Beyond the ticker: Female brands and fund manager investment decisions *

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Abstract

Using image recognition on an extensive dataset comprising images linked to over 80 brands, we calculate a brand gender score based on the feminine characteristics associated with each brand. Our study shows that female fund managers are more likely to incorporate stocks into their portfolios with higher gender (female) score. As an identification strategy, we examine changes in the management of single-managed funds. Funds transitioning from male to female management exhibit an increase in holdings of stocks associated with female-centric brands compared to funds that remain under male management.

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1 Introduction

From the marketing literature, it is well established that many brands possess a strong gender identity. To offer some accessible examples, Marlboro is associated with a masculine identity, while Chanel is often linked with feminine imagery. The concept of brand gender significantly impacts individual perception and behavior. A brand with a distinct gender identity can create a deep psychological connection with consumers, leading to stronger brand loyalty and preference. For instance, a brand perceived as masculine might be associated with traits such as strength and ruggedness, appealing to consumers who identify with or aspire to these qualities. Conversely, a brand with a feminine identity, often associated with elegance and nurturing, might resonate more with consumers who value these attributes. The literature suggests that this alignment between brand gender identity and consumer self-concept enhances the individual's affinity towards the brand, in turn influencing their purchase decisions and their willingness to recommend the brand to others.

While this concept is well-established in the realm of consumer choice, we pose a related question in the area of investments: Does the identity and affinity with a brand similarly affect the propensity to hold a given stock? More specifically, we investigate whether a female (male) mutual fund manager is more likely to select stocks from companies owning brands predominantly feminine (masculine). For instance, Estée Lauder, the renowned manufacturer and marketer of prestige beauty products, can be considered an example of a 'feminine' stock, while Caterpillar, a prominent manufacturer of heavy machinery and construction equipment, represents a typical 'masculine' stock. With this perspective, we explore whether the likelihood of observing Estée Lauder (Caterpillar) stock in a fund portfolio is greater in females (males) funds managed.

However, the definition and classification of brand gender is far from being unambiguous. While some brands possess a predominantly gender-defined customer base, others aim at a more unisex audience, influenced by the nature of their product or specific marketing choices. Moreover, over the years, there has been an increasing trend of cross-gender extensions among brands (Jung and Lee, 2006), further complicating the task of brand gender classification. To determine the degree of femininity or masculinity of brands, this paper employs machine learning and image recognition techniques. Similar methodologies have been used in other studies for various objectives, such as constructing a daily market-level investor sentiment index (Obaid and Pukthuanthong, 2022), sector indexes (Kaczmarek and Pukthuanthong, 2023), measures of visual readability of annual reports (Ben-Rephael, Ronen, Ronen, and Zhou, 2021) or metrics of nonverbal communication during press conferences (Curti and Kazinnik, 2023). For each of the 81 brands in our sample, we initially download one hundred images from web searches containing the brand name and a specific keyword. The use of a keyword (such as 'Customer' or 'Testimonial') is intended to refine the search results, maximizing the likelihood of obtaining images that represent the typical customer base, while minimizing the retrieval of images solely related to the product or, worse, unrelated to the brand. Additionally, employing different and alternative keywords captures various aspects and nuances of the brand, thereby providing further robustness to our measure. While 'Customer' may more directly point toward the actual customer base and be less influenced by the company's advertising campaigns, 'Testimonial' might reveal who the stereotypical client is that the company portrays in its external communication. From the downloaded images, we first automatically detect and count the number of people and then classify them based on their gender. The brand gender score is then computed as the percentage of female individuals detected in those images. This score is a continuous variable, ranging from zero (indicating 100% of individuals detected in the images are men) to one (indicating 100% are women). To refer to our prior examples, Estée Lauder is associated with a 0.82 (0.70) gender score, while Caterpillar has a 0.23 (0.30) score using Testimonial and Customers, respectively, denoting the former a clear feminine attribute and the latter a distinctive masculine classification.

We then shift our focus to the investment choices of single-managed funds of U.S. active mutual funds in the period from 2008 to 2021. We exclusively consider single-managed funds to avoid the confounding effects of a fund management team's gender mix, as well as all interactions within the team that influence decisions regarding fund asset allocation. Similarly, we focus solely on active funds where managers have discretionary control over the stocks included in the portfolio, as opposed to passive strategies where security selection merely follows the composition of a stock index. Controlling for stock characteristics, along with time, industry, and fund fixed effects, we find that female fund managers are more likely to hold 'feminine' stocks, and this effect is particularly pronounced when the gender attribution is strong, i.e., at the tails of the gender score distribution. A one standard deviation increase in the brand gender score raises the likelihood of a female fund manager including the stock in her portfolio by 58 basis points. Further, at the right-hand side of the gender score distribution, this effect approximately doubles (triples) at the 75th (90th) percentile.

To address concerns that our results are not causal but rather driven by an omitted factor influencing both the presence of a female fund manager and the choice of stocks with a high brand gender score, we examine fund asset allocation around instances of manager gender change, i.e., when a fund transitions from a male to a female manager or vice versa. Despite the limited number of such instances (we document 87 manager changes from female to male and 86 changes from male to female), which reduces the likelihood of observing statistically significant results, we observe that when a male manager of a single-managed fund is replaced by a female manager, there is a notable increase in the proportion of feminine stocks within the fund's portfolio.

These results clearly suggest that female fund managers have a tendency to tilt their portfolios towards stocks associated with more feminine brands. However, if feminine brands were larger advertising spenders, this might increase the stock's visibility and, consequently, the likelihood of its inclusion in a fund portfolio. In this regard, Grullon, Kanatas, and Weston (2004) show that, ceteris paribus, firms with greater advertising expenditures attract a larger number of both individual and institutional investors and enjoy improved liquidity of their common stock. If advertising were a primary influencing factor, one would expect an increased likelihood of feminine stocks being selected by fund managers irrespective of their gender. Contrary to this hypothesis, our findings indicate that the effect is specifically associated with female fund managers. However, to address any remaining uncertainties, we also control for advertising expenditure. Our results reveal no significant association between advertising expenditure and a stock's inclusion in fund portfolios. More importantly, even after controlling for advertising spending, the positive correlation between the gender score of a brand and its presence in portfolios managed by females remains strong and consistent.

In the realm of related literature, Frieder and Subrahmanyam (2005) are the first in studying the perceptions of companies' brands and the institutional holdings in firm stocks. They propose two potential mechanisms to explain why individual investors may show a preference for stocks of companies with high brand recognition. Firstly, brand recognition may act as a focal point, providing key information about these companies. Secondly, individuals might resort to simple heuristics when making decisions in the face of uncertainty (Kahneman and Tversky, 1982), often naively equating product quality with superior stock price performance. However, their findings reveal a significant and negative association between institutional holdings and brand recognition, with no substantial correlation to perceived brand quality. Importantly, they do not attempt to classify brands by gender, nor do they examine the gender of institutional investment fund managers. In contrast, Bradley, Lahtinen, and Shipe (2021) introduce a gender classification of firms based on a textual analysis of gender-specific keywords in firms' 10-K filings. They find that female households significantly overweight and underperform in female-focused firms, and while trading significantly less than males in their overall portfolio, they exhibit similar trading patterns to males in female-focused firms.

We argue that the preference for 'feminine' stocks stems from the brand image and qualities that appeal to female fund managers who identify with or aspire to these attributes. This concept somewhat echoes the notion of closeness and familiarity. Our study contributes to the literature on fund manager investment bias by presenting a novel and previously unexplored aspect of stock familiarity and identity, and its impact on fund manager investment decisions. While the literature on biases affecting investment decisions among retail investors is extensive[1], there are relatively few studies that document deviations from rational investment behavior among professional investors. In a previous study, Pool, Stoffman, and Yonker (2012) demonstrate how familiarity influences the portfolio choices of mutual fund managers. They provide evidence that funds overweight stocks from the home states of their managers.

[1] Among others, Bailey, Kumar, and Ng (2011) investigate the impact of behavioral biases on the mutual fund selections of a large cohort of U.S. discount brokerage investors. They find that behaviorally biased investors typically make suboptimal decisions regarding fund style and expenses, trading frequency, and timing, which ultimately results in poor performance. Additionally, they observe that trend chasing is more likely related to behavioral biases than to rational inferences about managerial skill based on past performance. In a similar vein, Ben-David, Li, Rossi, and Song (2022) demonstrate that mutual fund investors tend to rely on simple signals and are unlikely to engage in sophisticated learning about managers' alpha, contrary to popular belief. Their research suggests that simplistic performance chasing is the primary driver of aggregate flows to the mutual fund sector, as well as flows across individual funds. This trend is observed in both actively managed and passive index funds.

However, home-state stocks do not outperform other holdings, ruling out the hypothesis that these investments are based on superior information. Similarly, Alok, Kumar, and Wermers (2020) find that fund managers from major disaster regions underweight stocks from those disaster zones more than managers located farther away. This aversion to disaster zone stocks decreases with time and distance from the disaster and is not attributable to superior information possessed by close managers. Finally, Pool, Stoffman, and Yonker (2015) document that socially connected fund managers exhibit more similar holdings and trading patterns. The portfolios of managers residing in the same neighborhood overlap significantly more than those of managers living in the same city but in different neighborhoods. They also present evidence that these effects are amplified when managers share a similar ethnic background.

We also contribute to the limited literature on female fund managers. Despite increasing attention to gender issues, the financial literature has largely overlooked the underrepresentation of women among professional fund managers. As it stands, only one in ten U.S. fund managers is female, a proportion that has remained relatively stable throughout the period analyzed. To our knowledge, few studies have delved into the presence of female investors in investment funds, the asset allocation of these funds, and their respective performances. Atkinson, Baird, and Frye (2003) analyze the performance and investment behaviors of female versus male fund managers, finding no significant differences in performance, risk, or other fund characteristics. Yet, they document lower net asset flows into funds managed by females, particularly for managers at the onset of their careers. Niessen-Ruenzi and Ruenzi (2019) report significantly lower inflows to female-managed funds compared to male-managed funds, despite similar performance. Through field data and laboratory experiments, they demonstrate that subjects with stronger gender biases invest considerably less in funds managed by women, suggesting a possible root cause for the low proportion of women in the mutual fund industry. Rau and Wang (2022) present evidence that investors pay less attention to female fund managers. They show that while fund flows respond to prior-month performance, the flow-performance relationship is significantly weaker if the fund manager is female, notwithstanding comparable performance between male and female managers. Lastly, Dezső, Rawley, and Ross (2018) find that the presence of female fund managers correlates with increased risk-taking, as funds with a higher proportion of female managers exhibit a higher market beta. They posit that female managers may encourage their peers to embrace their investing individuality by taking on more risk.

Finally, we aim to contribute to the burgeoning literature in finance that utilizes machine learning for image recognition. Obaid and Pukthuanthong (2022) construct a daily market-level investor sentiment index ('Photo Pessimism') by applying machine learning to a vast sample of news media images, finding that this Photo Pessimism index predicts market return reversals and trading volume. Kaczmarek and Pukthuanthong (2023) adopt a similar methodology to identify graphical objects that accurately represent companies' operations, with the aim of constructing Image Industry Classifications (IIC). They demonstrate that the IIC surpasses common sector classifications (such as SIC, GICS, NAICS) in providing superior diversification benefits and industry momentum profits. Ben-Rephael et al. (2021) develop machine learning algorithms to create metrics of visual readability in firms' annual reports. Curti and Kazinnik (2023) utilize facial recognition on FOMC (Federal Open Market Committee) press conference videos to discern and quantify the information content of nonverbal cues. Their findings indicate that investors respond negatively to expressions of negativity during press conferences, even after controlling for the verbal content.

2 Data and Methodology

2.1 Data collection and filtering

We start with the complete list (10,074) of U.S. equity mutual funds from Morningstar. We then combine this data with holdings information from the Center for Research in Security Prices (CRSP) Mutual Fund Holdings database. To integrate these sources, we create a mapping file using identifiers from Morningstar (*Ticker*, *SecId*, *FundId*, and *Cusip*, all at the share-class level) and merge it with the CRSP database using Morningstar *Cusip* and CRSP *Ncusip* identifiers. This mapping is crucial for linking CRSP portfolio data (*crsp_portno*) to share-class information (*crsp_fundno*). We use data from Morningstar and CRSP, as the former contains high quality data on fund characteristics, manager information and performance, while the latter is the primary source for holdings. To further clean the dataset, we: i) focus on funds with an average percentage Total Net Assets (TNA) between 70% and 110%; ii) select only funds that have an average number of assets above 10 and TNA above 1 million USD; iii) exclude funds-of-funds and index funds. This process yields a quarterly dataset of 5,544 U.S. equity mutual funds spanning Q1 2008 to Q4 2021. The starting point of 2008 aligns with Zhu (2020), noting comprehensive coverage in the CRSP database from this year. Following Niessen-Ruenzi and Ruenzi (2019), we focus only on single-managed funds and therefore exclude all team-managed funds or funds for which Morningstar lists multiple fund managers' names at a given point in time. Fund managers' gender is inferred from their first names in Morningstar, cross-referenced with U.S. newborn name and gender statistics from the Social Security Administration.[2] For foreign names or unisex names (e.g., Andrea), we manually classify the gender of individual fund managers by

[2] See: https://www.ssa.gov/oact/babynames/.

searching for relevant information on the web (e.g., Linkedin profile or reading articles and reports). Similar to Niessen-Ruenzi and Ruenzi (2019), we were able to identify the gender of 99.4% of the fund managers' names, resulting in a dataset of 2,484 single-managed funds, including 348 female-managed and 2,291 male-managed funds.[3] Figure 1 shows the total number of female- and male-managed funds over the period from Q1 2009 to Q4 2021. In line with prior literature, the fraction of female-managed funds is low and relatively constant over the time, averaging about 10%. This ratio remains stable even in the recent years.

At the stock level, we gather accounting and market data from Compustat North America and CRSP. Market characteristics include monthly and cumulative returns, 12-month volatility, 5-year beta (requiring at least 48 months of return data), and a liquidity proxy (monthly trading volume divided by the number of shares outstanding). Accounting characteristics cover ROE, leverage ratio, cash holdings, sales volume, advertising expenditures, dividend yield, and Tobin's q. Following Albuquerque, Koskinen, Yang, and Zhang (2020), we winsorize these variables at the 1st and 99th percentiles and align year t market data with year $t-1$ accounting data to reflect the actual information set available to investors.

[INSERT FIGURE 1 ABOUT HERE]

2.2 Constructing brands' gender scores

Our approach to developing a brand gender score involves analyzing gender representation in images linked to a company's target customers or testimonials. We utilize a Python API to download images from the Bing search engine, which ranks thousands of images based on relevance. Following Kaczmarek and Pukthuanthong (2023), we focus on the first 100

[3] These numbers are computed over the entire sample period. Therefore manager changes over time can lead to a fund being counted as both female-managed and male-managed in the above statistic.

images, considering them the most relevant due to their origin from highly credible sources. Our search query is structured as: 'Brand Name' + 'Testimonial' (or 'Customer').

For image collection, our attention is on large companies known for strong branding. We employ the brand list curated by Pogacar, Angle, Lowrey, Shrum, and Kardes (2021), which amalgamates two distinct sets of companies: all brands featured in the Interbrand Global Top Brands list from 2000 to 2019, and a randomly selected group of companies each with a market capitalization over 2.5 billion USD. This method yields a comprehensive list of 343 brands associated with 314 international parent companies.

We then implement a data cleaning process to refine this list to the final set of brand-company names. We limit our analysis to brands whose names overlap, either perfectly or substantially, with the names of their corresponding stocks. This is done both when the company has a single or multiple brands. This is crucial because, despite we focus on professional fund managers who are presumably capable of associating well-known brands with their owning firms, the psychological impact and emotional trigger induced by a stock that audibly resembles the brand might differ from a stock lacking this phonetic association.[4] Following the initial image download, we compile a list of 275 brands. To ensure the validity of our gender score measure, we further refine this list by excluding 64 brands whose images do not depict a sufficiently large sample of individuals (fewer than 30). Subsequently, we conduct a gender classification of individuals in the images using the DeepFace Python

[4] The influence of a name on the decision to include stocks in a portfolio is well-established in the literature. Psychological research indicates that individuals tend to favor stimuli that are easier to process. For example, Green and Jame (2013) show that firms with short, easy-to-pronounce names have higher share turnover, broader ownership, and increased liquidity and valuations. This trend is also evident in funds, where fluently named closed-end funds trade at smaller discounts, and fluent mutual funds attract larger flows. Similarly, Cooper, Dimitrov, and Rau (2001) note an inexplicably positive stock price reaction following corporate name changes to Internet-related dotcom names. The power of the name sounding is also documented in Kumar, Niessen-Ruenzi, and Spalt (2015), who find that fund managers with foreign-sounding names experience lower annual fund flows, particularly when funds with investor clientele are more likely to be suspicious of foreigners.

library. This allows us to calculate the *GenderScore* for each brand, defined as the ratio of images featuring female individuals to the total number of people depicted in the images. The *GenderScore* is then integrated into the mutual fund holdings dataset outlined in Section 2.1. It is important to note that as we start sample construction from international brands, in contrast to the predominantly U.S. and Canadian company coverage of CRSP/Compustat, the final sample used for analysis results in a reduced number of 81 companies. These companies comprise about 10% of the market value of the equity holdings of the single-managed mutual funds analyzed. Figure 2 plots the fraction of holdings covered in our dataset over time.

[INSERT FIGURE 2 ABOUT HERE]

[INSERT TABLE 1 ABOUT HERE]

3 Results

3.1 Descriptive statistics

Table 1 presents the *GenderScore* variables for the brands in our sample, calculated using both 'Testimonial' and 'Customers' keywords. This table also includes market capitalization data and one-digit SIC classification for each firm, following Bali, Engle, and Murray (2016). The brands are sorted in descending order based on their *GenderScore* derived from 'Testimonials'. Upon examining firm size and industry classification, no discernible pattern emerges. The top (bottom) brands ranked by *GenderScore* are not consistently large (small) firms, indicating that firm size is not correlated with *GenderScore*. Similarly, the score does not serve as a proxy for any specific industry. While Estée Lauder, the top-ranked company, operates uniquely in the cosmetics industry, pharmaceutical companies – which could be considered a related industry – are evenly distributed throughout the list. This pattern extends to other sectors as well; financial institutions generally align with more masculine brands, yet American Express stands in the top quartile of the score. Similarly, despite clothing brands often achieving high scores (such as Gap or Ralph Lauren), Nike is positioned in the lower quartile. The table includes scores derived from two distinct keywords. While there is a strong correlation between these scores, they are not identical, reflecting the dual facets they aim to capture. As discussed previously, the keyword 'Customer' tends to more accurately reflect the actual consumer base, possibly less affected by the brand's marketing efforts, whereas 'Testimonial' often showcases the idealized customer as depicted by the company's marketing narrative. Despite these differences, these scores largely overlap: Estée Lauder is by far the top brand regardless of the measure, and FedEx, the most masculine brand according to 'Testimonial', is among the lowest in the 'Customer' score.

[INSERT TABLE 2 ABOUT HERE]

Table 2 presents the descriptive statistics for the two metrics, categorized by industry, reinforcing the previously discussed observations. Although there are variations in both the mean and median values across industries, these differences are generally minor and not statistically significant. Yet, some noticeable differences among industries emerge as the standard deviation of these metrics varies by sector, with Transportation displaying considerable variation, while Retail exhibits relatively uniform metrics across the board.

[INSERT TABLE 3 ABOUT HERE]

Table 3 outlines the control variables employed in our regression analysis, categorized into fund-level and stock-level variables. The variables presented align with those commonly used in mutual fund literature and the reported values are consistent with findings from other studies (e.g., Niessen-Ruenzi and Ruenzi, 2019; Alok et al., 2020; Ben-David et al., 2022). Among the fund-level characteristics, the dummy variable identifying female single-managed funds (Female Manager) shows a mean value of 9%, mirroring the distribution depicted in Figure 2, which indicates that approximately one in ten funds is managed by a female. Nr.Stocks reflects the count of stocks in each fund portfolio that align with our brand stock criteria, distinct from the total stock count in the fund. As Figure 1 illustrates, focusing on major brand-associated stocks for our gender score computation allows us to match on average (median) roughly one in ten (twenty) stocks per fund portfolio to our specified brand criteria. For each fund, we are able to match on average (median) 5 (2) stocks.[5]

Upon analyzing the control variables at the stock level, we find the standard control metrics based on profitability, size, risk, leverage, liquidity, and valuation. These measures do not exhibit any significant deviations when compared to similar studies. Additionally, Table 3 includes the $GenderScore$, uniformly reporting an average and median of 0.27 for both 'Testimonial' and 'Customer' metrics, indicating a consistent trend across these measures.

3.2 Regression analysis

In this section, we provide evidence of a distinct investment pattern among female fund managers, who are more inclined to allocate their portfolios toward stocks linked to brands with higher female gender scores, compared to their male counterparts.

[5]A potential concern in our study is the high dropout rate, which might introduce a selection bias. However, it's important to note that the unmatched firms are generally smaller and less representative compared to the stocks in our sample, which are more typical of mutual fund holdings. Predominantly, major brands, due to their market valuation, are associated with large-cap companies. This suggests a lower likelihood that a company frequently found in U.S. mutual fund portfolios would be absent from our sample. Thus, while the numeric representation of stocks in the sample might be partial, the impact on market capitalization due to dropout is significantly less pronounced.

[INSERT TABLE 4 ABOUT HERE]

In Table 4, we present the results of panel ordinary least squares (OLS) regressions, where the dependent variable is a binary indicator that takes the value of 1 if a fund holds a specific stock in a given quarter, and 0 otherwise. Specifically, the operate the following regression model:

We run the following regression:

$$Y_{i,j,t} = \beta FemaleDummy_{i,t} \times GenderScore_j + X_{i,t} + Z_{j,t} + f_t + f_z + \epsilon_{i,j,t}\,, \tag{1}$$

where $Y_{i,j,t}$ is a dummy that takes value 1 if fund i at year-quarter t holds stock j, belonging to industry z. As a result, our unit of observation is conducted at the fund-stock-quarter level. We control for time-variant characteristics of both the fund ($X_{i,t}$) and stock ($Z_{i,t}$), along with year-quarter, industry, and fund fixed effects. Fund characteristics include total net assets, quarterly return, and the fund's age in years since inception. Stock characteristics encompass return on equity, leverage (measured as book value of debt over book assets), cash holdings over book assets, log of total firm sales, dividend yield, Tobin's q, past year stock return and volatility, stock beta, and liquidity (measured by the ratio of monthly trading volume to total outstanding shares). Crucially, we include a dummy variable, $Female\ Manager$, identifying female-managed funds, and our brand gender score, $GenderScore(Testimonial)$, which is calculated as the fraction of females depicted in images from searches combining 'Brand Name' and 'Testimonial'. Standard errors are clustered at the at the fund-stock and year-quarter levels.

Our variable of interest is the interaction between the $Female\ Manager$ dummy and the $GenderScore(Testimonial)$. The $Female\ Manager$ variable independently assesses the likelihood of a stock appealing to a female fund manager, while the $GenderScore(Testimonial)$ gauges the likelihood of a 'female' stock being included in a mutual fund portfolio, irrespective of the manager's gender. This interaction directly addresses our research question, providing insight into whether female fund managers show a stronger preference for 'female' stocks compared to male fund managers. The first regression model in your analysis reveals that the interaction variable, as hypothesized, is positively and strongly significant statistically. Economically speaking, a one standard deviation increase in the gender score results in a 58 basis point rise in the probability of a stock being included in a female-managed fund. For context, the unconditional likelihood of a stock being held in any portfolio is 8%. This finding robustly supports the research hypothesis and offers a previously undocumented bias within the mutual fund industry.

Two comments are in order. First, as previously noted, defining brand gender is not straightforward. For instance, while Estée Lauder and Caterpillar may have a strong gender characterization, other brands may have a weaker or non-existent gender connotation. Observing the distribution of brand gender scores, it appears that this characterization is more pronounced at the top and bottom ends, but less so towards the center. The second comment relates to the correlation between the gender of fund managers and the gender characterization of stocks. Previous results indicate a clear preference for feminine-branded stocks among female fund managers. However, the interaction variable does not conclusively show whether male fund managers have a similar preference for 'masculine' stocks. To explore this, the second regression model (Table 4) introduces a double interaction variable, combining the $FemaleManager$ dummy with two others that are valued at 1 when $GenderScore(Testimonial)$ is at its highest or lowest relative to the quartile, labeled as $GenderScore(Testimonial)$ $Above75$ and $GenderScore(Testimonial)$ $Below25$, respectively. The results reveal that at the higher end of the gender score distribution, the coefficient doubles, suggesting a stronger preference by female fund managers for distinctly feminine brands. In contrast, at the lower end of the spectrum, the coefficient is not significant, indicating no notable difference between female and male-managed funds in holding masculine stocks. This suggests that the preference for gender-branded stocks is predominantly exhibited by females rather than their male counterparts. In the third and final regression model presented in Table 4, we introduce an interaction between the $Female\ Manager$ dummy and a dummy variable that assumes a value of 1 for the brands in the top 90th percentile of the gender score. This essentially focuses on the top 8 feminine brands according to our methodology. The findings corroborate the patterns observed in the previous model, indicating a progressively stronger effect at elevated gender score levels. Specifically, within the top decile, the propensity of a female fund manager to select a feminine stock is about threefold greater than the average effect.

Previous results clearly demonstrate that stocks with a strong feminine brand characterization are more prevalent in portfolios managed by female fund managers. However, this correlation alone does not necessarily establish causality. To address the possibility that our findings might be influenced by an omitted variable simultaneously driving the presence of a female fund manager and the preference for stocks with a marked brand gender score, we undertake an in-depth analysis. Specifically, similarly to Niessen-Ruenzi and Ruenzi (2019), we study the changes in fund asset allocation during periods of gender transition in fund management, such as when a fund's management changes from male-to-female, or vice versa. By analyzing the fund composition both before and after such transitions, and contrasting these findings with a control group of funds that have not experienced a change in managerial gender, we aim to establish a more robust causal link between the appointment of a female manager and the increased inclusion of feminine-branded stocks in fund portfolios. While this identification strategy aids in substantiating the hypothesized causal effect, it also presents a limitation due to the scarce instances of gender transitions in fund management observed in our sample. Specifically, throughout our entire sample period, we document only 87 cases where female-managed funds transitioned to male management, and 86 instances of the reverse. This limited number of occurrences poses challenges in generating statistically significant results.

[INSERT TABLE 5 ABOUT HERE]

The first model in Table 5 details the results of this empirical strategy. The regression structure closely mirrors that previously described in the paper. We use a dummy as the dependent variable, assigned a value of 1 when a particular stock is included in the fund portfolio for a given quarter. Our analysis is limited to funds that, throughout the sample period, are either consistently male-managed (constituting the control group) or undergo a transition from male to female management (forming the treated group).

The $MaleToFem$ dummy variable identifies the treated sample, assigned the value of 1 from the quarter when there is a transition from male-to-female management up until a subsequent manager change, if any. We lag this variable by one quarter. The model incorporates control variables, fixed effects, and error clustering consistent with the approaches used in previous regressions. Consistent with our hypothesis, we find a positive and significant coefficient associated with the 'treat' interaction variable ($GenderScore \times MaleToFem$). This result not only confirms but also strengthens our earlier findings, suggesting a distinct preference for more feminine stocks in fund portfolios post-transition from male to female management, compared to the allocations in the same funds before the change and in those that remain under male management. The second model mirrors the first, with the key distinction being the inversion of gender roles. In this regression, the control group comprises funds consistently managed by females, while the treated group includes funds transitioning from female-to-male management. The $FemToMale$ dummy variable identifies this treated sample. The interaction term $GenderScore \times FemToMale$ is used to assess the likelihood of including a feminine stock in the fund portfolio during the transition from female-to-male management, compared to the same funds before the transition and those that remain under female management. The coefficient of this interaction variable is negative, aligning with the hypothesis that the replacement of a female manager by a male leads to a higher likelihood of incorporating more masculine (or less feminine) stocks into the portfolio. However, the lack of statistical significance in this coefficient precludes any definitive conclusions in support of this hypothesis.

[INSERT TABLE 6 ABOUT HERE]

So far, this study has compellingly indicated the existence of a propensity among female fund managers to favor stocks linked to brands that exhibit more feminine characteristics. However, we have not yet considered the potential role of the influence of brand advertising expenditures. In fact, larger advertising budgets could potentially enhance the visibility of a stock, thereby increasing its likelihood of being incorporated into a fund's portfolio. In this context, Grullon et al. (2004) find that, all other factors being equal, companies with higher advertising spending tend to attract a more substantial number of both individual and institutional investors, resulting in increased liquidity of their common stock. Should advertising be a predominant factor, one might anticipate a higher inclination among fund managers, regardless of gender, to choose stocks associated with feminine brands. Yet, in contradiction to this premise, our analysis reveals that the observed pattern is distinctly linked to female fund managers. However, to further validate these findings and address this potential confounding factor, we also incorporate a control for advertising expenditures. Results reported in Table 6 suggest that there is no significant relationship between the level of advertising spending ($LogAdvertising$) and the likelihood of a stock being selected for inclusion in fund portfolios, nor are female fund managers more influenced by advertising spending than their male counterparts ($Female\ Manager \times LogAdvertising$). Crucially, even when accounting for advertising expenditures, the correlation between the femininity score of a brand and its selection in portfolios managed by a female manager remains robust and consistent ($Female\ Manager \times GenderScore(Testimonial)$). This evidence once again confirms the investment behavior exhibited by female fund managers in their selection of stocks aligned with feminine brand attributes.

[INSERT TABLE 7 ABOUT HERE]

[INSERT TABLE 8 ABOUT HERE]

We also conduct three main robustness checks. First, we conduct our analyses using a gender score computed with the keyword 'Customers' instead of 'Testimonial' (while still combined with the brand name). As previously noted, although these two keywords yield similar scores, they are designed to gauge different nuances and characterizations of the brand. Consequently, it is not surprising that, despite being highly correlated, these scores are not perfectly overlapping. The outcomes of this modified approach are detailed in Table 7, where we can notice that the evidence reported in the previous section is largely confirmed. With the sole exception of the interaction variable between $Female\ Manager$ and $GenderScore(Customers)\ Above90$, which shows a still positive but no longer significant coefficient, the other regression models consistently confirm the signs, statistical significance, and even larger coefficients. Second, instead of merely explaining whether a fund i holds stock j (using the dummy variable $Y_{i,j,t}$ as dependent variable), we regress portfolio weights $W_{i,j,t}$ on the interaction variable $Female\ Manager \times GenderScore(Testimonial)$, controlling for fund and stock characteristics. As documented in Table 8, our results prevail also under this specification. Column (i) mirrors the main effect displayed in Table 4, while the next columns use interaction terms constructed from quantiles of the gender score and confirm that the preference for gender-branded stocks is predominantly exhibited by females rather than their male counterparts. Third, we observe that one brand stands out from the others in terms of gender score. Specifically, Estée Lauder has a brand gender score of 0.82, while the next highest, Tiffany & Co., follows with a score of 0.53. This discrepancy raises a legitimate question about whether our findings are heavily influenced by a single brand. To address this concern, we rerun our regressions excluding Estée Lauder from our sample, but our results remain unchanged. Finally, in all our regressions, we cluster errors at the fund level due to the potential non-independence of observations within each fund, as individual investment decisions are likely influenced by fund-specific strategies and characteristics. Clustering error terms corrects for potential intra-fund correlation and ensures more accurate standard error estimation, thereby enhancing the reliability and robustness of our statistical inferences. To further control for unobserved heterogeneity in stocks, we repeat our analyses by clustering the errors at the stock level, without observing any appreciable difference.

4 Conclusions

This paper presents, for the first time in the financial literature, an exploration of the influence of brand gender on the stock selection process of mutual fund managers. Employing machine learning and image recognition techniques, we propose a novel methodology for assessing the gender identity of brands based on the proportion of female individuals depicted in images associated with each brand. Our investigation, spanning from 2009 to 2021, reveals a compelling propensity among female fund managers to favor 'feminine' stocks, that is, stocks associated with more feminine brands, especially those with a strong gender attribution. The findings are economically significant, with a one standard deviation increase in the brand gender score correlating with a 58 basis point rise in the probability of a 'feminine' stock's inclusion in a female-managed fund's portfolio – a likelihood that intensifies at the higher percentiles of the gender score distribution. By controlling for confounding variables, we aim to mitigate concerns regarding causality. The composition of fund portfolios following managerial gender changes within funds further substantiates our results, reducing the likelihood that omitted variables may be driving our findings. Moreover, advertising expenditure, previously shown to be an important factor in the inclusion of stocks in fund portfolios, does not significantly influence our results. In summary, our research contributes to the literature by presenting a previously undocumented aspect of behavioral finance: the alignment of fund managers' stock selections with brand gender identity. This alignment is particularly pronounced among female fund managers, suggesting an intrinsic connection between gender identity and investment decisions, independent of other financial indicators and investment behaviors.

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Table 1: List of companies analysed

Brand	GenderScore (Testimonial)	GenderScore (Customers)	Market Cap (millions USD)	Industry
Estée Lauder	0.82	0.70	16,915.05	Manufacturing
Tiffany & Co.	0.53	0.36	8,521.37	Retail
AT&T	0.49	0.41	174,936.55	Transportation
ICU Medical	0.48	0.36	1,548.76	Manufacturing
American Airlines	0.47	0.53	5,812.00	Transportation
HP	0.40	0.34	62,054.99	Manufacturing
Johnson & Johnson	0.39	0.36	238,806.95	Manufacturing
Hilton	0.39	0.50	27,743.68	Services
HCA Healthcare	0.38	0.33	41,642.43	Services
American Express	0.38	0.26	69,105.49	Finance
Celgene	0.37	0.38	35,806.29	Manufacturing
Sotheby's	0.36	0.20	1,778.91	Services
Salesforce.com	0.36	0.30	68,030.57	Services
Gap	0.36	0.30	13,900.62	Retail
Blackbaud	0.35	0.32	2,437.68	Services
Cisco	0.35	0.36	156,155.04	Manufacturing
Starbucks	0.34	0.25	45,178.29	Retail
Texas Roadhouse	0.34	0.29	2,723.03	Retail
Cintas	0.34	0.27	11,547.37	Manufacturing
Hewlett Packard Enterprise	0.33	0.38	16,368.70	Services
Oracle	0.33	0.10	136,005.80	Services
Ralph Lauren	0.33	0.16	4,452.11	Manufacturing
Cigna	0.33	0.32	26,039.75	Finance
CenterPoint Energy	0.33	0.26	8,183.58	Utilities
Choice Hotels	0.32	0.23	2,850.36	Services
Citi	0.32	0.34	165,694.07	Finance
UnitedHealth	0.31	0.31	104,537.83	Finance
Pinnacle Financial Partners	0.31	0.24	2,174.95	Finance
Ormat Technologies	0.31	0.18	2,157.49	Utilities
Marriott	0.30	0.40	20,681.48	Services
J.P. Morgan	0.30	0.15	196,943.94	Finance
HubSpot	0.30	0.32	30,050.87	Services
Colgate	0.30	0.26	45,692.44	Manufacturing
McDonald's	0.29	0.25	83,416.83	Retail
Netflix	0.29	0.24	61,581.90	Services
Avery Dennison	0.29	0.18	6,603.13	Manufacturing
Coca-Cola	0.28	0.37	154,510.65	Manufacturing

Continuation of Table 1				
Brand	GenderScore (Testimonial)	GenderScore (Customers)	Market Cap (millions USD)	Industry
Amgen	0.28	0.38	85,927.70	Manufacturing
John Deere	0.28	0.13	31,614.52	Manufacturing
Amazon	0.27	0.35	315,685.79	Services
Centene	0.27	0.38	10,641.13	Finance
IBM	0.26	0.26	156,905.35	Manufacturing
Baxter	0.26	0.21	33,880.50	Manufacturing
Raytheon	0.26	0.21	72,656.29	Manufacturing
Pfizer	0.26	0.36	197,988.03	Manufacturing
Apple	0.26	0.23	486,756.66	Manufacturing
Robert Half	0.25	0.49	5,454.50	Services
Campbell's	0.24	0.29	12,928.47	Manufacturing
Ford	0.24	0.16	36,136.96	Manufacturing
Waste Management	0.23	0.29	25,104.73	Utilities
Visa	0.23	0.32	247,737.24	Services
PTC	0.23	0.33	4,262.23	Services
Caterpillar	0.23	0.30	49,804.26	Manufacturing
UPS	0.23	0.15	64881.06	Transportation
Disney	0.22	0.28	67,437.62	Services
Facebook	0.22	0.53	481,404.46	Services
Intel	0.21	0.07	163,950.39	Manufacturing
Northern Trust	0.21	0.33	14,717.42	Finance
Jeffries	0.21	0.10	4,467.93	Services
Parker-Hannifin	0.20	0.12	13,990.93	Manufacturing
Texas Instruments	0.20	0.28	63,125.62	Manufacturing
Motorola	0.20	0.18	27,344.96	Manufacturing
Tetra Tech	0.20	0.20	2,030.79	Services
Moody's	0.20	0.25	18,282.20	Services
Morgan Stanley	0.19	0.06	65,299.97	Finance
SeaWorld	0.19	0.28	2,341.10	Services
Leggett & Platt	0.18	0.24	4,213.57	Manufacturing
Mobil	0.18	0.30	354,857.21	Manufacturing
AIG	0.17	0.16	93,803.93	Finance
Nike	0.16	0.14	57,365.08	Manufacturing
Tesla	0.16	0.11	178,463.11	Manufacturing
Boeing	0.15	0.32	79,308.90	Manufacturing
Pepsi	0.14	0.38	120,522.31	Manufacturing
FedEx	0.08	0.15	34,316.76	Transportation

Table 2: Descriptive statistics of the Gender Score variable by industry

Industry	Min	Pctl(25)	Median	Mean	Pctl(75)	Max	Std. Dev.	N
GenderScore(Testimonial)								
Finance	0.17	0.22	0.30	0.28	0.32	0.38	0.07	10
Manufacturing	0.14	0.20	0.26	0.28	0.31	0.82	0.13	31
Retail	0.29	0.34	0.34	0.37	0.36	0.53	0.09	5
Services	0.19	0.22	0.29	0.28	0.33	0.39	0.07	21
Transportation	0.08	0.19	0.35	0.32	0.48	0.49	0.20	4
Utilities	0.23	0.27	0.31	0.29	0.32	0.33	0.05	3
GenderScore(Customers)								
Finance	0.06	0.18	0.29	0.26	0.33	0.38	0.10	10
Manufacturing	0.07	0.18	0.27	0.27	0.36	0.70	0.12	31
Retail	0.25	0.25	0.29	0.29	0.30	0.36	0.05	5
Services	0.10	0.24	0.32	0.31	0.35	0.53	0.11	21
Transportation	0.15	0.15	0.28	0.31	0.44	0.53	0.19	4
Utilities	0.18	0.22	0.26	0.24	0.27	0.29	0.06	3

This table reports descriptive statistics of the *GenderScore(Testimonial)* and *GenderScore(Customers)* variables by industry group. Industry codes to industry descriptions following Bali et al. (2016).

Table 3: Summary statistics of fund and stock characteristics

Variable Name	Mean	Std. Dev.	P10	P25	Median	P75	P90	N
Fund Chars								
Equity Holdings	3,129.92	9,947.49	26.78	85.07	444.02	1,909.35	7,280.41	657
TNA	3,125.80	9,978.12	27.07	83.27	406.71	1,873.39	7,270.36	657
Return	0.05	0.05	-0.03	0.01	0.05	0.08	0.11	657
Female Manager	0.09	0.29	0.00	0.00	0.00	0.00	0.00	657
Nr.Stocks	5.00	6.98	0.00	0.00	2.00	7.00	14.00	657
Fund Age	19.52	14.32	3.25	7.99	18.97	27.22	35.80	657
Stock Chars								
ROE	0.05	1.21	-0.34	0.05	0.21	0.36	0.78	81
Leverage	0.36	0.19	0.14	0.22	0.34	0.46	0.57	81
Cash	0.16	0.11	0.04	0.07	0.13	0.21	0.30	81
Sales	49.57	65.68	1.43	6.49	24.11	63.49	125.98	81
LogAdvertising	5.99	2.02	3.19	4.66	6.15	7.60	8.17	49
Dividend	1.43	1.48	0.00	0.00	1.14	2.32	3.04	81
Tobin's q	3.03	2.15	1.06	1.36	2.40	3.70	5.80	81
Ret	0.06	0.07	-0.04	0.02	0.07	0.10	0.14	66
Last 12M return	0.28	0.30	-0.07	0.11	0.24	0.40	0.62	66
Last 12M Vola	0.26	0.11	0.16	0.20	0.24	0.29	0.37	66
Beta	1.07	0.41	0.58	0.76	1.02	1.32	1.62	66
TradingVol/ShareOut	0.17	0.14	0.08	0.10	0.12	0.18	0.28	66
GenderScore(Testimonial)	0.27	0.11	0.16	0.20	0.27	0.33	0.38	81
GenderScore(Customers)	0.27	0.12	0.13	0.18	0.27	0.33	0.38	81

This table provides means, standard deviations, and quantiles of the main variables of interest, as of Q4 2021. Accounting data refer to the 2021 year. **Fund Chars** include the following variables: Equity Holdings is the value of the equity holdings in each mutual fund (in USD million). TNA is the total net assets for the fund (in USD million). Fund Return is the fund quarterly return. Female Manager is a dummy variable, which takes value 1 if the fund is managed by a female manager, 0 otherwise. Nr Stocks is the total number of stocks held by the fund. Fund Age is the age of the fund in years since inception. **Stock Chars** include the following variables: ROE is net income (NI) over book equity (CEQ). Leverage is book value of debt (DLTT+DLC) over book assets (AT). Cash is cash holdings (CHE) over book assets (AT). Sales is the total firm's sales (in USD billion). LogAdvertising is the log of 1 plus adverstising expeditures (XAD). Dividend is dividend per share (DVPSX) over stock price (PRCC), multiplied by 100. Tobin's q is book value of assets (AT) minus the book value of equity (CEQ) plus the market value of equity (CSHO*PRCC), all divided by book value of assets (AT). Ret is monthly stock return. Last 12M return is the cumulative stock returns over the last 12 months. Last 12M vola is stock volatility computed over the last 12 months. Beta is the stock beta computed using 5 years of data and requiring at least 48 months with return data. TradingVol/ShareOut is trading share (VOL) divided by total outstanding shares (SHROUT). Accounting and stock market variables are winsorized at the 99^{th} percentile. GenderScore(Testimonial) (or C) is the fraction of images with female people that appear online when using the query search: "Brand Name" + Testimonial (or Customer).

Table 4: Regression of funds' stock holding dummy

	Dummy Holding		
	[i]	[ii]	[iii]
Female Manager × GenderScore(Testimonial)	0.0525***		
	(3.031)		
Female Manager × GenderScore(Testimonial) Above75		0.0106**	
		(2.265)	
Female Manager × GenderScore(Testimonial) Below25		0.0000	
		(0.0148)	
Female Manager × GenderScore(Testimonial) Above90			0.0159**
			(2.474)
Observations	2,667,108	2,667,108	2,667,108
R^2	0.2048	0.2051	0.2047
Fund Controls	(Yes)	(Yes)	(Yes)
Stock Controls	(Yes)	(Yes)	(Yes)
Year-Quarter FEs	(Yes)	(Yes)	(Yes)
Industry FEs	(Yes)	(Yes)	(Yes)
FundId FEs	(Yes)	(Yes)	(Yes)

This table shows estimates from regressions of funds' stock holding dummy on fund and stock characteristics. Female Manager is a dummy variable, which takes value 1 if the fund is managed by a female manager, 0 otherwise. GenderScore(Testimonial) is the fraction of images with female people that appear online when using the query search: "Brand Name" + Testimonial. Fund characteristics include: the total net assets for the fund; the fund quarterly return; the age of the fund in years since inception. Stock characteristics include: Return on equity; leverage measured as the book value of debt over book assets; cash holdings over book assets; total firms' sales; dividend per share over stock price; Tobin's q; stock return and volatility; stock beta; and trading share divided by total outstanding shares. Accounting and stock market variables are winsorized at the 99^{th} percentile. Standard errors are double clustered at the fund-stock and year-quarter levels. ***,**,* denote that estimates are statistically significant at the 1, 5 and 10 percent levels.

Table 5: Regression of funds' stock holding dummy around fund manager gender change

	Dummy Holding	
	Male Control Group	Female Control Group
GenderScore(Testimonial) $\times$ MaleToFem$_{i,t-1}$	0.0893*	
	(1.995)	
GenderScore(Testimonial) $\times$ FemToMale$_{i,t-1}$		-0.0325
		(-0.9151)
Observations	2,368,019	243,979
R^2	0.2052	0.2101
Fund Controls	(Yes)	(Yes)
Stock Controls	(Yes)	(Yes)
Year-Quarter FEs	(Yes)	(Yes)
Industry FEs	(Yes)	(Yes)
FundId FEs	(Yes)	(Yes)

This table shows estimates from regressions of funds' stock holding dummy on fund and stock characteristics around fund manager gender change. Column [i] refers to the subsets of male-only funds or fund managed by a male manager then replaced by a female one. Column [ii] refers to the subsets of female-only funds or fund managed by a female manager then replaced by a male one. GenderScore(Testimonial) is the fraction of images with female people that appear online when using the query search: "Brand Name" + Testimonial. MaleToFem$_{i,t-1}$ dummy variable equal to 1 if a male manager is replaced by a female one in the previous quarter, zero otherwise. FemToMale$_{i,t-1}$ dummy variable equal to 1 if a female manager is replaced by a male one in the previous quarter, zero otherwise. Fund characteristics include: the total net assets for the fund; the fund quarterly return; the age of the fund in years since inception. Stock characteristics include: Return on equity; leverage measured as the book value of debt over book assets; cash holdings over book assets; total firms' sales; dividend per share over stock price; Tobin's q; stock return and volatility; stock beta; and trading share divided by total outstanding shares. Accounting and stock market variables are winsorized at the 99^{th} percentile. Standard errors are double clustered at the fund-stock and year-quarter levels. ***,**,* denote that estimates are statistically significant at the 1, 5 and 10 percent levels.

Table 6: Regression on stock holding dummy adding the Advertising variable

	Dummy Holding	
	[i]	[ii]
Female Manager × LogAdvertising	0.0001	0.0002
	(0.1018)	(0.1362)
Female Manager × GenderScore(Testimonial)		0.0602***
		(3.100)
LogAdvertising	-0.0010	-0.0010
	(-0.9252)	(-0.9304)
Observations	1,662,913	1,662,913
R^2	0.2204	0.2204
Fund Controls	(Yes)	(Yes)
Stock Controls	(Yes)	(Yes)
Year-Quarter FEs	(Yes)	(Yes)
Industry fixed effects	(Yes)	(Yes)
FundId FEs	(Yes)	(Yes)

This table shows estimates from regressions of funds' stock holding dummy on fund and stock characteristics. LogAdvertising is log of 1 plus advertising expenditures (XAD). Female Manager is a dummy variable, which takes value 1 if the fund is managed by a female manager, 0 otherwise. GenderScore(Testimonial) is the fraction of images with female people that appear online when using the query search: "Brand Name" + Testimonial. Fund characteristics include: the total net assets for the fund; the fund quarterly return; the age of the fund in years since inception. Stock characteristics include: Return on equity; leverage measured as the book value of debt over book assets; cash holdings over book assets; total firms' sales; dividend per share over stock price; Tobin's q; stock return and volatility; stock beta; and trading share divided by total outstanding shares. Accounting and stock market variables are winsorized at the 99^{th} percentile. Standard errors are double clustered at the fund-stock and year-quarter levels. ***,**,* denote that estimates are statistically significant at the 1, 5 and 10 percent levels.

Table 7: Regression of funds' stock holding dummy using GenderScore(Customers)

	Dummy Holding		
	[i]	[ii]	[iii]
Female Manager × GenderScore(Customers)	0.0746***		
	(4.281)		
Female Manager × GenderScore(Customers) Above75		0.0109**	
		(2.174)	
Female Manager × GenderScore(Customers) Below25		-0.0090**	
		(-2.171)	
Female Manager × GenderScore(Customers) Above90			0.0090
			(1.433)
Observations	2,667,108	2,667,108	2,667,108
R^2	0.2047	0.2048	0.2047
Fund Controls	(Yes)	(Yes)	(Yes)
Stock Controls	(Yes)	(Yes)	(Yes)
Year-Quarter FEs	(Yes)	(Yes)	(Yes)
Industry FEs	(Yes)	(Yes)	(Yes)
FundId FEs	(Yes)	(Yes)	(Yes)

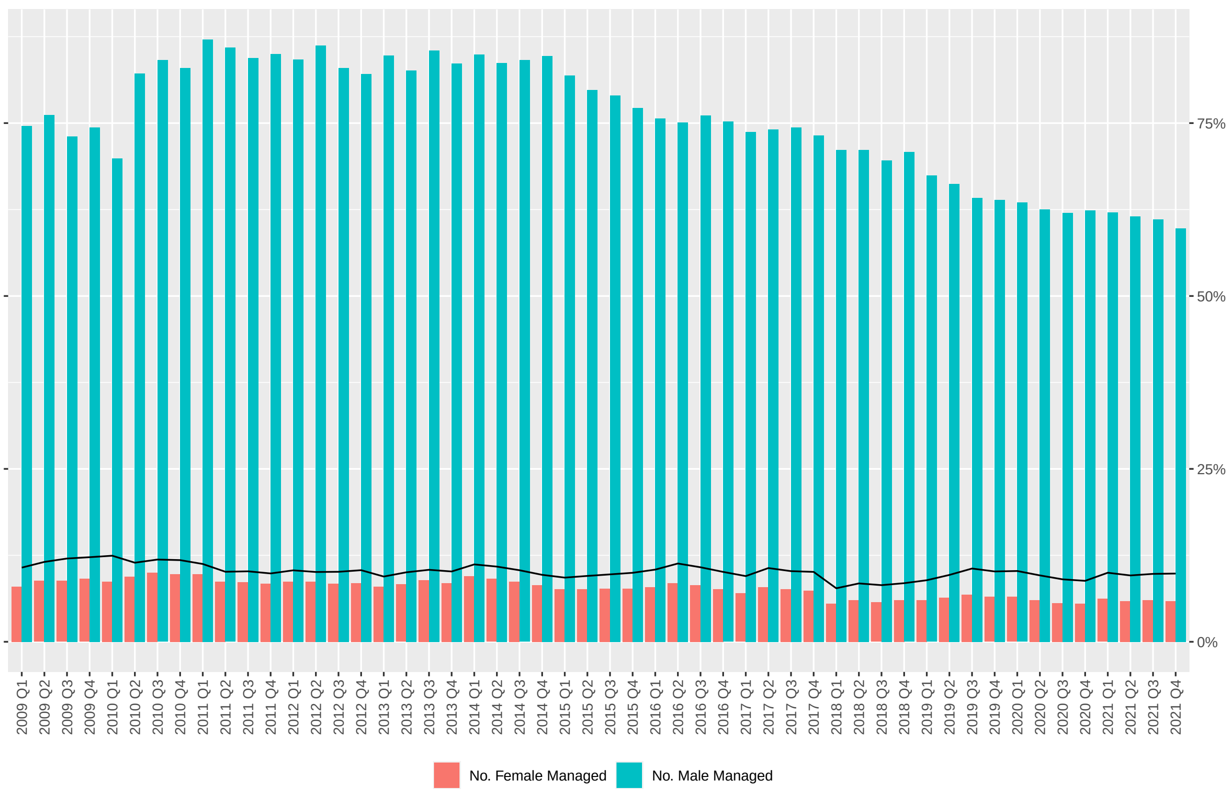
This table shows estimates from regressions of funds' stock holding dummy on fund and stock characteristics. FEMALE MANAGER is a dummy variable, which takes value 1 if the fund is managed by a female manager, 0 otherwise. GENDERSCORE(CUSTOMERS) is the fraction of images with female people that appear online when using the query search: "Brand Name" + Customers. Fund characteristics include: the total net assets for the fund; the fund quarterly return; the age of the fund in years since inception. Stock characteristics include: Return on equity; leverage measured as the book value of debt over book assets; cash holdings over book assets; total firms' sales; dividend per share over stock price; Tobin's q; stock return and volatility; stock beta; and trading share divided by total outstanding shares. Accounting and stock market variables are winsorized at the 99^{th} percentile. Standard errors are double clustered at the fund-stock and year-quarter levels. ***,**,* denote that estimates are statistically significant at the 1, 5 and 10 percent levels.

Table 8: Regression of funds' stock weight dummy

	Stock weight		
	[i]	[ii]	[iii]
Female Manager × GenderScore(Testimonial)	0.0009^{**}		
	(2.249)		
Female Manager × GenderScore(Testimonial) Above75		0.0003^{*}	
		(2.007)	
Female Manager × GenderScore(Testimonial) Below25		5.74×10^{-5}	
		(0.4180)	
Female Manager × GenderScore(Testimonial) Above90			0.0004^{*}
			(1.956)
Observations	2,667,108	2,667,108	2,667,108
R^2	0.0800	0.0811	0.0800
Fund Controls	(Yes)	(Yes)	(Yes)
Stock Controls	(Yes)	(Yes)	(Yes)
Year-Quarter FEs	(Yes)	(Yes)	(Yes)
Industry FEs	(Yes)	(Yes)	(Yes)
FundId FEs	(Yes)	(Yes)	(Yes)

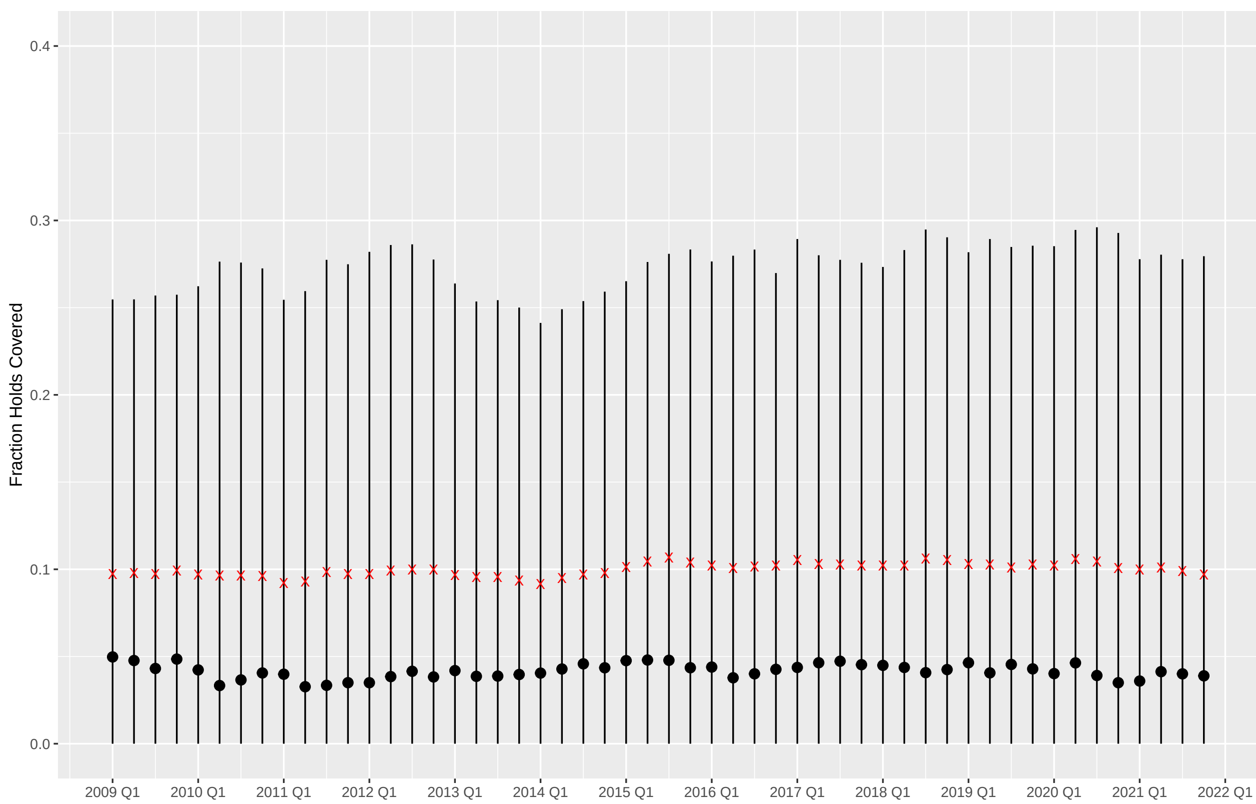
This table shows estimates from regressions of funds' stock weights on fund and stock characteristics. Female Manager is a dummy variable, which takes value 1 if the fund is managed by a female manager, 0 otherwise. GenderScore(Testimonial) is the fraction of images with female people that appear online when using the query search: "Brand Name" + Testimonial. Fund characteristics include: the total net assets for the fund; the fund quarterly return; the age of the fund in years since inception. Stock characteristics include: Return on equity; leverage measured as the book value of debt over book assets; cash holdings over book assets; total firms' sales; dividend per share over stock price; Tobin's q; stock return and volatility; stock beta; and trading share divided by total outstanding shares. Accounting and stock market variables are winsorized at the 99^{th} percentile. Standard errors are double clustered at the fund-stock and year-quarter levels. ***,**,* denote that estimates are statistically significant at the 1, 5 and 10 percent levels.

Figure 1: Distribution of funds by manager gender



This figure shows the total number of female- and male-managed funds over the period from Q1 2009 to Q4 2021. The black line indicates the fraction of female-managed funds.

Figure 2: Fraction of fund holdings covered



This figure shows the fraction of holdings covered in the dataset for the period from Q1 2009 to Q4 2021. Specifically, coverage at the fund level is computed as the ratio between the market value of stocks analysed (see Table 1) and the total market value of equity holdings. The black vertical lines indicate the 10^{th} and 90^{th} quantiles, the black point refers to the median, while the red cross to the mean.