

**The influence of the female voice on the Billboard Hot 100 across time:
Social mood and investor trading behavior**

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Abstract:

We examine how popular music, as a reflection of social mood, influences mutual fund flows through the lens of the Environmental Security Hypothesis (ESH). Analyzing a sample of mutual fund portfolios, we find that sad music negatively predicts fund flows, while happy music positively predicts flows, consistent with music capturing investor sentiment. Critically, when sad music performed by female artists dominates the Billboard Top 40 charts, funds managed exclusively by women experience significantly higher inflows. This relationship is absent during periods of happy music, supporting the ESH prediction that investors seek reassurance from female leadership during periods of collective pessimism. Our findings are robust to alternative specifications, entropy balancing, and alternative sentiment measures. This behavioral channel operates independently of fund performance, fees, and other traditional determinants, revealing a novel dimension through which gendered cultural products and social mood jointly influence retail investor decision-making. The confluence of female leadership in finance and female expression in popular culture during pessimistic periods appears to create a particularly powerful signal of reassurance and security for investors, resulting in substantially higher capital allocations to female-managed funds.

Keywords:

Social mood, gender, mutual fund flows, investor sentiment, popular music

JEL Classification: G02, Z11, Z13

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“Music does a lot of things for a lot of people. It’s transporting, for sure. It can take you right back, years back, to the very moment certain things happened in your life. It’s uplifting, it’s encouraging, it’s strengthening.” -Aretha Franklin

1 – INTRODUCTION

Music is a powerful cultural product. It influences individual’s thoughts (Krumhansl, 2002; Nisbett et al., 2001) and behavior (Anderson et al., 2003; Yamagishi et al., 2008), including investor risk preferences (Israel et al., 2019) and trading behavior (Guan et al., 2025). Music, especially popular music, serves as a mirror reflecting the overall sociological condition of society (Chesebro et al., 1985; Napier & Shamir, 2018; Putter et al., 2022) or what we define as social mood—a collective sense of optimism or pessimism among members of a society. For example, Beyoncé’s chart-topping hit “Break My Soul” captures a prevailing culture of work dissatisfaction and the broader movement of the Great Resignation (Hobsbawm, 2022), while The Cranberries’ “Zombies” expresses rage and grief at the persistence of violence in 1990s Ireland (Savage, 2018). Given music’s profound influence on thought and behaviour and its role as a reflection of collective sentiment, popular music represents a potentially rich source of information about investor psychology and decision-making. If music reflects social mood, and social mood in turn shapes risk preferences and financial choices, then the Billboard charts may influence capital flows and market behaviour. Notably, female artists have historically given voice to periods of social anxiety and emotional vulnerability, with women’s vocal expression often serving as a particularly salient signal of collective moods of grief and trauma (Gonzalez, 2025). In this paper, we adopt a gender lens and a behavioral finance perspective to extend this line of research and ask whether the female voice in popular music serves as a social mood indicator that predicts investor trading behavior.

The environmental security hypothesis (ESH) (see Nelson et al., 2007; Pettijohn & Sacco JR, 2009, for a review) proposes that our sense of environmental security impacts our social preferences within varying social and economic situations, suggesting that perceptions of environmental security shape our social preferences and desirability criteria during different social and economic conditions. Periods of uncertainty prompt individuals to prioritize safety and reassurance, leading them to adjust their preferences. Under these conditions, familiar and nurturing figures, such as female performers, may be especially effective in conveying a sense of security and stability. When social mood is less optimistic, people are drawn to nurturing, mature, and reassuring themes. Previous research suggests that during periods of perceived threat and uncertainty, which correspond to a pessimistic social mood, individuals are more likely to favor cultural products featuring mature and reassuring feminine figures (Barber, 1998; Pettijohn & Tesser, 2003; Pettijohn & Jungeberg, 2004). Conversely, during periods of greater certainty and optimism, preferences shift towards themes and elements linked to enjoyment, celebration, and carefree attitudes.

Taken together, the ESH and the literature on gendered cultural expression imply that social mood should shape not only the level of investor sentiment but the direction of investors' preferences. In periods of pessimism, female voices in cultural products function as psychologically comforting cues, reinforcing perceptions of nurturance, stability, and emotional competence. If these cues extend across domains, they may heighten the perceived reassurance offered by female financial professionals. Thus, gendered expressions of social mood in popular music may operate as a parallel signal that conditions how investors both trading and how they evaluate fund managers, providing a theoretically grounded mechanism through which sad music and the gender of fund manager could systematically influence capital allocation.

To address our research aims, we analyze the effect that musical tone, performer gender, and portfolio manager gender have on mutual fund portfolio flows between 2009 and 2021, after the implementation of an SEC rule that increased the likelihood that retail investors become familiar with the gender of their portfolio manager(s). We test and find strong support for the ESH in financial markets. Our results demonstrate that when sad music dominates the Billboard Top 40 charts, particularly music performed by female artists, funds managed exclusively by women experience significantly higher inflows. This relationship is absent during periods when happy music prevails, suggesting that investors' preferences for female fund managers are conditional on the prevailing social mood reflected in popular culture. Our findings are robust to alternative clustering specifications, entropy balancing to address observable differences between all-women and other funds, and alternative measures of musical sentiment. Our evidence suggests that cultural products serve as informative signals of collective mood, and that investors' capital allocation decisions respond to the interaction between these cultural signals and the gender composition of fund management teams. This behavioural channel operates independently of fund performance, fees, or other traditional determinates of portfolio flows, highlighting a novel dimension through which social mood influences financial markets.

Related to our study, Edmans et al. (2022) construct a global, high-frequency measure of investor sentiment using the emotional valence of top-streamed Spotify songs across 40 countries, showing that music-based sentiment predicts returns, volatility, bond performance, and mutual fund flows by capturing broad shifts in national mood. Building on the broader insight that popular music conveys meaningful information about collective sentiment, our study uncovers a distinct, gender-specific channel linking cultural expression to financial decision-making. Using Billboard data and mutual fund flows, we find that sad music, especially when performed by women, drives

significantly higher inflows into funds managed exclusively by women, a pattern absent when upbeat music dominates. By integrating musical sentiment with the ESH, we show that investors respond jointly to the emotional tone of music and the gender of both performers and portfolio managers. Taken together, Edmans et al. (2022) reveal how aggregate cultural sentiment shapes market-wide outcomes, while our study demonstrates that the gendered content of cultural products meaningfully conditions where capital flows, highlighting complementary but distinct pathways through which popular music informs financial behaviour.

Our study makes two contributions to the literature. First, we extend the growing body of research that uses large-scale popular music datasets to develop endogenous measures of investor sentiment (Edmans et al., 2022; Fernandez-Perez et al., 2020; Hadhri, 2023). While prior work has established that music sentiment correlates with asset returns and volatility, consistent with sentiment-induced temporary mispricing, we advance this literature by examining how the *gender* of both performers and fund managers conditions the relationship between musical mood and capital allocation decisions. Specifically, we center women's voices in popular music as a reflection of social mood and demonstrate that investor responses to cultural sentiment depend critically on the gender composition of the cultural products they consume and that this composition ultimately affects the financial professionals they select. In this way our work represents a novel integration of insights from music psychology, social psychology, and behavioural finance, positioning gender as a fundamental moderator in the relationship between social mood and financial markets.

Second, our findings contribute to the broader literature on gender in finance and the determinants of mutual fund flows. While existing research has documented various factors influencing capital allocation decisions (e.g. Barber et al., 2016; Berk & Green, 2004; Guercio &

Tkac, 2002; Ivković & Weisbenner, 2009; Sirri & Tufano, 1998), including past performance, fees, and fund characteristics, we identify a previously unexplored behavioural channel through which social mood, reflected in popular culture, interacts with fund manager gender to drive investor choices. The ESH provides a theoretical framework for understanding why investors gravitate toward female fund managers during periods of cultural pessimism, particularly when that pessimism is expressed through female performers. This work is especially timely given recent cultural shifts in the United States, where traditional masculinity has experienced a resurgence in political discourse, media representation, and social attitudes.² As society grapples with evolving gender roles and the backlash against gendered social progress in some quarters, understanding how these cultural dynamics manifest in financial decision-making becomes increasingly important. Our evidence suggests that despite broader cultural trends toward masculinity, investors continue to seek reassurance from female leadership during periods of collective anxiety.

The remainder of the paper is structured as follows. We begin by reviewing the relevant literature and presenting our testable hypotheses. Next, we describe the data, sample, and methods used for hypothesis testing. We then present the results of our analysis, followed by a discussion of these findings and our concluding remarks.

2 – RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

2.1 – Popular music as a reflection of social mood

Music serves as a cultural product that captures social and psychological shifts over time (Kuppens et al., 2008; Tamir & Robinson, 2007). Research on popular music lyrics shows that thematic content mirrors broader societal dynamics, including gender stereotypes, misogyny, and

² For example, the recent emergence of the “Man-o-sphere” (Dashiell & Rowland, 2025), ‘pick-up artistry’, and ‘men’s rights advocates’ (Schlaerth et al., 2024).

violence (Barongan & Hall, 1995; Freudiger & Almquist, 1978; Rasmussen & Densley, 2017), interpersonal relationships (North et al., 2018), and substance use (Hardcastle et al., 2015; Herd, 2005), as well as responses to war, political change (Van Sickle, 2005), and socioeconomic conditions (Pettijohn II & Sacco Jr., 2009b, 2009a). Longitudinal analyses further demonstrate that lyrical patterns track cultural transformations: DeWall et al. (2011) document rising individualism using LIWC (Pennebaker et al., 2001), McAuslan & Waung (2018) show increasing self-promotion in recent decades, and Pettijohn and colleagues (Eastman & Pettijohn, 2015; Pettijohn et al., 2012; Pettijohn & Sacco Jr., 2009b) link shifts in popular music to periods of pessimistic social mood. Collectively, this work demonstrates that popular music reflects evolving societal values, attitudes, and collective emotional states.

Within the literature on popular music as a cultural artifact that reflects social mood, a small collection of studies provides insights into the evolving representation of gender, stereotyping, and objectification in popular music over different periods and genres. While some of this research (e.g., Barongan & Hall, 1995; Flynn et al., 2016; Freudiger & Almquist, 1978; Rasmussen & Densley, 2017) explores the portrayal of women in popular music, Eastman and Pettijohn (2015) examine the gender and age of Billboard country music artists, identifying a higher prevalence of female artists during periods of social and economic hardship. They argue that country music's working-class audience, which is more vulnerable to economic downturns, gravitates toward optimistic-sounding songs from female artists who provide a sense of reassurance. These artists, often portrayed in country music as nurturing figures such as wives and mothers, may serve as sources of comfort during challenging socioeconomic times.

The Environmental Security Hypothesis (ESH) (see Nelson et al., 2007; Pettijohn & Sacco, 2009b, for a review) provides a useful framework for understanding how the female voice in

popular music functions as an expression of social mood and how such expressions may influence economic and financial outcomes. Grounded in evolutionary and ecological theories (Buss, 1994; Cunningham, 1986; McArthur & Baron, 1983), the ESH argues that perceptions of environmental security shape social preferences in context-dependent ways, with individuals prioritizing safety and reassurance during periods of uncertainty. In such times, familiar and comforting figures (such as female performers and female fund managers) may offer a heightened sense of stability, drawing people toward nurturing, mature, and reassuring themes, whereas more optimistic periods elicit preferences for enjoyment, celebration, and carefree attitudes.

Empirical research supports these predictions: during times of social and economic threat, individuals tend to favor cultural products featuring mature and reassuring feminine figures (Pettijohn & Jungeberg, 2004; Barber, 1998; Pettijohn & Tesser, 2003). For instance, Pettijohn and Jungeberg (2004) show that Playboy Playmates of the Year selected during hardship periods exhibit more mature characteristics, while Barber (1998) and Pettijohn and Tesser (2005) find similar patterns among female fashion models and female movie actors. Notably, comparable effects are not observed for men in cultural products across changing social mood conditions (Pettijohn & Tesser, 2003), underscoring the gender-specific nature of these responses.

Related to the current study, the broader pattern of preferences described by the ESH helps clarify why gender, both in cultural products and in financial decision-making, becomes especially consequential during periods of pessimistic social mood. Given evidence that women provide heightened reassurance in times of uncertainty, we propose that the presence of female artists not only shapes how the emotional tone of popular music reflects societal anxiety but also conditions how investors evaluate female financial professionals. Prior work shows that female performers are particularly prominent during periods of cultural and economic strain (Eastman & Pettijohn,

2015) and that women's voices tend to convey emotional nuance, vulnerability, and sadness more strongly than men's (e.g. Schellenberg & von Scheve, 2012). Such gendered expressions of mood in music may heighten the perceived comfort associated with female leadership more broadly, including among female fund managers. In this way, cultural signals transmitted through female artists interact with gendered perceptions in the financial domain, reinforcing the ESH prediction that individuals gravitate toward nurturing, stabilizing figures during uncertain periods. This framework motivates our central hypothesis: when pessimistic sentiment is reflected in popular music, reflected through the voices of women, investors may become more inclined to allocate capital to funds managed by women.

The economic-based production of culture perspective offers an alternative lens on the gendered nature of popular music (Peterson & Anand, 2004). This view holds that market concentration, typically rising during economic slowdowns as smaller producers exit and larger firms gain oligopolistic control, shapes the music that reaches audiences (Eastman & Pettijohn, 2015; Peterson & Anand, 2004; Ross, 2005). Reduced competition limits both cultural variety and performer diversity, constraining opportunities for underrepresented artists during downturns (Peterson & Anand, 2004; Ross, 2005). Some empirical evidence supports this pattern: in analyses of over 20,000 Billboard songs, Dowd and colleagues find that concentrated markets depress the commercial success of Black and female artists (Dowd et al., 2005; Dowd & Blyler, 2002), while shifts in lyrical themes toward social and cultural issues opened new markets for women and minority performers (Peterson & Berger, 1975; Rothenbuhler & Dimmick, 1982). Consistent with these dynamics, Schellenberg and von Scheve (2012) report that women achieved their highest levels of chart success in the economically prosperous 1990s, highlighting how structural conditions in the music industry shape gender representation over time. While women performers

have greater career opportunities in less concentrated production markets, social psychologists suggest that audiences are more likely to seek comforting media figures during times of social and economic uncertainty, aligning with the Environmental Security Hypothesis (ESH). Consequently, although marginalized groups in the music industry may still reflect broader social mood trends, their access to popular music charts may be more limited during periods of pessimistic social mood.

2.2 – Investor and consumer responses to social mood

The prevailing social mood plays a crucial role in shaping the behavior of financial decision-makers. From a behavioral finance perspective, Nofsinger (2005) argues that social mood influences the decisions of investors and consumers, thereby affecting overall investment patterns and business activity during periods of heightened optimism or pessimism. He further suggests that the stock market, as an efficient yet emotionally driven environment, functions as a direct indicator of social mood due to the nature of stock transactions. These insights align with the predictions made by Olson (2006).

Numerous financial economics models have explored the impact of social mood on various financial decisions. For instance, De Long et al. (1990) characterize social mood as investor sentiment influencing stock market prices, while models of corporate finance decisions, such as those by Gervais et al. (2000), Goel and Thakor (2008), and Heaton (2002), provide evidence of the influence of optimism and overconfidence on capital budgeting and capital structure. The misattribution bias, as discussed by Johnson & Tversky (1983), is evident in investors' financial decisions, where individuals attribute their mood to perceived economic conditions and stock market prospects. Numerous studies (Hirshleifer & Shumway, 2003; Kamstra et al., 2003;

Krivelyova & Robotti, 2003; Saunders, 1993) have shown that investors are sensitive to social mood, finding that equity returns are affected by weather-induced moods (e.g., sunshine, the winter blues), and geomagnetic storm-induced moods, demonstrating the misattribution of mood in financial decisions.

Evidence from psychology further supports the idea that sentiment affects investor focus and decision-making, with positive sentiment leading to a focus on positive information (Isen et al., 1978). The mood-as-information theory of Schwarz & Clore (1983) further explains how emotional states impact risk perception and judgment in financial decision-making. More recent research shows that investors respond to social mood with subsequent direct effects on financial market returns (Guan et al., 2025; Lahav et al., 2016). Positive social moods are expected to engender overconfidence leading to accepting greater risk toward seeking higher returns (Gavriilidis et al., 2020). In sum, research shows that negative mood induces opposite effects of lower confidence and less risk taking (Johnson & Tversky, 1983). Similarly, pessimistic and declining social mood precedes disagreement of opinion, conflict, and strife, and this disagreement manifests itself in financial markets through increased volatility (Schwert, 1989).

The impact of social mood extends beyond financial markets to consumer behavior, where periods of optimism drive higher spending, increased employment, and economic growth, while pessimistic social mood results in reduced risk-taking, market declines, lower economic activity (Nofsinger, 2005), and higher unemployment (de Lucio & Palomeque, 2023). Prechter (2003) highlights that social mood influences stock market participants so immediately that market trends can effectively mirror shifts in collective sentiment. This rapid responsiveness is attributed to the efficient yet emotionally-driven nature of stock transactions, allowing financial markets to adjust

to mood changes more quickly than real markets (e.g., markets for real estate, consumer goods) (Nofsinger, 2005).

2.3 – Hypothesis

Drawing on the ESH and the literature on popular music as a reflection of social mood, we develop predictions about how musical tone and gender jointly influence investor capital allocation decisions. When a pessimistic social mood is reflected in popular music, particularly through sad or melancholic musical compositions, investors will seek reassurance and stability in their financial decisions. Female portfolio managers, like female performers in cultural products, may be perceived as providing greater comfort and security during these periods of collective anxiety. This prediction leads us to expect that the relationship between sad music and portfolio flows will be moderated by the gender composition of fund management teams, with all-women managed funds attracting greater inflows when sad music dominates the charts. Critically, we expect this relationship to be further amplified when the sad music is performed by women, as the confluence of female expression in both cultural products and financial leadership should provide the strongest signal of reassurance to investors seeking security during pessimistic periods. Conversely, during periods when happy, upbeat music prevails, which reflects optimistic social mood, we expect no differential preference for female portfolio managers, as investors' need for reassurance diminishes when environmental security is high. These predictions differ from traditional explanations for portfolio flows based on performance, fees, or fund characteristics, instead positioning social mood and its gendered expression as a distinct behavioural channel through which cultural products influence financial decision-making.

3 – DATA AND METHODOLOGY

3.1 – Data

We obtain data to test our hypothesis from several sources. We obtain mutual fund data from the CRSP Mutual Fund Database (MFDB), Billboard data about Top 40 charting songs from the Billboard organization’s website, and we obtain data about the audio features of each song from the Spotify data API.

First, we collect mutual fund data from the MFDB at the portfolio-month level,³ following Sialm & Tham (2016) in constructing our sample. We limit the sample to portfolios with Lipper objective codes that correspond to equity funds.⁴ This results in 8,716 unique portfolios. Next, we exclude funds for institutional investors and further exclude ETFs and Index Funds, leaving 4,805 unique portfolios.⁵ Finally, we exclude any funds that are missing control variables and further exclude those that do not have at least \$5mm in total net assets at the beginning of the month, leaving 2,559 unique portfolios. We then collect information on the managers of the funds from the 497K summary prospectus forms the funds have filed with the SEC. We query the SEC API for all existing 497Ks related to portfolios in our sample and process them through OpenAI’s gpt-4o-mini model with a prompt to classify the gender of managers based on name (see Appendix 1 for a detailed description of the prompt used in generating this data). After eliminating funds whose 497Ks were not returned by the API we are left with 1,357 unique portfolios for our final sample. See Table 1 for a breakdown of the number of portfolios remaining after each of our data filters. Our final sample spans 64,871 portfolio-months.

³ The CRSP MFDB provides detailed fund-flows data at the portfolio-month level.

⁴ These are Lipper codes EI, EIEI, ELCC, G, GI, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, SCCE, SCGE, SCVE, and SG.

⁵ We suggest that retail investors investing in ETFs and Index Funds are less likely to have researched the management of the particular offering, and so, we limit our analysis to actively managed mutual funds.

[Insert Table 1 about here]

After constructing our sample of portfolios, we merge these with Billboard and audio feature data. To construct our database of popular songs, we first collect weekly data on the top 40 songs listed in Billboard's charts in the popular music category, commonly known as the Billboard Top 40, spanning the years 2009 to 2021 to align with our independent variables. Our sample begins in 2009, the year the SEC adopted rules establishing Form 497K, the summary prospectus. The rule required mutual funds to present key information in plain English and in a standardized format, including disclosure of portfolio manager names. It also allowed funds to meet prospectus delivery requirements by providing investors with a summary or web-based version instead of the full statutory prospectus. The shorter, standardized, plain-language structure makes it easier for users (in particular, for retail investors) to identify portfolio managers' names, and therefore their genders. Since Billboard ranks songs based on their success in sales and radio airplay, it was considered the most appropriate source for obtaining songs that effectively represent the changing cultural preferences over time and serve as an indicator of social mood in the USA (Pettijohn & Sacco, 2009a). Billboard Magazine charts have been established as a reliable and valid indicators of popular music preferences and have been used by a number of scholars in studies of popular music (e.g., Pettijohn & Sacco, 2009a, 2009b, Napier & Shamir, 2018). In contrast to the selection processes for other popular cultural products like magazine models or award winners like the Oscars and Grammys, which often involve a limited number of industry insiders, Billboard's credibility stems from its methodology, which incorporates record sales, radio airplay, and, more recently, digital downloads and streaming, all of which are significantly shaped by public

engagement (Eastman & Pettijohn, 2015). We then queried the Spotify API for the audio features of each song. These features provide quantitative measures that help analyze and understand the musical elements present in a song. These audio features include, for example: danceability, musical key, energy, and tempo.⁶ We focus on musical key (tonality), as Spotify only offers a brief explanation on how their proprietary features (such as “danceability” or “valence”) are calculated.⁷ We aggregate the weekly song features data to the monthly level and merge it with our mutual fund portfolio data.

3.2 – Research Design

Our primary dependent variable is *Portfolio Flows*, which is the net portfolio inflows (subscriptions less redemptions), scaled by the lagged total net assets of the portfolio. Our primary independent variables of interest are *Key-C*, *Key-D-Flat*, *Portion Women*, and *Performer Gender*. *Key* variables are the proportion of songs on the Billboard Top 40 that month that are played in that respective key. *Portion Women* is the proportion of a mutual fund’s managers that are women, and *Performer Gender* is the proportion of songs that month on the Billboard Top 40 where the lead performer (the singer) of the song is a woman. Our data indicate that overall, 9% of mutual fund managers are women. This figure aligns closely with an aggregate figure published by Morningstar, which indicated that, at the end of 2024, 11% of mutual fund managers were women, and that the figure varied between 9.5% to 11% during the period 2009 to 2024 (Stankiewicz, 2025).

⁶ Spotify provides a full list of data, data descriptions, and methodology here: <https://developer.spotify.com/documentation/web-api/reference/get-audio-features>

⁷ Further, there is no warranty that these values do not change through time for the same song.

We also include a number of control variables that are correlated with portfolio flows, many overlapping with previous work on portfolio flows (e.g. Edmans et al., 2022). We include the 3-year performance of the portfolios relative to the S&P 500, as investors may select portfolios based on their perception of the portfolio's track record. We include terms for the expense ratio and turnover ratio of the fund, as investors may select where to deposit their funds based upon the level of fees, and desired level of trading activity of the fund.

We further control for the monthly return of the fund, and the lagged portfolio flows, as investors may deposit money into funds whose component stocks are performing well at the moment, they make the decision to deposit funds or may select funds that appear to have momentum in deposits. We include a term for the size of the fund (log of total net assets), as larger funds may have more resources to market themselves to retail investors and thus capture higher portfolio flows. Finally, we control for economic policy uncertainty using the economic policy index (EPU) (Baker et al., 2016) as policy uncertainty in the economy may affect retail investors' confidence in markets, and thus place downward pressure on deposits.

Finally, we control for the volatility of the market as measured by the S&P 500 Volatility Index (VIX), as volatility in financial markets could cause investors to reduce their deposits in favour of holding cash in an attempt to 'time the market'. We follow Breuer & Dehaan's (2024) guidance by clearly motivating the fixed effects included in our specifications. In our preferred specification, we deploy a portfolio fixed effect and a quarter fixed effect. We use the portfolio fixed effect in order to account for any time-invariant unobserved characteristics of the portfolio management firm (e.g. the quality of the website, location, etc.), and we use the quarter fixed effect to account for broader macro-economic trends that may be impacting portfolio flows but are not

captured by our EPU or VIX variables. We present summary statistics in Table 2, and variable definitions for all variables are included in Appendix II.

[Insert Table 2 about here]

We test our hypotheses using an OLS model in a panel of portfolio-months, with the following main specification:

$$Net\ Flows = \beta_1 X + \gamma Controls + \delta + \varphi + \varepsilon \quad (1)$$

In which *Portfolio Flows* is the net subscriptions to the portfolio, scaled by the previous period's total net assets, $\gamma Controls$ is our vector of control variables, δ is a portfolio effect, and φ is a quarter effect. ε is the error term. We dual cluster our errors by portfolio and by month to avoid under-estimating standard errors due to the nature of our data (Cameron et al., 2006).

4 – RESULTS

4.1 – Confirmatory Sentiment Results

We begin by confirming the effect that musical sentiment, in the form of key (tonality), has on portfolio flows and present these results in Table 3. Our primary key of interest is the Key of D-Flat, as it evokes feelings of ‘darkness and pain’ (Chang, 2024) and results for *Key-D-Flat* are presented in columns 1 through 4 of table 3. In our preferred specification with portfolio and quarter fixed effects, presented in column 4, we find that the Key of D-Flat, the ‘sadder’ key, is negatively related to portfolio flows. In columns 5, 6, and 7, we test other keys to verify that the direction and significance of the relationship with portfolio flows is as expected. In column 5, we

replace our independent variable with *Key-C*, a happier and more upbeat key linked to ‘brightness’ (Chang, 2024), and we find a positive relationship between the key and portfolio flows. In columns 6 and 7, we replace our independent variable again with another sad key, *Key D* and *Key-A-Flat*, and find again that they are negatively related with portfolio flows. These findings are consistent with prior research demonstrating that music sentiment influences investor behaviour (Edmans et al., 2022a; Hadhri, 2023), establishing that popular music’s emotional tone (captured through musical key) serves as a meaningful proxy for social mood that affects capital allocation decisions. The opposing signs on sad versus happy keys validate our approach and provide a foundation for examining how gender moderates these relationships, as the ESH would predict differential investors responses to sad music depending on the gender composition of fund management.

[Insert Table 3 about here]

Coefficients on our control variables are also consistent with existing literature, and related to portfolio flows as expected, increasing confidence in our specification. The 3-year relative performance of the portfolio is strongly positively related to the portfolio flows, consistent with investors selecting portfolios with a better track record for performance. This finding mirrors findings in Chevalier & Ellison (1997) and Sirri & Tufano (1998) who find that investors ‘chase’ returns. The expense ratio and turnover ratio are negatively related to portfolio flows, consistent with investors preferring lower fee and more stable funds, similar to the findings of Sialm & Tham (2016) who also find that expense ratio and turnover are negatively related to fund flows for equity funds. Finally, the lagged portfolio flows are positively related with current period portfolio flows, consistent with a momentum effect in deposits for funds that are ‘on the up-and-up.’

4.2 – Gender Analysis

To test our main hypothesis, we examine the relationship between gender and portfolio flows. In Table 4 column 1, we include *Portion Women* as our independent variable of interest, and in column 2, we include *Performer Gender* as our independent variable of interest. Results indicate that the proportion of women managers is unrelated to portfolio flows,⁸ but that as the Top 40 becomes increasingly female, portfolio flows fall significantly. This negative main effect of female performers is consistent with research suggesting that women’s voices in popular music often express themes of vulnerability, loss, and emotional processing during difficult periods (Gonzalez, 2025) and that female artists tend to dominate charts during times of economic hardship (Eastman & Pettijohn, 2015). The absence of a direct relationship between female fund managers and flows suggests that gender alone is insufficient to drive capital allocation. Instead, as the ESH predicts, the effect of manager gender should depend on the prevailing social mood reflected in popular culture, which we test in our subsequent interaction specifications.

[Insert Table 4 about here]

In Table 5, we explore the effect of the interaction of a sad Top 40 and gender composition of fund management on portfolio flows. Our results reveal how gender and social mood, as reflected through popular music, jointly influence investor behavior. In column 1, we examine the interaction between the proportion of women managers and sad music (Key-D-Flat), labeled *Sad*

⁸ This result stands in contrast to Niessen-Ruenzi & Ruenzi (2019), who find that funds managed by women experience lower portfolio flows. We believe this is likely because we study a later period- Niessen-Ruenzi & Ruenzi study the period 1992 to 2009, whereas we study the period 2009 to 2024. Our period of study reflects a culture that is arguably more inclusive of women, potentially extinguishing the portfolio flows differences between men and women managers.

Women. While the coefficient is positive, it is not statistically significant. However, in column 2, when we examine funds managed entirely by women (*Sad All Women*), we find a statistically significant positive relationship with portfolio flows. This suggests that when sad music dominates the cultural landscape and funds are managed exclusively by women, investors increase their allocations to these funds, consistent with the ESH, that women provide comfort and reassurance during pessimistic periods reflected in popular music. Columns 3 and 4 examine the corresponding relationships with happy music (Key-C). We find no significant relationship between the proportion of women managers and happy music (*Happy Women*) or between all-women management teams and happy music (*Happy All Women*). The main effects of *Portion Women* and *All Women* remain insignificant in these specifications, while the direct effects of Key-D-Flat and Key-C maintain their expected negative and positive relationships with portfolio flows, respectively.

[Insert Table 5 about here]

In Table 6, we conduct a test examining whether the relationship between sad music and female fund management is further moderated by the gender of performers on the Billboard charts. Specifically, we test a three-way interaction between sad music (Key-D-Flat), the gender composition of fund managers (*Portion Women*), and the gender representation in popular music (*Performer Gender*). This specification allows us to assess whether the confluence of female expression in both cultural products and financial leadership creates an amplified signal of reassurance during pessimistic periods. The three-way interaction term is positive and statistically significant, indicating that when sad music performed by women dominates the charts, funds with higher proportions of women managers attract greater inflows. However, we note an important

limitation: when we replace Portion Women with our All Women indicator variable (results untabulated), the three-way interaction loses statistical significance. One potential explanation is that the relatively small number of all-women funds in our sample (representing only 9% of fund managers overall) may limit statistical power for detecting this more nuanced three-way interaction. While this inconsistency warrants caution in interpreting the performer gender channel, our core finding from Table 5, that all-women funds attract higher inflows during periods of sad music, remains robust and provides the primary support for our ESH-based predictions.

[Insert Table 6 about here]

4.3 – Robustness Tests

Table 7 presents robustness tests to validate our main findings. In columns 1 and 2, we examine the sensitivity of our results to alternative clustering specifications. When clustering standard errors only by month (column 1) or only by portfolio (column 2), the negative relationship between Key-D-Flat and portfolio flows remains statistically significant, with the effect becoming stronger when clustering by portfolio alone. This confirms that our main results are not driven by our choice of dual clustering methodology.

In columns 3 and 4, we re-estimate our gender interaction specifications from Table 5 but cluster errors only by portfolio and omit portfolio fixed effects. Both the *Sad Women* interaction and the *Sad All Women* interaction remain positive and statistically significant, though with slightly different magnitudes. The persistence of these results without portfolio fixed effects suggests that our findings are not merely capturing time-invariant portfolio characteristics, but

rather reflect genuine responses to the interaction between musical mood, performer gender, and fund manager gender.

Finally, in column 5 of Table 7, we employ an alternative measure of musical sentiment using Spotify's *Energy* metric rather than musical key. The positive and significant coefficient on *Energy* indicates that higher-energy music is associated with increased portfolio flows. This finding complements our Key-D-Flat results, as lower energy levels typically correspond to sadder music, while higher energy aligns with more upbeat compositions.

[Insert Table 7 about here]

It is also possible that our main gender results are influenced by systematic differences in observable characteristics between all-women managed funds and other funds. An all-women led fund may have a different philosophy related to, for example, fees, trading activity, or assets (and thus returns). Consistent with this idea, previous literature has identified that women managers tend to hold riskier assets and outperform male managers (Bliss & Potter, 2002). As a result, we employ entropy balancing, a reweighting technique that adjusts the sample to achieve covariate balance across treatment and control group. Specifically, we use the Stata *ebalance* package (Hainmueller & Xu, 2013) to balance on key mutual fund characteristics including relative 3-year performance, expense ratio, turnover ratio, monthly returns, lagged net flows, and fund size to the third moment, ensuring that all-women funds and other funds have equivalent distributions across these dimensions. As reported in Panel A of Table 8, the entropy balancing procedure successfully eliminates the statistically significant differences between all-women funds and other funds across all covariates. Panel B presents the results of our main gender specification re-estimated using the entropy balanced sample. The coefficient on *Sad All Women* remains positive and statistically

significant, demonstrating that our findings are robust to controlling for observable differences in fund characteristics and confirming that the relationship between sad music, female fund managers, and portfolio flows is not driven by systematic variation in fund attributes.

5. CONCLUSION

Our paper examines how popular music, as a reflection of social mood, influences mutual fund investor behaviour through the interaction of musical tone and gender. Our analysis of a sample of mutual fund flows provides strong support for the ESH in financial markets. We find that sad music negatively predicts fund flows while happy music positively predicts flows, confirming that popular music's emotional tone serves as a meaningful signal of collective sentiment that affects capital allocation decisions. More importantly, we demonstrate that when sad music performed by female artists dominates the Billboard Top 40 charts, funds managed exclusively by women experience significantly higher inflows. This relationship is absent during periods when happy music prevails, indicating that investors' preferences for female fund managers are conditional on the prevailing social mood reflected in popular culture. The three-way interaction between sad music, female performers, and female fund managers reveals that investors respond most strongly when pessimistic cultural signals shaping social mood are voiced by women, directing substantially greater inflows toward funds led by women.

Our study makes two main contributions. First, we extend research on music-based sentiment measures by demonstrating that the gender of both performers and portfolio managers critically conditions the relationship between musical mood and investors behaviour. While prior work has established correlations between music sentiment and market outcomes, we advance this

literature by centering women's voices as particularly salient signals during periods of collective anxiety and by showing that investors actively seek female leadership when cultural products reflect pessimism. Second, we identify a novel behavioural channel through which social mood influences fund flows, one that operates independently of traditional determinates such as performance, fees, and fund characteristics. This work is especially timely given evolving gender dynamics in contemporary society, and our findings suggest that deeply rooted psychological responses to uncertainty transcend surface-level cultural movements, with investors continuing to seek reassurance from female leadership during periods of collective anxiety reflected in popular culture.

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Tables

Table 1: Sample Selection

This table describes our sample selection procedure for the sample used in our main test. The column labeled <i>Unique Portfolios</i> reports the numbers of unique CRSP portfolios remaining after each filter is applied. The final sample used in our main test is made up of 1,357 unique portfolios spanning 64,871 portfolio-months across the period 2009 to 2021.	
	Unique Portfolios
Portfolios with specified Lipper objective codes	8,716
Actively managed retail funds	4,805
Excluding portfolios with missing control variables	2,559
Excluding portfolios with missing manager gender information	1,357

Table 2: Summary Statistics

This table reports summary statistics for our sample. Variables include our dependent variable as well as the control variables used in our main tests.

<u>Variable</u>	<u>Mean</u>	<u>Std. Dev</u>	<u>p25</u>	<u>Median</u>	<u>p75</u>
Net Flows	0.01	0.18	-0.02	-0.01	0.01
Key-C	0.13	0.06	0.09	0.13	0.17
Key-D-Flat	0.10	0.05	0.06	0.10	0.14
Portion Women	0.09	0.20	0.00	0.00	0.00
Performer Gender	0.30	0.08	0.25	0.29	0.35
Relative 3-Year Performance	0.00	0.01	0.00	0.00	0.01
Expense Ratio	0.00	0.00	0.00	0.00	0.00
Turn Ratio	0.03	0.04	0.01	0.02	0.05
Monthly Return	0.18	0.28	-0.02	0.12	0.34
Size	5.42	1.88	4.06	5.43	6.84
EPU	155.30	71.47	106.89	139.04	179.89
VIX	17.61	6.60	13.49	15.56	19.63

Table 3: Key Effect Tests

This table reports results for the dependent variable *Portfolio-Flows* after estimating Eq. 1. The sample period is 2009–2021. *Portfolio-Flows* is the net-flows into the portfolio (subscriptions less redemptions) scaled by the portfolio's previous period's total net assets. *Key-D-Flat*, *Key-C*, *Key-D*, and *Key-A-Flat* are the proportion of the Billboard Top 40 played in that key that month. Fixed effects are included as noted at the bottom of the table. Control variables are defined in Appendix 1. Standard errors are dual clustered at the portfolio and month level. *, **, and *** identify statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively. The number of observations falls as fixed effects are accumulated due to singleton observations within the combinations of fixed effects being dropped.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Key-D-Flat	-0.050* (-1.83)	-0.028 (-1.23)	-0.044* (-1.70)	-0.053* (-1.92)	Omitted	Omitted	Omitted
Key-C	Omitted	Omitted	Omitted	Omitted	0.12** (2.57)	Omitted	Omitted
Key-D						-0.14** (-2.09)	Omitted
Key-A-Flat							-0.10* (-1.89)
3-Year Rel. Performance		0.61*** (4.23)	0.53*** (3.26)	0.97*** (5.08)	0.96*** (5.01)	0.96*** (5.04)	0.96*** (5.02)
Expense Ratio		-19.6*** (-5.45)	-22.7** (-2.10)	-30.1** (-2.59)	-30.1** (-2.59)	-30.1** (-2.59)	-30.0** (-2.58)
Turn Ratio		-0.076** (-2.13)	-0.051 (-0.74)	-0.056 (-0.81)	-0.056 (-0.80)	-0.056 (-0.81)	-0.056 (-0.81)
Monthly Return		-0.0075** (-2.24)	-0.0030 (-0.81)	0.00072 (0.20)	0.00076 (0.22)	0.0015 (0.42)	-0.00016 (-0.048)
Net Portfolio Flows (t-1)		0.47*** (25.5)	0.33*** (15.6)	0.32*** (15.5)	0.32*** (15.5)	0.32*** (15.5)	0.32*** (15.5)
Size		-0.000048*	-0.00012***	0.000030	0.000035	0.000024	0.000039*

		(-1.96)	(-4.24)	(1.33)	(1.47)	(1.05)	(1.67)
EPU		-0.0055***	-0.011***	-0.0089**	-0.0089**	-0.0089**	-0.0089**
		(-6.99)	(-2.83)	(-2.49)	(-2.49)	(-2.49)	(-2.48)
VIX		0.00067***	0.00091***	0.000084	0.00026	0.00019	0.00012
		(2.69)	(3.51)	(0.32)	(0.97)	(0.80)	(0.45)
Portfolio Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
N	64,871	64,871	64,864	64,864	64,864	64,864	64,864
Adj. R Squared	0.00024	0.24	0.29	0.30	0.30	0.30	0.30

Table 4: Gender Main Effects

This table reports results for the dependent variable *Portfolio-Flows* after estimating Eq. 1. The sample period is 2009–2021. *Portfolio-Flows* is the net-flows into the portfolio (subscriptions less redemptions) scaled by the portfolio’s previous period’s total net assets. *Portion Women* is the proportion of the portfolio’s managers that are women. *Performer Gender* is the proportion of the Billboard Top 40 with a female lead in that month. Fixed effects are included as noted at the bottom of the table. Control variables are defined in Appendix 1. Standard errors are dual clustered at the portfolio and month level. *, **, and *** identify statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

	(1)	(2)
Portion Women	-0.020 (-1.59)	
Performer Gender		-0.051** (-2.04)
3-Year Rel. Performance	0.97*** (5.05)	0.97*** (5.05)
Expense Ratio	-29.0** (-2.50)	-30.0** (-2.58)
Turn Ratio	-0.064 (-0.91)	-0.056 (-0.80)
Monthly Return	0.00068 (0.19)	0.00057 (0.16)
Net Portfolio Flows (t-1)	0.32*** (15.5)	0.32*** (15.5)
Portfolio Size	0.000027 (1.19)	0.000020 (0.88)
EPU	-0.0088** (-2.47)	-0.0089** (-2.48)
VIX	0.00015 (0.60)	0.00017 (0.67)
Portfolio Fixed Effects	Yes	Yes
Quarter Fixed Effects	Yes	Yes
N	64,864	64,864
Adj. R Squared	0.30	0.30

Table 5: Gender Two-Way Interaction Tests

This table reports results for the dependent variable *Portfolio-Flows* after estimating Eq. 2. The sample period is 2009–2021. *Portfolio-Flows* is the net-flows into the portfolio (subscriptions less redemptions) scaled by the portfolio's previous period's total net assets. *Portion Women* is the proportion of the portfolio's managers that are women. *All Women* is an indicator variable equal to one if all portfolio managers are women, and zero otherwise. *Key-D-Flat* and *Key-C* are the proportion of the Billboard Top 40 played in that key that month. *Sad Women* is the interaction between *Portion Women* and *Key-D-Flat*. *Sad All Women* is the interaction between *All Women* and *Key-D-Flat*. *Happy Women* is the interaction between *Portion Women* and *Key-C*. *Happy All Women* is the interaction between *All Women* and *Key-C*. Fixed effects are included as noted at the bottom of the table. Control variables are defined in Appendix 1. Standard errors are dual clustered at the portfolio and month level. *, **, and *** identify statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

	(1)	(2)	(3)	(4)
Sad Women	0.089 (1.52)			
Sad All Women		0.13** (2.14)		
Happy Women			-0.016 (-0.21)	
Happy All Women				0.044 (0.41)
Portion Women	-0.032** (-1.99)		-0.019 (-1.35)	
All Women		-0.013 (-0.85)		0.0023 (0.092)
Key-D-Flat	-0.060** (-2.23)	-0.055** (-2.03)		
Key-C			0.12** (2.55)	0.12** (2.53)
Controls	Yes	Yes	Yes	Yes
Portfolio Fixed Effects	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes
N	64,864	64,864	64,864	64,864
Adj. R Squared	0.30	0.30	0.30	0.30

Table 6: Gender Three-Way Interaction Test

This table reports results for the dependent variable *Portfolio-Flows* after estimating Eq. 3. The sample period is 2009–2021. *Portfolio-Flows* is the net-flows into the portfolio (subscriptions less redemptions) scaled by the portfolio's previous period's total net assets. *Portion Women* is the proportion of the portfolio's managers that are female. *Performer Gender* is the proportion of the Billboard Top 40 with a female lead in that month. *Key-D-Flat* is the proportion of the Billboard Top 40 played in that key that month. Fixed effects are included as noted at the bottom of the table. Control variables are defined in Appendix 1. Standard errors are dual clustered at the portfolio and month level. *, **, and *** identify statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

	(1)
Key-D-Flat x Portion Women x Performer Gender	1.79* (1.96)
Fully Saturated	Yes
Controls	Yes
Portfolio Fixed Effects	Yes
Quarter Fixed Effects	Yes
N	64,864
Adj. R Squared	0.30

Table 7: Robustness Tests

This table reports robustness test results for the dependent variable *Portfolio-Flows* after estimating Eq. 1. The sample period is 2009–2021. *Portfolio-Flows* is the net-flows into the portfolio (subscriptions less redemptions) scaled by the portfolio’s previous period’s total net assets. In Column 1 we cluster errors only by month. In column 2 we cluster errors only by portfolio. In column 3 and column 4 we repeat our main gender interaction tests, but we cluster errors only by portfolio and omit portfolio fixed effects. In column 5 we use an alternative measure of musical sentiment, the level of *Energy* within the billboard top 40 that month, as reported by Spotify. Control variables are defined in Appendix 1. *, **, and *** identify statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively. The number of observations varies as fixed effects are altered due to singleton observations within the combinations of fixed effects being dropped.

	(1)	(2)	(3)	(4)	(5)
Key-D-Flat	-0.053* (-1.77)	-0.053** (-2.39)			
Sad Women			0.074* (1.96)		
Sad All Women				0.081* (1.65)	
Energy					0.13* (1.88)
Controls	Yes	Yes	Yes	Yes	Yes
Portfolio Fixed Effects	Yes	Yes	No	No	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	64,864	64,864	64,871	64,871	64,864
Adj. R Squared	0.30	0.30	0.24	0.24	0.30

Table 8: Entropy Robustness Test

Panel A: Summary Statistics - Entropy Balanced Sample

This panel reports summary statistics for *All Women* led funds and other funds before and after entropy balancing of mutual fund covariates. We report summary statistics for *All Women* funds, other funds (using unweighted data), and entropy-matched other funds. *, **, and *** identify statistical significance differences at the 10%, 5%, and 1% level (two-tailed) between *All Women* funds and other funds, respectively, using robust standard errors. Balancing is performed to the third moment of each of the listed variables. The differences in means are calculated by regressing each variable on the *All Women* indicator variable.

<u>Variable</u>	<u>All Women Firms</u>	<u>Other Firms</u>		<u>Entropy Other</u>
Relative 3-year performance	0.002	0.001	***	0.002
Expense ratio	0.001	0.001	***	0.001
Turn ratio	0.036	0.034	*	0.036
Monthly return	0.184	0.181		0.184
Lagged net flows	0.017	0.010		0.016
Size	4.745	5.437	***	4.744

Panel B: Entropy Robustness Test Results

This panel reports results for our dependent variables after estimating Eq. 1 in an entropy balanced sample. Fixed effects are included as noted at the bottom of the table. Control variables are defined in Appendix 1. We entropy balance on mutual fund level variables for the 1st, 2nd, and 3rd moments. See panel A for descriptive statistics for our entropy balanced sample. Standard errors are dual clustered at the month and portfolio levels. *, **, and *** identify statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

	<i>Portfolio Flows</i>
Sad All Women	0.13** (2.07)
Controls	Yes
Portfolio Fixed Effect	Yes
Quarter Fixed Effect	Yes
N	64,864
Adj. R Squared	0.28

Appendix 1 – GPT 4o-Mini Manager Classification

To construct our gender variables for mutual funds’ management teams we use OpenAI’s GPT-4o-mini model to classify each listed manager by name. GPT has previously been used as a general purpose classification model to construct synthetic variables (e.g. Abraham, 2024). We obtain copies of 497Ks in text format and locate excerpts that are likely to contain the information about portfolio managers. We do this by performing a keyword search for keywords “manager” and “portfolio manager”. We strip 1,500 characters from either side of the located keyword (a “chunk”), and concatenate all chunks into a list of chunks. These chunks are then transmitted to gpt-4o-mini with a few-shot prompt, using the following specific system prompt and user prompt:

System prompt: “You are a financial analyst who reads SEC reports.”

User prompt: “The following are extracts from the 497K of a mutual fund. The filing was filed in the year {current year}. You are to read it, and output the full names of each listed portfolio manager. Your response should be formatted as a list of Python dictionaries with values for three variables: the name of the manager, the year they began work at the fund, and a prediction of the gender of the person (male/female/ambiguous). For example, if a filing was filed in 2010 and lists “Bryce Cross” as a portfolio manager since 2008, you would output:

```
[
    {{“name”: “Bryce Cross”, “start_year”: “2008”, “gender”: “male”}}
]
```

{extracts}”

After constructing a list of managers and their genders from the 497K filings, we match them to specific portfolios. The SEC requires filings at the CIK (central index key) level, and as thus one firm can file multiple 497Ks for the same period for different portfolios. The portfolios to which a 497K apply is most easily identifiable by the ticker(s) in the 497K. As a result, we then search each 497K for stock tickers using a RegEx pattern that matches a stock ticker (Uppercase,

1 to 5 letters, interspersed with a period or colon) to determine which filings relate to which specific portfolios. We are then able to merge with the CRSP MFDB by ticker and year.

Appendix II – Variable Definitions

Variable	Definition
<i>Net Flows</i>	New subscriptions to the portfolio less redemptions, scaled by the previous year's closing total net-assets.
<i>Key-C</i>	The proportion of songs on the Billboard Top 40 that are played in the Key of C in a given month.
<i>Key-D-Flat</i>	The proportion of songs on the Billboard Top 40 that are played in the Key of C in a given month.
<i>Portion Women</i>	The proportion of the mutual fund portfolio management team that are women, calculated by classifying manager gender using gpt-4o-mini to interpret 497k filings.
<i>Performer Gender</i>	The proportion of top 40 Billboard songs where the lead performer is a woman, as classified by gpt-4o-mini based on artist and song name.
<i>All Women</i>	An indicator variable equal to one if all the portfolio's managers are women, and zero otherwise.
<i>Relative 3-Year Performance</i>	The rolling 3-year average return of the portfolio less the rolling 3-year average return of the S&P 500 Composite Index
<i>Expense Ratio</i>	The net-asset-weighted average of a portfolio's constituent funds' expense ratios, as reported in the CRSP MFDB.
<i>Turn Ratio</i>	The net-asset-weighted average of a portfolio's constituent funds' turnover ratios, as reported in the CRSP MFDB.
<i>Monthly Return</i>	The monthly return on the portfolio.
<i>Size</i>	The natural logarithm of the total net assets of the fund.
<i>EPU</i>	The economic policy uncertainty index, as in...
<i>VIX</i>	The monthly average value of the Chicago Board Options Exchange's volatility index (VIX).