> - second best (only if applicable)
> - third best (only if applicable)
> - and so on.

The employment contract of one of the two RAs ended before the task was fully completed. This RA's assignment includes 6-digit GICS codes and one consumption category is missing. The other RA "A" completed the task fully, so we made use only of A's work.

Step 2: Input "B" and "C"

In 2021 we decided to base our assignment on the input from more than one research assistant and to refine our instructions. We asked two additional student RAs "B" and "C" to assign 8 digit GICS codes to the consumption categories. The task was specified in detail as follows:

> Your task is to find 8 digit GICS codes ("sub-industries") that match the 29 consumption categories from the consumer expenditure survey listed below. Specifically, you should answer the following question:
>
> Which GICS codes represent firms which produce goods/provide services that fall into this consumption category? If there are multiple GICS codes that fit, then you should list all of them. You should, however, assign a GICS code to a consumption category if and only if you find the assignment sufficiently plausible. In case of doubt, please mark up your entry in excel, so that we can have your entry double-checked.
>
> Note that it may be the case that one GICS code will be assigned to more than one consumption category. More detailed information about the consumption categories can be found on the following pages. The GICS codes are listed in the enclosed excel sheet. Source: https://www.msci.com/gics.

Step 3: Our own choices

Our final mapping between GICS codes and consumption categories is based on the intersection of the individual assignments by the two RAs who produced Input BC. Intersection means that we assigned a GICS code to a consumption category if and only if both RAs independently suggested the same GICS code as a plausible one, thus ensuring that it is a convincing match. For the following three consumption categories, the intersection was empty: Audio, Pets, Shelter. In those cases, we picked the top GICS code that was proposed as Input by research assistant A and also coincided with one of the other two RAs B or C. Thus, the additional mappings were:

- Audio 25201010 (A proposed only one category)
- Pets 25202010 (A also has 30202010 in common with B)
- Shelter 60101060 (A's second code does not match any of the other two RAs' codes)

We eliminated the following consumption categories, as these were either too vague or too broad:

- Miscellanea. This category was considered too vague based on the wording. One research assistant assigned 11 GICS codes to this category.
- Household Operations. This category was considered too vague based on the wording. One research assistant assigned 10 GICS codes to this category.
- Other vehicle expenses. This category was considered too vague based on the wording.
- Utilities, fuels, and public services. This category was considered as too broad.

We also eliminated the following sector, as it was too broad:

- 25302020 Specialized Consumer Services

Based on the intersection mapping by the two RAs B and C, the consumption category "Gasoline, other fuels, and motor oil" was matched with GICS 55101010 "Electric Utilities". We as the authors agreed that this is the only really poor match. Hence, we decided to drop this match, i.e., we overruled the research assistants. As a consequence, we gained another 1-to-1 match for the consumption category "Household operations", which otherwise would have had to be integrated with "Gasoline, other fuels, and motor oil".

Step 4: Bundling

We iteratively bundled consumption categories and 8-digit GICS categories until we obtained a 1-to-1 mapping between sets of consumption categories and sets of GICS codes. We started with the first (according to the alphabetical order) consumption category and assigned the GICS codes in the way specified above. Then we combined the consumption categories that were associated with the same GICS codes to form a bigger consumption category. We repeated the process until there were no other consumption categories with the same GICS code to combine. We then continued with the next available consumption category. This process leads to a unique outcome, independently of the ordering of the set of consumption categories. This procedure ensures that two consumption categories or two GICS codes are grouped together only if this is necessary to get a 1-to-1 mapping. Figure 5 displays the final mapping.

Consumption categories (rows) \ GICS codes (columns)	30 20 10 10	30 20 10 20	25 20 30 10	25 20 30 30	35 20 20 10	25 30 20 10	25 30 10 30	30 20 20 30	30 20 20 10	25 20 30 20	10 10 20 10	10 10 20 30	40 30 10 20	40 30 10 30	40 30 10 40	25 20 10 20	25 20 10 40	25 20 10 50	30 30 10 10	35 10 20 15	35 10 20 20	35 10 10 20	25 30 20 20	25 20 20 10	30 30 20 10	20 30 20 10	20 30 30 10	20 30 40 10	20 30 40 20	50 20 10 40	30 20 30 10	50 10 20 10	25 10 20 10	25 10 20 20	25 20 10 10	25 20 20 10	60 10 10 60
Alcoholic beverages	A	A																																			
Apparel (except footwear & other apparel products)			B																																		
Other apparel products and services			B	B																																	
Audio and visual equipment and services																																			T		
Cash contributions																																					
Drugs					C																																
Education						D																															
Entertainment - fees and admissions							E																														
Food								F	F																												
Footwear										G																											
Gasoline, other fuels, and motor oil											H	H																									
Health insurance													I																								
Personal insurance and pensions													I	I	I																						
Household furnishings and equipment																J	J	J																			
Household operations																																					
Housekeeping supplies																			K																		
Medical services																				L	L																
Medical supplies																						M															
Miscellaneous																																					
Other entertainment supplies, equipment, and services																								N													
Other vehicle expenses																																					
Personal care products and services																									O												
Pets, toys, hobbies, and playground equipment																																				U	
Public and other transportation																										P	P	P	P								
Reading																														Q							
Shelter																																					V
Tobacco products and smoking supplies																															R						
Utilites, fuels, and public services																																					
Vehicle purchases (net outlay)																																	S	S			

Figure 5: Final mapping between consumption categories and GICS-codes. Each letter denotes one bundle in the matching. For example, both A-cells belong to the same bundle (which contains one consumption category and 2 GICS sub-industries). The grey shading indicates categories or codes that were dropped from the mapping, see section A.3.

A.4 Matching of consumption categories with 49 industries

In order to match our CES consumption data with Kenneth French's returns data for 49 industries, we asked two large language models (LLMs) to assign an industry to each consumption category. We used these two LLMs—ChatGPT 4 and Claude 3.5 Sonnet—on 22 September 2024,[22] with the following prompt:

> I will first give you a list of categories, and then a list of SIC groups. For every category, I want you to give me the SIC group that best matches the category.
>
> Here is the list of categories:
>
> Alcoholic beverages
>
> Apparel (except footwear & other apparel products) + Other apparel products and services
>
> Audio and visual equipment and services
>
> Drugs
>
> Education
>
> Entertainment - fees and admissions
>
> Food
>
> Footwear
>
> Gasoline, other fuels, and motor oil
>
> Health insurance + Personal insurance and pensions
>
> Household furnishings and equipment
>
> Housekeeping supplies
>
> Medical services
>
> Medical supplies
>
> Other entertainment supplies, equipment, and services
>
> Personal care products and services
>
> Pets, toys, hobbies, and playground equipment
>
> Public and other transportation
>
> Reading
>
> Shelter

[22] Since these LLMs do not have precise version numbers, we want to at least record the date of usage.

Tobacco products and smoking supplies

Vehicle purchases (net outlay)

And here are the 49 SIC groups:

1 Agric Agriculture

2 Food Food Products

3 Soda Candy & Soda

4 Beer Beer & Liquor

5 Smoke Tobacco Products

6 Toys Recreation

7 Fun Entertainment

8 Books Printing and Publishing

9 Hshld Consumer Goods

10 Clths Apparel

11 Hlth Healthcare

12 MedEq Medical Equipment

13 Drugs Pharmaceutical Products

14 Chems Chemicals

15 Rubbr Rubber and Plastic Products

16 Txtls Textiles

17 BldMt Construction Materials

19 Steel Steel Works Etc

20 FabPr Fabricated Products

21 Mach Machinery

22 ElcEq Electrical Equipment

23 Autos Automobiles and Trucks

24 Aero Aircraft

25 Ships Shipbuilding, Railroad Equipment

26 Guns Defense

27 Gold Precious Metals

28 Mines Non-Metallic and Industrial Metal Mining

29 Coal Coal

30 Oil Petroleum and Natural Gas

31 Util Utilities

32 Telcm Communication

33 PerSv Personal Services

34 BusSv Business Services

35 Hardw Computers

36 Softw Computer Software

37 Chips Electronic Equipment

38 LabEq Measuring and Control Equipment

39 Paper Business Supplies

40 Boxes Shipping Containers

41 Trans Transportation

42 Whlsl Wholesale

43 Rtail Retail

44 Meals Restaurants, Hotels, Motels

45 Banks Banking

46 Insur Insurance

47 RlEst Real Estate

48 Fin Trading

49 Other Almost Nothing

ChatGPT-4 returned the following:

Here's the list of categories matched with the SIC groups that best align with each:

1. Alcoholic beverages: 4 Beer (Beer & Liquor)

2. Apparel (except footwear & other apparel products) + Other apparel products and services: 10 Clths (Apparel)

3. Audio and visual equipment and services: 37 Chips (Electronic Equipment)

4. Drugs: 13 Drugs (Pharmaceutical Products)

5. Education: 33 PerSv (Personal Services)

6. Entertainment - fees and admissions: 7 Fun (Entertainment) 7. Food: 2 Food (Food Products)

8. Footwear: 10 Clths (Apparel)

9. Gasoline, other fuels, and motor oil: 30 Oil (Petroleum and Natural Gas)

10. Health insurance + Personal insurance and pensions: 46 Insur (Insurance)

11. Household furnishings and equipment: 9 Hshld (Consumer Goods)

12. Housekeeping supplies: 9 Hshld (Consumer Goods)

13. Medical services: 11 Hlth (Healthcare)

14. Medical supplies: 12 MedEq (Medical Equipment)

15. Other entertainment supplies, equipment, and services: 6 Toys (Recreation)

16. Personal care products and services: 33 PerSv (Personal Services)

17. Pets, toys, hobbies, and playground equipment: 6 Toys (Recreation)

18. Public and other transportation: 41 Trans (Transportation)

19. Reading: 8 Books (Printing and Publishing)

20. Shelter: 47 RlEst (Real Estate)

21. Tobacco products and smoking supplies: 5 Smoke (Tobacco Products)

22. Vehicle purchases (net outlay): 23 Autos (Automobiles and Trucks)

Claude 3.5 returned the following:

I'll match each category with the best corresponding SIC group. Here are the matches:

1. Alcoholic beverages - 4 Beer (Beer & Liquor)

2. Apparel (except footwear & other apparel products) + Other apparel products and services - 10 Clths (Apparel)

3. Audio and visual equipment and services - 37 Chips (Electronic Equipment)

4. Drugs - 13 Drugs (Pharmaceutical Products)

5. Education - 33 PerSv (Personal Services)

6. Entertainment - fees and admissions - 7 Fun (Entertainment)

7. Food - 2 Food (Food Products)

8. Footwear - 10 Clths (Apparel) [Note: This is the closest match, though not perfect]

9. Gasoline, other fuels, and motor oil - 30 Oil (Petroleum and Natural Gas)

10. Health insurance + Personal insurance and pensions - 46 Insur (Insurance)

11. Household furnishings and equipment - 9 Hshld (Consumer Goods)

12. Housekeeping supplies - 9 Hshld (Consumer Goods)

13. Medical services - 11 Hlth (Healthcare)

14. Medical supplies - 12 MedEq (Medical Equipment)

15. Other entertainment supplies, equipment, and services - 6 Toys (Recreation)

16. Personal care products and services - 33 PerSv (Personal Services)

17. Pets, toys, hobbies, and playground equipment - 6 Toys (Recreation)

18. Public and other transportation - 41 Trans (Transportation)

19. Reading - 8 Books (Printing and Publishing)

20. Shelter - 47 RlEst (Real Estate)

21. Tobacco products and smoking supplies - 5 Smoke (Tobacco Products)

22. Vehicle purchases (net outlay) - 23 Autos (Automobiles and Trucks)

The assignments of both LLMs match for every single consumption category. After manual inspection, we see no errors, and given that two independent LLMs agree without exception, we are confident this is a robust assignment of industries to consumption categories.

B Additional tables and results

B.1 Further summary statistics

Table 11 displays summary statistics for whether a fund is invested in a certain consumption category, by gender.

B.2 Gender differences in diversification across sectors

To get a more formal indication of gender differences in portfolio allocations across sectors and industries, we run regressions where the dependent variable is the number of different assets (NumItems), sectors (NumSectors), or industries (NumIndustries) in which a fund is invested, while holding the quarter constant.[23] The GICS classification system has four levels, and sectors are the coarsest level of aggregation, with 12 sectors overall (such as healthcare or energy, plus unclassified). Industries are the second finest level, with 70 industries overall (for example, within healthcare, it distinguishes between biotech, pharmaceuticals, healthcare providers and more).

The results are presented in Table 12. Column (1) reveals that male managers, on average, hold about 15 assets more in their portfolios; however, this difference is not statistically significant. Column (2), which controls for the fund objective to account for potential differences in the types of funds managed by male and female managers, shows that the gender difference in the number of different stocks remains insignificant. Therefore, male and female managers do not differ in portfolio diversification based on the number of different assets held. However, columns (3) and (4) of Table 12 indicate that male fund managers invest in significantly fewer sectors than female fund managers, even after controlling for the fund objective (in column 4). On average, male fund managers are invested in about 10.3 sectors, whereas female managers average investments in 10.7 sectors, out of 12 possible sectors. Columns (5) and (6) repeat this analysis at the finer industry level rather than the sector level, yielding similar results. Female fund managers, on average, invest in significantly more industries - over 2 out of 70 - even after controlling for the fund objective. The fact that female fund managers are invested in more sectors and industries compared to male fund managers might enable them to better diversify their portfolios.

B.3 Effect of consumption weights on returns by gender

Table 13 shows regressions where the effect of the consumption weight on returns is separated by gender. It shows that the gender difference is not significantly different from zero in any of the regressions. Thus, the effect of the consumption weight on fund performance does not differ by gender. We omit regressions with fund fixed effects, as we are looking at gender specific effects here, whereas regressions with fixed effects would exploit the change in gender for the same fund.

B.4 Gender differences in investments across industries

In the main part of the paper, we use GICS sectors, the coarsest level of aggregation, to investigate gender differences in mutual fund managers regarding diversification and investment targets. GICS sectors—11 plus one "unclassified" category—are thus very aggregated and may

[23]Holding the quarter constant is crucial because, without it, we would obtain spurious estimates of the gender difference if both the share of female managers and overall fund diversification increase over time.

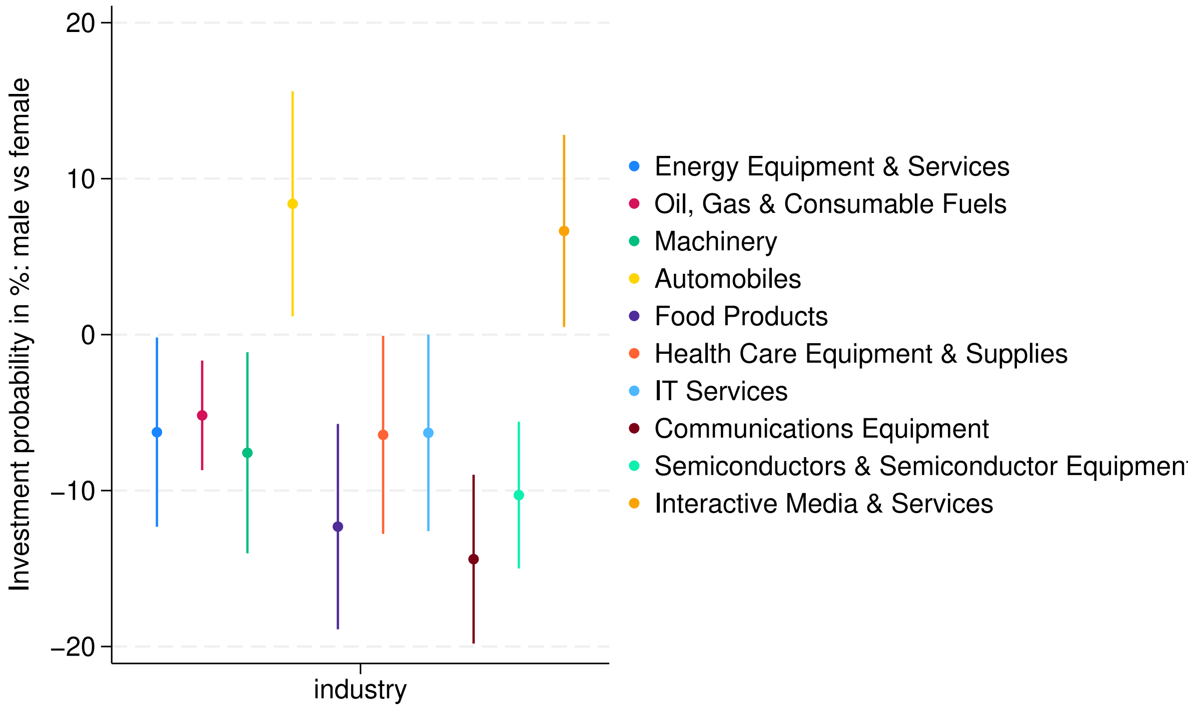

Figure 6: Male vs female difference in probabilities that fund is invested in a specific industry, holding quarter constant. The graph only lists industries with significant differences at the 5% level. The lines represent the 95% confidence intervals of the difference, clustering on fund manager level.

hide further differences. For this reason, we here repeat the exercise at the level of GICS industries, of which there are 69 (before 2023, which is the state of our data) plus again one for "unclassified" in case we were not able to obtain a GICS code for an investment.

The following Figure 6 plots all these industries where there is a significant gender difference in the probability to be invested in a given industry (without adjustment). Out of the 70 sectors, there are 10 with significant differences. As we would expect from the previous regression, given there is a significant difference, female fund managers typically have a higher probability to be invested. Two exceptions out of 10 are the automobile industry and the interactive media industry, where male fund managers are significantly more likely to be invested.

We can also look at gender differences in the portfolio share by industry. Figure 7 plots the industries which have a significant difference at the 5% level (without adjustment). Male fund managers have higher shares in the automobile, transportation and finance/insurance industries, whereas female fund managers have higher shares in communications, packaging, machinery, and semiconductors.

Going beyond specific industries, we can test for equality of the distribution as for sectors in the main part. The resulting χ^2 test without adjustment strongly rejects that male and female

Figure 7: Male vs female difference in portfolio shares in a specific industry, holding quarter constant. The graph only lists industries with significant differences at the 5% level. The lines represent the 95% confidence intervals of the difference, clustering on fund manager level.

fund managers have the same probabilities to invest in industries ($\chi^2(70) = 337.68$, $p < .0001$). Similarly, for portfolio shares, equality is rejected ($\chi^2(70) = 308.07$, $p < .0001$).

B.5 Returns of consumption-based investment strategies

Do women or men benefit from investing according to their consumption preferences? At least one theory, Grüner and Siemroth (2019), can explain why under-proportionally represented groups such as women may be able to obtain higher returns. This is because firms supplying the consumption of these groups are not able to obtain enough financing to meet demand, thus being very profitable, as their goods are highly sought after with limited supply. This explanation aims at firm profits. Alternatively, one can imagine stocks of firms supplying the consumption of under-proportionally represented groups to be less in demand on the stock market, thus having lower prices and higher returns. This explanation aims at stock prices.

Since it is challenging to distinguish aspects such as stock picking ability, investment heuristics, informational advantages, etc., we construct two very simple investment strategies that are based on male consumption preferences (M) and on female consumption preferences (F). We then compare the historical performance of these two consumption-investment strategies over our sample period. Thus, stock picking ability or informational advantages are ruled out in this hypothetical computation. Instead, what matters for returns are the weights assigned to each industry, and these in turn depend on the gender consumption preferences. Thus, these computations give us a hint as to whether investments according to consumption preferences are advantageous.

Our analysis is based on the simplest possible consumption-based investment strategy. Consumption shares translate one-to-one into investment shares. Hence, suppose men spend 10% of their consumption on cars, whereas women spend 5% on cars. Then the M-portfolio invests 10% into the car industry whereas the F-portfolio invests only 5% in the car industry. Within each industry, the strategies diversify across all firms in that industry, either with equal weighting or with value weighting. To stay consistent with the prior analyses, we use the same consumption data and consumption groups as before when we matched them with GICS codes (see Figure 5 in the appendix for the consumption groups in our data).

We obtain returns of monthly industry portfolios from Kenneth French's website, using the equal weighted and the value weighted versions separately.[24] In order to match the 49 industries for which we have returns to our consumption categories, we used two different large language models (LLMs) with the same prompt to construct a mapping. These two LLM models—ChatGPT 4 and Claude 3.5 Sonnet—returned the exact same mapping. After inspecting the mapping ourselves, we saw no reason to overrule any of the matches from consumption category to industry, so we continued with that mapping. The prompt as well as the answers are reported in full in appendix A.4.

While our consumption data are yearly—so the weights of the portfolios do not change within the year—the returns data are monthly. In order to have the most statistical power, we calculate returns and Sharpe-ratios (risk-adjusted returns) on a monthly level, with standard deviations calculated based on monthly returns in the calendar year.

Table 14 reports the average monthly returns as well as the monthly Sharpe ratios for both the male consumption-preference investment strategy (M) and the female consumption preference investment strategy (F). As before, our sample window is from 2004 to 2019 (192 months overall), and we separately calculate the performance of these two strategies using equal-weighted industry portfolios (i.e., every firm in the industry receives the same weight in the portfolio) and value-weighted industry portfolios (i.e., every firm in the industry receives a weight proportional to their market capitalization). We also report p-values of the test of equality between the M and F portfolio performance using a t-test.

[24] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. We use the finest split into 49 industries to ensure the best match with our consumption categories. In the coarser splits, the industries more often include sub-industries that are not relevant for the consumption categories.

In short, for none of the performance measures there is a significant difference between the M and F consumption-based investment strategies. Thus, even if fund managers were to invest quite extremely according to their consumption preferences, as we do in this exercise, it would not lead to significantly different returns. Consequently, with this test, we cannot detect whether one gender's consumption preferences are more valuable as a basis for investment than the other's.

Table 11: Summary statistics: Investment indicators in % by consumption category, fund-quarter level

	% male	% female	difference
InvInd Food	60.23	72.68	-12.44***
InvInd Medical supplies	28.32	39.16	-10.83***
InvInd Shelter	16.07	23.32	-7.25***
InvInd Other entertainment	27.68	34.17	-6.48***
InvInd Pets/toys/hobbies	27.68	34.17	-6.48***
InvInd Personal care	31.12	37.48	-6.36***
InvInd Transportation	64.42	70.40	-5.97***
InvInd Education	24.17	28.61	-4.44***
InvInd Drugs	73.08	77.50	-4.42***
InvInd Entertainment	14.90	18.55	-3.64***
InvInd Other apparel	13.60	16.39	-2.79***
InvInd Medical services	69.16	71.51	-2.35**
InvInd Apparel	41.39	41.61	-0.22
InvInd Reading	16.67	16.70	-0.03
InvInd Insurance	69.81	69.75	0.06
InvInd Footwear	31.29	30.59	0.70
InvInd Housekeeping supplies	46.96	46.04	0.91
InvInd Alcohol	26.04	24.70	1.34
InvInd Household furnishings	35.69	32.44	3.25***
InvInd Tobacco	31.44	27.02	4.42***
InvInd Vehicle	28.66	20.70	7.97***
InvInd Gasoline/fuels	56.10	46.94	9.16***

Note: T-test for difference. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table 12: Gender differences in length of portfolio and spread across sectors/industries

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	NumItems	NumItems	NumSectors	NumSectors	NumIndustries	NumIndustries
Male Manager	21.341	20.661	-0.274**	-0.269**	-1.793*	-1.309
	(16.771)	(16.239)	(0.126)	(0.119)	(1.045)	(0.976)
Control Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Control Fund Objective	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.006	0.023	0.010	0.068	0.010	0.074
Observations	26685	25017	26685	25017	26685	25017
Clusters	1526	1332	1526	1332	1526	1332

Note: NumItems is the number of different assets in the fund portfolio in a given quarter. NumSectors is the number of GICS sectors that the fund is invested in in a given quarter (up to 12). NumIndustries is the number of GICS industries that the fund is invested in in a given quarter (up to 70). The unit of observation is the fund-quarter. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table 13: Is more weight on consumption associated with better fund performance? By gender

	(1)	(2)	(3)
Dependent variable	Return	1-F alpha	4-F alpha
Consumption Weight	-0.085***	-0.006	0.008
	(0.017)	(0.006)	(0.005)
Consumption Weight × Female	0.035**	0.008	0.003
	(0.017)	(0.007)	(0.006)
Year FE	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes
Fund FE	No	No	No
Adjusted R^2	0.843	0.097	0.081
Observations	5596	5056	5055
Clusters	1116	1030	1030

Note: Fund controls: (1) the fund objective, (2) fund age in years, (3) expense ratio of the previous year, (4) the log of the sum of total net assets from last year, and (5) the fund flow from last year. The unit of observation is the fund-year. Standard errors are shown in brackets below the point estimates, and are clustered on fund level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table 14: Average monthly performance of consumption-preference based investment strategies by gender

Value-weighted returns		Value-weighted Sharpe ratios	
M-portfolio:	0.7933%	M-portfolio:	0.2463
F-portfolio:	0.7997%	F-portfolio:	0.2459
t-test difference (p-value):	0.9905	t-test difference (p-value):	0.9966
Equal-weighted returns		Equal-weighted Sharpe ratios	
M-portfolio:	0.9208%	M-portfolio:	0.2370
F-portfolio:	0.9229%	F-portfolio:	0.2345
t-test difference (p-value):	0.9971	t-test difference (p-value):	0.9816

C Variable descriptions

This table defines the variables used in the empirical analysis. The data sources are:
(i) CRSP: CRSP Survivorship Bias Free Mutual Fund Database
(ii) GICS: GICS classifications from Compustat, CRSP stock dataset and from the Thomson Reuters Eikon API
(iii) EST: Estimated by the authors
(iv) KF: Kenneth French Data Library
(v) MS: Morningstar Direct Database
(vi) TR: Thomson Reuters Fund Holdings Database (formerly known as CDA/Spectrum)
(vii) CES: Consumer Expenditure Surveys data on US consumer spending

Panel A: Main dependent variables

Variable name	Description	Source
NumItems	Number of different assets that the fund is invested in	TR
NumSectors	Number of different GICS sectors that the fund is invested in	TR, GICS
NumIndustries	Number of different GICS industries that the fund is invested in	TR, GICS
$\text{SectorIndicator}_{iqs}$	An indicator whether fund i had at least one position in GICS sector s in quarter q	TR, GICS
SectorShare_{iqs}	A real number in $[0, 1]$ with the portfolio share of fund i invested in GICS sector s in quarter q	TR, GICS
InvShare_{iqc}	A number (percentage) in [0,100] with the portfolio share of fund i in quarter q invested in firms supplying consumption category c	TR, GICS, CES
InvInd_{iqc}	An indicator scaled to $\{0, 100\}$, indicating whether fund i in quarter q was invested in firms supplying consumption category c	TR, GICS, CES
Return	The annual return of the fund, after trimming the bottom and top 1% of outliers	CRSP
1-F alpha	The alpha in a 1-factor capm model, estimated based on daily excess fund returns with at least 100 days. Outlier alphas above 0.3 and below -0.3 have been trimmed.	CRSP, KF, EST
4-F alpha	The alpha in a F-factor model, estimated based on daily excess fund returns with at least 100 days. Outlier alphas above 0.3 and below -0.3 have been trimmed.	CRSP, KF, EST

Panel B: Main independent variables

Variable name	Description	Source
Male Manager	Indicator whether the fund manager is male or female, based on the fund manager name	MS
PMI	Portfolio Maleness Index. See section 2.5 for a detailed derivation. A PMI of 1 indicates a portfolio that is the same as the average portfolio of male fund managers in that quarter in terms of GICS sector shares. A PMI of 0 indicates a portfolio that is the same as the average portfolio of female fund managers. The larger PMI, the more male the portfolio.	TR, GICS, EST
Consumption-Share$_{iqc}$	A number (percentage) in [0,100] with the share of spending by members of that fund manager's gender in the top income category on consumption category c in the year belonging to quarter q	CES, MS
Consumption-Share-Ratio$_{iqc}$	A number defined as the ratio of fund manager i's gender consumption share in consumption category c in quarter q, divided by the consumption share of the other gender in consumption category c in quarter q. This variable indicates whether spending on a consumption category is skewed towards one gender (if the ratio is different from 1), whereas the consumption share indicates whether a consumption category is big (in the sense that people spend a lot on it).	CES, MS
Consumption weight	Coefficient β_{iy} in regression (6), which represents (for each fund-year) how much the manager relies on consumption when determining investments.	EST, TR, CES

Panel C: Other control variables

Variable name	Description	Source
Fund Objective	Set of dummy variables categorizing different objectives of funds	CRSP
Fund Age	In years	CRSP
Lag Expense Ratio	Fund's expense ratio from previous year in %	CRSP
Lag Annual Return	Fund's annual return from previous year, after trimming the bottom and top 1% of outliers	CRSP
Lag Fund Flow	Fund's fund flow from previous year in %, computed as in Sirri and Tufano (1998), after trimming the bottom and top 5% of outliers	CRSP
Lag Log TNA	Fund's logged sum of total net assets from last year	CRSP
Quarter (Fixed Effects)	Set of dummy variables indicating the quarter. Thus, the regression estimates effects within quarter rather than across quarters	TR
Quarter-Category (Fixed Effects)	A set of dummy variables for every consumption category and quarter pair. Thus, the cars consumption category in Q1 of 2010 can have different levels than the cars consumption category in Q1 of 2011. Thus, the regression estimates effects within quarter *and* consumption category.	TR, CES
Fund-Quarter (Fixed Effects)	A set of dummy variables indicating for every fund and quarter pair. When these are used, there are multiple observations per fund-quarter—one for every consumption category—so these can capture time-specific fund effects across consumption categories.	CRSP