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Abstract

Using the recent AAPI Hate around 2020-2021 as an exogenous shock, we show that sociopolitical racial animus impairs the performance of mutual funds managed by at least one Asian female manager, the most targeted group by the Hate-induced violence. The decline in performance is greater in states with higher levels of anti-Asian animus, when the portfolio is more actively managed, has an aggressive investment objective, or when the Asian female manager plays a more influential role in fund management. The poor fund performance is not attributed to fund investors' redemption, low managerial quality, increased childcare burden, concerns for the pandemic situation of family members in home countries, or solely workplace discrimination. Placebo tests show that the same performance decline is absent among funds managed by non-Asian-looking minority and index funds. Taken together, the evidence is consistent with perceived vulnerability to the AAPI Hate crimes inducing distraction and stress and leading to impaired performance. Corroborating this view, we only find some limited evidence in a subset of Asian male managers that they suffer from a performance decline when they are based in states with higher levels of anti-Asian animus. Our study contributes to the scarce evidence on the impact of sociopolitical racial animus on productivity and explores racial animus beyond the workplace and marketplace.

JEL classification: G23, J150

Keywords: Racial Animus, Mutual Funds.

1. Introduction

Race-based bias undermines equality and justice. While there is a growing body of research, mostly on the existence of racial animus (Stephens-Davidowitz, 2014; Fang and Huang, 2017; Kline, Rose, and Walters, 2022), in workplace and (credit access) marketplace (Bartlett et al., 2022; Butler, Mayer, and Weston, 2022; Elton, Gruber, and Blake, 1995), there is only limited evidence on the economic consequences of racial animus. This study extends this literature by examining the effect of sociopolitical racial animus on the work performance of targeted groups, using the surge in social hostility and hate crimes against Asian Americans and Pacific Islanders (AAPI) communities during the COVID-19 pandemic as a shock (Gover, Harper, and Langton, 2020).

The AAPI Hate (hereafter "Hate") was largely fueled by the stigma of the origin surrounding the start of COVID-19 pandemic in 2020. Many people blamed the Asian community for the pandemic and used it as an excuse to target and discriminate against individuals of Asian descent. The victims of the Hate, however, were not limited to ethnically Chinese but included people (disproportionately women) who have an appearance that could be perceived as being of East and Southeast Asian descent because the Hate was targeted for what people "look like". [1] President Biden acknowledged the severity of the situation when he stated, "Too many Asian Americans have been walking up and down the streets and worrying, waking up each morning the past year feeling their safety and the safety of their loved ones are at stake. They've been attacked, blamed, scapegoated, and harassed. They've been verbally assaulted, physically assaulted, and killed."[2] The safety threat in the background can hurt the productivity of its targets even in the absence of

[1] Michelle Tran, a Chinese and Vietnamese American medical student living in the [New York] city, was horrified by this spike in violence [against Asian Americans]... 'As an Asian American female, I've seen that we can be targeted for what we look like,' Tran said." (brackets are added by the authors) (Dunn, 2022).

[2] Sourced from "President Biden Announces Additional Actions to Respond to Anti-Asian Violence, Xenophobia and Bias". March 30, 2021.

workplace discrimination.[3] In this study, we focus on mutual fund managers as they are a group of professionals whose performance can be conveniently measured and compared. Additionally, their decision-making abilities are crucial in determining the performance of the funds they manage. Aligned with the group of individuals who are primarily targeted during the Hate, our "treatment" group consists of funds with at least one Asian manager who has an appearance that could be construed as being of East and Southeast Asian descent. We will refer to this group as "Asian" managers throughout this paper.

The AAPI Hate is an ideal setting for making causal inferences due to two key features. First, the sudden surge in anti-Asian animus was triggered by the pandemic and was not anticipated by the population,[4] making it a suitable and plausibly exogenous shock. Second, the setting offers a unique identification by itself. Before the recent AAPI Hate, there was no cohesion among people in the AAPI group because culturally they are very different. Because of haters' attribution of the origin of the pandemic, all AAPI people (especially females) who could be perceived as "looking Chinese," become common targets of hate crimes. By comparing the performance of portfolio managers who are Chinese to those who could be perceived as Chinese, and contrasting this targeted group with other minority managers, we can differentiate the impact of the AAPI Hate from other explanations such as discrimination against minorities, and the productivity toll caused by the pandemic which was disproportionately borne by women due to family care needs and school closure (e.g., Barber et al., 2021; Ain Tommar, Kolokolova, and Mura, 2022).

Our analyses begins with a sample of actively managed U.S. mutual funds from

[3] Psychology theory has long established that stress impairs productivity and decision making. The processing efficiency theory predicts that anxiety impairs the processing and storage capacity of working memory, thereby reducing the resources available for a given task and lowering work performance (Eysenck and Calvo, 1992). Eysenck et al. (2007) presents the attentional control theory, which suggests that anxiety can lead to decreased cognitive performance by impairing attentional control. Greenberg et al. (1999) estimate the economic cost of workers' anxiety and find that 88% of the cost is due to the loss of work productivity as opposed to absenteeism.

[4] Compared to the average number of anti-Asian incidents over the last decade (from 2010 to 2019), the FBI hate crime data show that the number of anti-Asian incidents increased by 151% in 2020.

2019 Q1 to 2021 Q1, which covers four quarters before and after the COVID-19 outbreak in the U.S. Hereafter, We will refer to the sample as the full sample. Since there exists a gender asymmetric effect of COVID-19 on work productivity (e.g., Barber et al., 2021; Ain Tommar, Kolokolova, and Mura, 2022) and the Hate disproportionately targeted Asian females (Jeung et al., 2021; Kaur, 2022), we also perform sub-sample analysis by constructing two mutually exclusive sub-samples: male-managed sample and female-present sample. The male-managed sample includes funds that were solely managed by male fund managers, while the female-present sample consists of funds that were managed by at least one female manager.

In the full sample, we find that there is a negative but statistically insignificant effect of the Hate on the risk-adjusted performance of mutual funds managed by at least one Asian manager (i.e., Asian-present funds). When examining male-managed sample and female-present sample separately, we find that the AAPI Hate has no detectable effect on the work performance of Asian male managers. In contrast, in the female-present sample, a higher proportion of Asian female managers is associated with a lower fund alpha after 2020 Q1. The effect is not only statistically significant but also economically sizable. A one-standard-deviation increase in the fraction of Asian female managers on the team is associated with a 0.98% decrease in annualized risk-adjusted returns. This contrast is in line with a plethora of anecdotal evidence and our hypothesis that Asian females are more frequently targeted and susceptible to street-hate crimes, leading to distraction, anxiety, and stress, all of which can diminish work productivity. Therefore, in the following analyses we focus on the female-present sample. In this sample, the performance of the treatment and control groups followed a parallel trend in performance before the pandemic, with a divergence appearing only after 2020 Q2 and remaining significant till 2020 Q4.

The finding in the female-present sample is robust to alternative measures of fund performance, such as "return gap" (Kacperczyk, Sialm, and Zheng, 2008), which captures the quality of a fund's intra-quarter investment decisions, and "DGTW-adjusted return" (Daniel et al., 1997), which measures a fund's security selection ability relative to a passive strategy.

Due to the coinciding timing of the AAPI Hate and the COVID-19 pandemic, both of which have had a significant impact on the social and economic landscape, we need to exercise caution in identifying the source of the performance setback by Asian female fund managers. We perform several cross-sectional heterogeneity tests to provide direct support to our hypothesis. First, we find that the performance of Asian female managers located in states with higher levels of hate crimes (according to FBI crime statistics) or anti-Asian sentiment (measured by tweets) suffered more.[5] Second, the AAPI Hate threat was associated with more damage in funds that were more actively managed or had an aggressive investment objective. These types of portfolios involve more frequent and demanding investment decisions that are particularly sensitive to distractions, anxiety, and stress. Third, the decline in fund performance was concentrated in funds when Asian female managers played a more influential role in the management team.

We conduct additional analyses to control for confounding factors, specifically, those that were concurrent with the pandemic. First, we find that investors' redemption and inferior managerial skills of Asian-female-present funds are not responsible for the decreased performance of these funds. Second, we show that Asian female managers aged between 35 and 49, who are typically considered to face a high childcare burden, did not perform worse than Asian females who were younger or older, suggesting that increased childcare responsibilities during the COVID-19 did not drive our results. Third, First-generation Asian female immigrants, who may have concerns for their families and relatives in countries

[5]We do not consider the Anti-Asian Hate Crime Tracker data used in Qiao, Xu, and Zhang (2023) because the data are only available in the post-event period, which rendered it unsuitable for our triple difference analyses. More importantly, the data source shows a decrease in the quarterly number of anti-Asian crimes in 2020 in New York, the most important financial center in the U.S., which is different from the prevailing observations and common belief.

devastated by COVID-19, were classified based on a combination of their first names and biographical information. They experienced similar performance setbacks as non-immigrant Asian females in the same demographic group, indicating that concerns for their families do not explain our findings. Additionally, we contrast the effect of the Hate on Chinese females with that on non-Chinese Asian females. We find that our finding is driven by Asian-looking appearance but not merely by the unfriendly sentiment towards Chinese in the workplace under the crossfire of COVID-19 and souring relations between the U.S. and China. Finally, we perform two sets of placebo tests. In the first test, we contrast the effect of the Hate on Asian female managers with that on non-Asian minority females and South Asian females who were subject to the heightened levels of xenophobia against all minorities during the pandemic but were not targets of the AAPI crimes. In the second test, we examine the effect of the AAPI Hate using pure index funds that track a pre-determined index benchmark and thus are not sensitive to managers' negative emotions. As expected, we find that the placebo groups are not responsive to the AAPI Hate.

Our study expands upon existing research on racial animus and discrimination that has primarily centered on unequal career opportunities and market transactions for minority groups, particularly Black individuals or institutions managed by Black individuals (e.g., Stephens-Davidowitz, 2014; Hsieh et al., 2019; Kumar, Niessen-Ruenzi, and Spalt, 2015; Kline, Rose, and Walters, 2022; Bartlett et al., 2022; Dougal et al., 2019). Our study explores racial animus beyond the workplace and marketplace. Despite a rich and growing literature on racial discrimination, there is limited evidence on the economic consequences of discrimination. Hsieh et al. (2019) find that improved allocation of talented women and Black men contributed to the growth in the aggregate market output per person in the U.S. Huber, Lindenthal, and Waldinger (2021) show that the expulsions of Jewish managers in Nazi Germany reduced the market value of German firms. Exploiting the recent surge in highly publicized AAPI Hate crimes, our study adds to the scant evidence on the economic consequences of racial animus by documenting the impaired work performance of the disadvantaged group.

A concurrent paper by Qiao, Xu, and Zhang (2023) shows that the AAPI Hate impaired forecast quality of East Asian sell-side analysts. Our paper examines the effect of the AAPI Hate on mutual fund managers whose productivity can be captured by return performance and is less subject to the potential bias in analyst forecasts arising from the existence of conflicts of interest (Michaely and Womack, 1999). We also carefully rule out numerous alternative explanations by using rich micro-level data. Our study complements the literature by exploiting the recent surge in the highly publicized AAPI Hate crimes in a well-defined setting to document the real effects of sociopolitical racial animus on work performance of the most targeted groups.

Our study is related to, but distinct from, the literature examining the effects of negative experiences such as economic recessions (Malmendier and Nagel, 2011; Schoar and Zuo, 2017), terrorist attacks (Agarwal, Ghosh, and Zhao, 2019; Wang and Young, 2020; Cuculiza et al., 2021), and natural disasters (Bernile, Bhagwat, and Rau, 2017; Hanaoka, Shigeoka, and Watanabe, 2018; Alok, Kumar, and Wermers, 2020) on individuals' economic behavior. In contrast to these studies that focus on changes in preferences such as risk tolerance following negative shocks, our study highlights the loss of work productivity due to distraction, anxiety, or stress. Additionally, these prior studies focused on shocks that created vulnerable groups based on characteristics related to economic outcomes (e.g., stock investors, childhood hardship, residents in disaster zones). In contrast, the AAPI Hate targets groups based solely on appearance associated with ethnicity, which, in the absence of bias, bears no relation to performance. This unique setting enables us to measure the impact of pure prejudice.

The study also contributes to the growing literature on the obstacles faced by women in the finance profession. Existing research finds that women face higher hurdles to succeed in their careers, including discrimination in entering the sell-side analyst profession (Kumar, 2010), receiving less support from colleagues and connections (Fang and Huang, 2017; Gompers et al., 2022), and experiencing smaller fund inflows (Niessen-Ruenzi and Ruenzi, 2019). Another strand of literature, which uses the COVID-19 pandemic as an exogenous shock to family responsibilities, shows that compared to men, women exhibit lower research productivity (Barber et al., 2021), produce less accurate earnings forecasts Li and Wang (2021), and yield lower performance in hedge fund management Ain Tommar, Kolokolova, and Mura (2022) during the pandemic. Our paper contributes to this literature by providing evidence of the adverse performance effect of racial animus against women.

The rest of the paper is organized as follows. Section 2 provides a detailed description of our data and sample. Section 3 presents our empirical analysis of the effect of racial animus on fund performance. Section 4 filters confounding factors and examines alternative hypotheses. Section 5 is on sensitivity checks. Section 6 concludes.

2. Data Sources, Variable Construction, and Sample Overview

2.1. Episodes of the AAPI Hate

The event window of our study begins with the first quarter of 2020 (2020 Q1) when COVID-19 cases first occurred in the U.S., accompanied by a surge in the AAPI Hate crimes (Lu and Sheng, 2022). Two important events define the event quarter. First, the World Health Organization (WHO) declared COVID-19 a public health emergency of international concern in January 2020, and upgraded the status to a pandemic in March 2020. Second, Hohl et al. (2022) document that then-President Trump's tweet about the pandemic on March 16, 2020 was followed instantly by a precipitous rise of anti-Asian hashtags. This Hate was largely fueled by the stigma surrounding the start of COVID-19 pandemic. Many people blamed the Asian community for the pandemic and used it as an excuse to target and discriminate against individuals of Asian descent. A report by the Center for the Study of Hate and Extremism revealed that anti-Asian hate crime in 16 of the largest cities in the US increased by 149% in 2020. Notably, New York City experienced the highest surge with an alarming increase of 833%. The fear of Hate spread much beyond direct victims and their families and friends, because Asians, including highly accomplished professionals, were targeted for simply what they look like. [6]

Asian women who are physically more vulnerable were disproportionately targeted by the AAPI Hate relative to their male counterparts. Women reported 2.3 times Hate incidences as men from March 2020 to February 2021 (Jeung et al., 2021). Women were even more over-represented among victims of violent or even deadly hate crimes (Kaur, 2022).[7] Moreover, the perceived safety threat to Asian women could be further amplified by media coverage (Logan and Walker, 2021). Our Factiva news search shows that women appeared as victims in the titles of AAPI hate-related news articles nearly 20 times more often than their male counterparts from March 2020 to March 2021. According to a survey conducted in 2022 by the National Asian Pacific American Women's Forum, 74% of AAPI women report personally experiencing racism and/or discrimination and 71% report feeling anxious or stressed due to fear of discrimination, violence, etc.

The passage of the "COVID-19 Hate Crimes Act" and the availability of COVID-19 vaccines to all Americans since May 2021 helped mitigate Hate-related worries and anxieties (Agrawal et al., 2021) but the heightened wave of anti-Asian crimes lasted throughout our sample period from 2019Q1 to 2021Q1.

2.2. Sample of mutual funds and fund managers

To construct our samples, we start with all U.S. open-ended, actively managed funds that primarily invest in U.S. securities, and are covered by the Morningstar Direct database. This leaves us with diversified U.S. equity funds, corporate bond funds, sector

[6] A survey by a global leading think tank Coqual shows that that 63% of Asian and Asian American professionals said the recent anti-Asian animus negatively impacted their mental health and half said it also negatively affected their ability to focus at work.

[7] Source: The Stop AAPI Hate Reporting Center. High profile cases involve the Atlanta spa shooting in 2021 and the murder of a female business executive in a New York city subway in 2022.

funds, allocation funds, and alternative strategy funds. Index funds identified by fund names as well as Morningstar and CRSP index fund identifiers are excluded. We collect fund characteristics and portfolio manager information from the Morningstar Direct database. The Morningstar Direct database is the source for fund characteristics including total net assets, turnover ratio, expense ratio, and fund style. Fund return data are sourced from the CRSP mutual fund database for its perceived higher return data quality (Kumar, Niessen-Ruenzi, and Spalt, 2015). Mutual fund quarterly holding data are obtained from the CRSP mutual fund holdings databases. For funds with multiple share classes, we aggregate assets under management (AUM) and compute the AUM-weighted returns and other fund characteristics (e.g., expense and turnover ratio) across share classes. Following the common practice in the literature (e.g., Chen et al., 2004), we further exclude funds with less than $15 million in total net assets and require a fund to be at least 36 months old before entering the sample to avoid the potential incubation bias (Evans, 2010). To avoid the confounding effects of managers' turnover on fund performance, we require no management team change from 2019 Q4 to 2020 Q2 (i.e., one quarter before, and one quarter after, the event quarter).

Because of the anti-Asian sentiment fueled by the COVID-19 pandemic, the rise in xenophobia and racism against Asian people has been particularly targeting those who "look like" Chinese, and extends to people who could be perceived to be of East Asian decent. Because the attacks on the street are based on how people "look" (instead of true nationality or ethnicity), the targeted group includes most East Asians and Southeast Asians. [8]

To identify Asian portfolio managers who were primarily targeted by the AAPI Hate, we first narrow the scope of our search using a Python program which calculates a probability score for four groups based on last names: Asian, Black, Hispanic, and White. If

[8]According to a 2021 report by The Stop AAPI Hate Reporting Center, East Asians were the most likely victims of anti-Asian hate. Among reported hate incidents against AAPI individuals, 75.0% were experienced by East Asians and 23.9% by Southeast Asians.

a name has 5% or higher chance of being Asian, we look for photographs of fund managers in LinkedIn, fund company websites, and other internet sources to determine whether a manager has an appearance that could be construed as being of East and Southeast Asian descent.

Due to the gender asymmetric effect of the COVID-19 on work productivity (Barber et al., 2021; Ain Tommar, Kolokolova, and Mura, 2022) and the highly skewed distribution of targeted population between women and men, we divide the full sample into two mutually exclusive sub-samples: the male-managed sample and the female-present sample. The male-managed sample includes funds that were solely managed by male fund managers. The female-present sample consists of funds that were managed by at least one female manager. Examining these two sub-samples separately enables us to compare the performance of Asian-male managed funds with that of funds managed by non-Asian male managers and compare the performance of Asian-female managed funds with that of funds managed by at least a non-Asian female manager.

We identify fund managers' gender based on the following procedure. First, we match portfolio managers' first names obtained from the Morningstar Direct database with a list of the most popular first names by gender for the last ten decades published by the U.S. Social Security Administration (Kumar, Niessen-Ruenzi, and Spalt, 2015). Second, for names that are not matched to the list of American popular names or those that are gender neutral, we utilize a gender API website, which calculates the gender probability scores based on first names. We classify a manager to be female if the probability value is 95% or above. Third, we manually classify the remaining ambiguous cases by searching managers' biographies in the Morningstar Direct database or internet sources such as fund prospectuses. We classify a manager to be female only where there is affirmative information for gender (e.g., pronouns and photos).

We use internet sources to determine fund managers' office locations during the sample period. Our primary sources are LinkedIn and fund company websites that include the location of a fund manager's office during the manager's employment. If the primary sources are not available, we resort to B2B data providers (e.g., ZoomInfo, RocketReach, and SignalHire). For the remaining managers, we use their co-managers' location if all the co-managers with available location information are located in the same state.

In the end, the full sample includes 16,543 fund-quarter observations for 2,316 unique funds from 2019 Q1 to 2021 Q1 (excluding 2020 Q1). The male-managed sample includes 13,628 fund-quarter observations for 1,880 unique funds that were solely managed by male managers. The female-present sample includes 2,915 fund-quarter observations for 436 unique funds that were managed by at least one female manager.

Appendix lists the definitions of the main variables. Table 1 reports their summary statistics. We provide the details for the construction of the variables in the discussion of our empirical analyses.

[Insert Table 1 here.]

3. Fund Performance During the AAPI Hate

3.1. Underperformance of Asian female fund managers during the AAPI Hate

The surge of the AAPI Hate in early 2020 was largely unexpected. Such a shock allows us to trace out its impact in a difference-in-differences (DiD) model analyzing the performance of mutual fund managers. More specifically, we start with the following baseline regression at the fund (i)-quarter (t) level:

$$Perf_{i,t} = \beta_1 AsianX_i \times Post_t + \gamma X_{i,t-1} + \theta_i + \delta_{s,t} + \epsilon_{i,t}. \quad (1)$$

In the equation above, the dependent variable $Perf$ stands for fund performance, which is the annualized monthly risk-adjusted abnormal return (alpha) averaged over a quarter. For diversified equity funds including equity funds and allocation funds with more than 50% of AUM in U.S. equities, we estimate the alpha using the Fama and French (1993) and Carhart (1997) four-factor model. For corporate bond funds, we estimate the alpha using the four-factor model based on Elton, Gruber, and Blake (1995) and Cici and Gibson (2012). For sector funds, alternative funds, and allocation funds with less than 50% of AUM in U.S. equities, we estimate the alpha using a one-factor model, where the factor is constructed as the average return of peer funds in the same Morningstar category (Ma, Tang, and Gomez, 2019). Following Ain Tommar, Kolokolova, and Mura (2022), a fund's abnormal return during the sample period (from 2019 Q1 to 2021 Q1) is based on the factor loadings that are estimated from the 36 monthly fund returns prior to a fund's first entry into the sample.

The key independent variable, $AsianX$ is a proxy for the fund management team's exposure to the AAPI Hate. In the full sample, $AsianX$ is the fraction of East and Southeast Asian managers, $Asian$. In the male-managed sample, $AsianX$ is the fraction of East and Southeast Asian male managers, $AsianMale$. In the female-present sample, $AsianX$ is the fraction of East and Southeast Asian female managers, $AsianFemale$. Correspondingly, the control funds in the full sample, the male-managed sample, and the female-present sample, consist of funds without Asian managers, funds without Asian male managers, and funds without Asian female managers, respectively. The variable, $AsianX$, ranging between 0 and 1, assumes positive values in 11.8% of the observation in the full sample, 8.6% in the male-managed sample, and 18.9% in the female-present sample. $Post_t$ is an indicator variable that equals one if a fund-quarter is after 2020 Q1. The event quarter 2020 Q1 per se is excluded from the regression sample because of the ambiguity in assigning it as the pre-event or post-event period. $X_{i,t-1}$ denotes a set of fund-level control variables of fund characteristics lagged by one quarter, including fund size or total net assets in logarithm ($Log(TNA)$), expense ratio ($Expense$), annualized monthly return volatility over the last 12 months(VOL), and fund turnover ratio ($Turnover$). Finally, fund fixed effects (θ_i) absorbs time-invariant unobserved heterogeneity at the fund level, and style-by-time fixed effects ($\delta_{s,t}$) filters out time-varying common return shocks to funds in a given category. The fixed effects subsume $AsianX_i$ and $Post_t$, leaving $AsianX_i \times Post_t$ the key variable of interest.

Table 2 reports the regression results for the difference-in-differences estimation of Equation (1). In column (1), we report the DiD results for the full sample and find that the Hate had a negative but statistically insignificant effect on the fund performance of Asian-present funds. In column (2), we restrict the analysis to the sample of funds that were solely managed by male managers. We find that there was no detectable effect of the Hate on the fund performance of Asian male-present funds. It is plausible because males typically possess a greater physical ability to defend themselves and thus they are less vulnerable and targeted during the AAPI Hate.

[Insert Table 2 here.]

In column (3), we focus on the female-present sample that consists of funds that were managed by at least one female manager. The results show that funds with more Asian female managers experienced a larger decline in performance during the AAPI Hate as evidenced by the negative and statistically significant coefficient estimate of $AsianFemale \times Post$ (p-value < 0.01). The magnitude of the anti-Asian animus effect is also economically significant. A one-standard-deviation increase in $AsianFemale$, the proxy of a fund's exposure to anti-Asian animus, results in a 0.98% decrease in annualized risk-adjusted returns.

Take together, the results in Table 2 are consistent with our prediction that anti-Asian animus introduced distraction, anxiety, and stress, to managers who belong to the primary group targeted by the AAPI Hate, thereby impairing the quality of their trading decisions. Since the impairment of the Hate is concentrated among Asian females who were disproportionately targeted and physically more vulnerable to the AAPI Hate, our subsequent analysis will focus on the female-present sample.

3.2. Parallel trends before the event and dynamic effects

We need to verify whether the observed performance decline among Asian-female-present funds were driven by the difference in fund characteristics or a pre-event trend between treatment and control funds. In Table 3, we first confirm that the two groups of funds were indistinguishable from each other along all observable dimensions of fund characteristics right before the event quarter.

[Insert Table 3 here.]

The key identifying assumption underlying regression equation (1) is that the performance of treatment and control funds exhibit a parallel trend in the absence of the AAPI Hate. In Figure 1a, We plot the average annualized alpha of treatment and control funds in the female-present sample four quarters before and after the outbreak of COVID-19 cases in the U.S. Figure 1a indicates that the performance of mutual funds was quite volatile around the pandemic with a significant decline in performance during the first quarter of 2020, followed by a gradual recovery in the subsequent four quarters. The performance changes perhaps reflect the changes in monetary policy and other economic activities. These patterns are in line with the findings of Pástor and Vorsatz (2020) on mutual fund performance around the pandemic. Importantly, the two trend lines in the performance of treatment funds and control funds, however, tightly intertwined together and exhibited no significant divergence before the pandemic. The figure also displays a notable under-performance of the treatment funds compared to the control funds from 2020 Q2 to 2021 Q1, aligning with our prior expectations.

Next, we formally verify the existence of a parallel trend and quantify the dynamic effect by extending equation (1) to:

$$Perf_{i,t} = \sum_{k=-3}^{+4} \beta_k AsianFemale_i \times Quarter_k + \gamma X_{i,t-1} + \theta_i + \delta_{s,t} + \epsilon_{i,t}, \qquad (2)$$

where $Quarter_k$ is an indicator variable that equals one if quarter t is k quarter(s) away from quarter 0 ($k = 0$), i.e., the beginning of the Hate. Figure 1b presents a graphical plot of the estimated coefficients of $\hat{\beta}_k$, for $-3 \leq k \leq +4$, and the 95% confidence intervals.

[Insert Figure 1 here.]

Figure 1b shows that the detrimental effect of anti-Asian animus on fund performance emerged in 2020 Q2 (albeit insignificant) and became statistically significant in 2020 Q3 and 2020 Q4, before reverting to par in 2021 Q1 (a full year after the shock). Importantly, the coefficients associated with the pre-shock quarters ($k = -3, -2, -1$) are indistinguishable from zero, in terms of both magnitude and statistical significance, consistent with the existence of a parallel trend between the two groups of funds before the event. The recovery of performance by the vulnerable population a year after the initial shock is an indication of adaptation by the professional managers to a new social regime, e.g., by exercising extra vigilance and avoiding high-risk venues such as subways. General developments in combating COVID-19 (e.g., emergence of effective vaccination in early 2021 and mutation of the virus which caused less severe symptoms)[9] and more societal recognition of the AAPI Hate and support for the community[10] likely help lessen the stress and anxiety of the vulnerable population.

3.3. Evidence from managerial actions

If managerial productivity is responsible for the poor performance of funds managed by Asian female managers during the AAPI Hate, we should observe a decline in Asian female-present funds' ability to engage in value-enhancing portfolio management activities.

For this purpose, we first use the "return gap" developed by Kacperczyk, Sialm, and Zheng (2008). *Return Gap* is calculated as the difference between a fund's actual return in a

[9] Agrawal et al. (2021) show that the COVID-19 vaccination significantly reduces anxiety and depression symptoms.

[10] President Biden signed the COVID-19 Hate Crimes Act into law on May 20, 2021, with particular emphasis on the surge in violence against Asian Americans.

quarter and the return that would be earned by the funds' disclosed holdings at the closest previous quarter end. Kacperczyk, Sialm, and Zheng (2008) argue that the return gap captures fund managers' unobservable actions that enhance the fund performance beyond a buy-and-hold strategy for the quarter.

In column (1) of Table 4, we replace the dependent variable in Equation (1) with *Return Gap* and restrict the regression sample to funds with 75% or more assets in U.S. equities and with non-missing holdings data from the CRSP Mutual Fund Holdings Database. We further exclude "alternative" funds as they often have significant positions other than long-equity. To avoid using stale information, we also require that the interval between the calendar quarter end and the previous holdings disclosure month be three months or shorter (allowing discrepancies between calendar quarter and fund fiscal quarter). Results, reported in the first column of Table 4, indicate that return gap deteriorated by 0.38% for one standard deviation increase in the proportion of Asian female manager (1.9%*0.20) during the Hate.

[Insert Table 4 here.]

Second, we employ "DGTW-adjusted return" (Daniel et al., 1997), which is calculated as the value-weighted stock returns of the equity holdings held at the end of the last quarter less the DGTW benchmark return based on value-weighted returns of 5×5×5 benchmark portfolios sorted on size, book-to-market, and momentum, to capture fund managers' stock-picking ability. The results are reported in column (2). We find that the annualized DGTW-adjusted returns decreased by 1.16% for one standard deviation increase in the proportion of Asian female manager (5.8%*0.20) during the Hate.

3.4. Cross-sectional variations in the under-performance of treatment funds

Naturally, there are cross-sectional variations in the under-performance documented in the previous section. This section explores such variations which bolster our inferences that attribute the performance deterioration to the racial animus prevalent during the pandemic.

3.4.1. State-level variations in anti-Asian animus

If the observed effect of anti-Asian animus documented in column (3) of Table 2 and Figure 1 is indeed caused by the AAPI Hate, we expect that performance declines more when Asian female fund managers are located in regions with higher levels of anti-Asian animus. We thus estimate a nested fully interacted triple-difference specification:

$$\begin{aligned} Perf_{i,t} = {} & \beta_1 AsianFemale_i \times Post_t \times HighAnimus_{j,t-1} + \beta_2 AsianFemale_i \times Post_t \\ & + \gamma_1 X_{i,t-1} + \gamma_2 X_{i,t-1} \times HighAnimus_{j,t-1} + \theta_i + \theta_i \times HighAnimus_{j,t-1} \\ & + \delta_{s,t} + \delta_{s,t} \times HighAnimus_{j,t} + \epsilon_{i,t}. \end{aligned} \tag{3}$$

In Equation (3), we interact the proxy of local anti-Asian animus, $HighAnimus$, with all the variables in the baseline regression model in Equation (1) and fund and style-by-time fixed effects.[11] In each quarter, we split 50 U.S. states and the District of Columbia into two sub-samples: the top decile of states based on an anti-Asian animus proxy and the rest of the states. Since female managers are concentrated in a few large states (e.g., New York, California, and Massachusetts), empirically we find that the top decile cutoff of the sorting variable gives us a rather balanced fund-quarter level observations across the high- and low- subgroups. $HighAnimus$ is an indicator variable that equals one if a state is in the top decile of the sorting variable on racial animus in a quarter and zero otherwise. We then assign each fund based on the office location of a fund's female managers into a high- or low-animus group. The coefficient of $AsianFemale \times Post \times HighAnimus$, β_1, captures the incremental effect of being exposed to a more stressful environment with a higher level of anti-Asian animus.

[11] Note that $AsianFemale \times HighAnimus$, $Post \times HighAnimus$, and $HighAnimus$ are all absorbed when $HighAnimus$ is interacted with fund and style-by-time fixed effects.

The first proxy for anti-Asian animus, $HateCrimeNum$, is the number of reported hate crime incidents in a state-quarter, based on statistics from the Uniform Crime Reporting (UCR) Program under the FBI. The UCR program generates comprehensive statistics on law enforcement, and is considered the most reliable information for researchers of criminal justice, the media, and the public. The sample becomes slightly smaller because of prudent trimming of the data as we exclude 35 funds with female managers who are located in multiple states, live in foreign countries, or have missing location information for the managers.

The results are reported in the first column of Table 5. The coefficient estimate of $AsianFemale \times Post \times HighAnimus$ is negative and statistically significant at the 1% level while that of $AsianFemale \times Post$ is negative but statistically insignificant. Moreover, the sum of estimates of β_1 and β_2 is negative and statistically significant at the 1% level. Overall, the results suggest that the under-performance is present and statistically significant only in the sub-sample of funds whose managers were based in states with high levels of anti-Asian animus. In fact, the magnitude of the effect from the funds whose Asian female managers are exposed to a higher level of anti-Asian animus (-0.090) is about 83% larger than that in the baseline test (i.e., -0.049 in Table 2 columns (3)).

[Insert Table 5 here.]

In addition to the proxy based on the FBI data, we also construct a second proxy that is based on the number of anti-Asian tweets posted in a state-quarter. Recent studies (e.g., Dougal et al., 2019; Fujiwara, Müller, and Schwarz, 2021; Müller and Schwarz, 2020) suggest that Twitter data can provide timely information on changes in racial animus of an area. We define anti-Asian tweets ($AntiAsianTweet$) at the state-quarter level as those containing racial slurs against Asians in a state where a fund's female managers are based. The Twitter data are collected via Twitter's API for Academic Research that is publicly available, which allows us to bulk-download tweets by keywords and time periods. Following

Fujiwara, Müller, and Schwarz (2021) and Müller and Schwarz (2020), we identify Twitter users' locations based on either their real-time geo-locations or their location information voluntarily disclosed in their profiles. If no state information is directly available, we match the city names among cities with more than 300,000 population because large cities can be more precisely mapped to a state. We delete tweets with missing location information or when their location information is ambiguous.

In column (2) of Table 5, the sample is divided based on the top decile of the number of anti-Asian tweets in a state-quarter, and the rest. We then perform the test in Equation (3) using this proxy. Again, the decline in the performance of funds managed by Asian female portfolio managers is concentrated in the state-quarters with a higher level of Twitter-borne anti-Asian animus.

3.4.2. The moderating effects of fund characteristics: Turnover, investment objective, and team size

The AAPI Hate should cause more damage when a fund is more actively managed as such portfolios require more frequent and timely investment decisions, which are more likely to be impaired by distraction, anxiety, and stress. To test this prediction, we perform a similar test in Equation (3) by replacing $HighAnimus$ with $HighTurnover$. $HighTurnover$ is an indicator variable that is sorted at the fund level and equals one if a fund's pre-event turnover ratio is above the sample median value. A fund's pre-event turnover ratio is calculated as the average turnover ratio over the five years prior to the event.

The estimation results are presented in column (1) of Table 6. Specifically, we find that the estimates of β_1 and the sum of $(\beta_1 + \beta_2)$ are both negative and statistically significant at the 1% level while β_2 is indistinguishable from zero. The results confirm our prediction that the performance deterioration because of the Hate is concentrated in funds with a more active trading strategy.

[Insert Table 6 here.]

Next, we explore the heterogeneity in funds' investment objective. We expect that the effect of the Hate on fund performance is stronger among funds with an aggressive investment objective. These funds typically require a higher level of focus and involve more demanding investment decisions, making them more susceptible to distractions, anxiety, and stress. Thus, we re-estimate the nested triple difference regression model in Equation (3) by replacing $HighAnimus$ with $AggressiveInvestment$. $AggressiveInvestment$ is an indicator variable that equals one if a fund is an aggressive growth fund or a high-yield bond fund in 2019 Q4. The results are reported in column (2) of Table 6. Consistent with our prediction, we find that performance decline during the Hate is primarily driven by the funds that have an aggressive investment objective.

Third, we expect that the performance decline effect are more pronounced among funds with smaller management teams. In a small team, each individual manager tends to assume a significant role, which makes their responsibilities less likely to be substituted by others. As a result, the influence of Asian female managers in smaller teams is expected to be more significant compared to those in larger teams. Thus, when Asian female managers' work productivity was compromised due to the AAPI Hate, fund performance would inevitably deteriorate. We re-estimate (3) by replacing $HighAnimus$ with $SmallTeam$. $SmallTeam$ is an indicator variable that equals one if a fund's management team size is below the sample median value in 2019 Q4 and zero otherwise. The results are reported in column (3) of Table 6. Consistent with our prediction, we find that the performance decline effect of the Hate is concentrated in the Asian-present funds with a small management team.

4. Filtering Confounding Factors and Alternative Hypotheses

4.1. Fund outflows

Discrimination could come from stakeholders. In the mutual fund context, Kumar, Niessen-Ruenzi, and Spalt (2015) find that flows to funds with managers with Middle-

Eastern-sounding names decreased abnormally after 9/11. Thus, another potential explanation of our main finding based on marketplace hostility is investors' redemption from Asian female-present funds during the wave of the Hate. Prior literature (e.g., Edelen, 1999; Coval and Stafford, 2007; Simutin, 2014) shows that large redemption hurts fund performance and thereby remaining shareholders as liquidation required to meet redemption incurs a fire sale discount. Moreover, because of such cost spillovers to remaining shareholders, the anticipation of redemption of some investors may trigger redemption by other investors (Chen, Goldstein, and Jiang, 2010). In this setting, the AAPI Hate may serve as a public signal that could trigger redemption.

We start with a test by replacing the dependent variable in Equation (1) to be $FundFlow$ to examine whether Asian female-present funds experienced more fund outflows. $FundFlow$ is defined as the return-adjusted change in fund total net assets (TNA) following the standard practice in the literature (Coval and Stafford, 2007). Column (1) of Table 7 shows that Asian-female-present funds experienced a decrease in fund flow relative to other funds but the effect is far from statistical significance. In column (2), we re-estimate the nested fully interacted triple-differences regression model in (3), by replacing $HighAnimus$ with $LargeOutFlow$. $LargeOutFlow$ is an indicator variable that equals one if the monthly outflow averaged over the contemporaneous quarter is 5% or more, and zero otherwise. If the alternative hypothesis that the observed poor performance is primarily driven by large fund outflow from Asian female-present funds were true, we expect that the performance decline effect is largely concentrated in funds with large outflow. Inconsistent with the prediction, the estimate of β_1 is not only negative and statistically significant at the 1% level but also of comparable magnitude to the baseline result (i.e., -0.049). In addition, the estimate of β_2 is negative and statistically significant at the 10% level, suggesting that a large fund outflow had additional negative impact on Asian female managers' performance. Taken together, the results are not supportive of the alternative explanation that our results are primarily driven by large fund outflow from Asian female-present firms.[12]

[Insert Table 7 here.]

4.2. Heterogeneity in fund quality

Another possibility is that "treatment" funds (i.e., funds with at least one Asian female manager) were less skilled, and faced greater challenge in portfolio management when COVID-19 triggered economic downturns. Such a hypothesis could generate an observationally equivalent result that treatment funds experienced greater deterioration during the event period. Note that the parallel trend test demonstrated in Section 3.2 does not support such a hypothesis. We further provide a direct test to refute this hypothesis. In column (3) of Table 7, we re-estimate the triple-difference regression model in Equation (3), by replacing $HighAnimus$ with $LowPerf$. $LowPerf$ is an indicator variable that equals one if a fund's pre-event fund performance is below the sample median value. A fund's pre-event performance is calculated as the average fund performance over the five years prior to the event. The estimate of β_1 continues to be negative and statistically significant at the 1% level. However, the coefficient estimate, β_2, that captures the incremental effect of a fund's under-performance during the pre-event time period is negative but statistically insignificant. Overall, there is no support for the hypothesis that the "treatment funds" were of inferior performance to start with.

4.3. Zoom into Asian female managers

In this section, we further zoom into Asian female managers' characteristics to provide evidence that reinforces our baseline findings in Table 2 column (3) and refute other alternative explanations in relation to increased childcare burden of females during the pandemic, extra concerns for extended families, and the unfriendly sentiment towards

[12]Large abnormal inflows may also have a negative impact on fund performance as fund managers are forced to make more buy decisions. Thus, we perform a similar DDD test and find our result on the estimate of β_1 continues to hold.

Chinese at the workplace.

4.3.1. Managerial roles

If performance deterioration of Asian female fund mangers is due to the AAPI Hate, we expect the impact to be stronger if such managers assume a more senior role in the team as senior managers are more likely to be decision makers in portfolio management. Recall that we have already shown that the performance decline effect is concentrated in Asian female-present funds with a small management team, which speaks to Asian female managers' influence in their funds. However, zooming into Asian female managers' roles in the management team enables us to provide more direct evidence.

To test for this channel, we decompose $AsianFemale$ into two mutually exclusive variables:$AsianFemale\_Senior$ and $AsianFemale\_Junior$. $AsianFemale\_Senior$ is the fraction of Asian female managers of a fund when at least one Asian female manager plays a senior role in its management team and zero otherwise, and $AsianFemale\_Junior$ is the fraction of Asian female managers of a fund when no Asian female manager plays a senior role in its management team and zero otherwise. [13]

To classify seniority, we collect managerial role information of each fund from the fund's SEC filings (Form 485BPOS or Form 497K) at both the end of 2019 and the last entry of the fund in our sample. We determine that a manager plays a senior role if the manager holds the title of "lead portfolio manager" or is the only manager of a fund. For funds that cannot be identified this way, we further classify a manager as playing a senior role if the manager commands the longest tenure with the fund in the team, or if the manager is listed before other fund managers in the fund management section of a fund's prospectus that follows a non-alphabetic order. The last requirement is motivated by our observation that fund companies usually list the name of the lead portfolio manager first when introducing

[13]Note that we only have information on Asian female manager but on other female managers, and hence a standard triple-difference test cannot be performed.

in a fund's prospectus its management team. To qualify as a senior manager, the manager's role needs to have the senior status at both the end of 2019 and the last entry of the fund in our sample to avoid that a fund manager is demoted in between.

We then re-estimate the baseline model Equation (1) by replacing $AsianFemale \times Post$ with $AsianFemale\_Senior \times Post$ and $AsianFemale\_Junior \times Post$. The results are reported in Table 8. As predicted, we find that the performance decline is only statistically significant in funds where Asian female managers play a senior role, and the performance decline is negative but statistically insignificant in funds where Asian female managers play a junior role. In addition, the difference in performance deterioration between the two sub-samples is statistically significant at the 10% level.

[Insert Table 8 here.]

4.3.2. Lack of childcare during the pandemic period

One alternative explanation for our finding could be that the closure of childcare services across the country. In particular, lack of services for an extended period of time in the pandemic-devastated states has been shown to have reduced the productivity of professional women (Barber et al., 2021; Li and Wang, 2021; Ain Tommar, Kolokolova, and Mura, 2022). Recall that our main sample was restricted to funds with at least female manager, and hence the potential gender effect of COVID-19 on productivity has been partially mitigated. We, nevertheless, address this issue more directly by sorting the sample by female manager's expected childcare burden. Following Kruger, Maturana, and Nickerson (2022), we classify a female manager to have high a childcare burden if she was aged between 35 and 49 in 2019.

We infer a manager's age according to the year when she completed her bachelor's degree following Greenwood and Nagel (2009), assuming that each manager obtained her bachelor's degree at the age of 22 where the graduation year information is retrieved from the Morningstar Direct database. When such information is missing, we supplement it with information from managers' LinkedIn profile pages (if any). If information is still missing, we classify managers with more than 28 years of working experience as of 2019 into the low-childcare-burden group. This classification is based on the assumption that a manager began her career at the age of 22, and as such, managers with more than 28 years of work experience should be aged 50 (the cutoff age for entering the low-childcare-burden group) or above as of 2019. Managers' working experience information is collected from the Morningstar Direct database or LinkedIn profile pages.

We again decompose $AsianFemale$ into two mutually exclusive variables:$AsianFemale\_HighCareBurden$ and $AsianFemale\_LowCareBurden$. The former is the fraction of Asian female managers who were aged between 35 to 49 as of 2019 in a fund, and the latter is the fraction of Asian female managers who were aged younger than 35 or older than 49 as of 2019.

We then re-estimate the baseline model Equation (1) by replacing $AsianFemale \times Post$ with $AsianFemale\_HighCareBurden \times Post$ and $AsianFemale\_LowCareBurden \times Post$. The results are reported in the first column of Table 9. Inconsistent with the alternative explanation that attributes performance deterioration to increased childcare burden, we find that both the coefficient estimates of $AsianFemale\_HighCareBurden \times Post$ and $AsianFemale\_LowCareBurden \times Post$ are negative and statistically significant at the 5% or lower level, suggesting that performance deterioration exists in both the high- and low-childcare burden subgroups. The magnitude of the estimate of $AsianFemale\_HighCareBurden \times Post$, β_1, is smaller than that of $AsianFemale\_LowCareBurden \times Post$, β_2 though the difference between them is not statistically significant as the F-test shows. This is perhaps because Asian grandparents are more involved in taking care of their young grandchildren than their non-Asian counterparts, thereby reducing Asian female managers' childcare burden during the pandemic (Yang, 2013; Xu, 2019). Moreover, we argue that results in column (1) of

Table 9 do not dismiss the negative impact of the shortfall of childcare services on the productivity of professional women since all funds examined in this test have at least one female fund manager; instead, the results indicate that performance deterioration of Asian female managers could not be explained by the childcare situations during the pandemic.

4.3.3. Concerns about families at home countries during the pandemic

Asian countries were among the first batch of countries to reach the pandemic situation, and many experienced waves of devastation. Because Asian professional in the U.S. are more likely to be recent immigrants compared to other race groups,[14] they may experience additional stress due to concerns about their original and extended families in their home countries, especially during COVID waves there. If this is true, we expect Asian female managers who are first-generation immigrants to endure more stress in relation to their family and relatives in countries of origination, as compared to managers who were born or grown in the U.S. On the other hand, both groups face the same risk of becoming targets of anti-Asian hate crimes.

We construct a new variable $AsianFemale\_FirstGen$ to be the fraction of managers in a fund that are classified as a first-generation immigrant. We determine a manager to have the first-generation status if one of the following conditions is satisfied: (1) the manager has first name spelled in Asian phonetics (i.e., a "non-Anglicised" name);[15] (2) the manager received her bachelor's degree in an Asian country according to one's biographic information; and (3) the manager's mother tongue is an Asian language according to the information from LinkedIn (if any). We then re-estimate the baseline model Equation (1) by decomposing $AsianFemale$ into $AsianFemale\_FirstGen$ and

[14] According to this Pew Research Center paper, about 57% of Asian Americans, including 71% of Asian American adults, were born in another country. By comparison, 14% of all Americans, and 17% of adults, were born elsewhere.

[15] Asian immigrants often Anglicise their names for a variety of reasons, including avoiding racism and xenophobia and providing ease of pronunciation and assimilation (Yeung, 2021). Hence, a non-anglicised name is a near sufficient, but far from necessary, condition for first generation classification.

$AsianFemale\_NonFirstGen$. The results are reported in column (2) of Table 9.

The coefficient estimates of $AsianFemale\_FirstGen \times Post$ and $AsianFemale\_NonFirstGen \times Post$ are both negative and statistically significant at the 1% level. Consistent with the expectation that Asian female managers who are first-generation immigrants suffer from both the stress from their surrounding racial animus and worries about their families in home countries, the magnitude of the coefficient estimate of $AsianFemale\_FirstGen \times Post$ is almost twice as that of $AsianFemale\_NonFirstGen \times Post$. However, the difference is statistically insignificant. The fact that both groups of managers, sorted by their immigration status, experience similar performance deterioration suggests that concerns for families and relatives in Asian countries of origin do not drive our main finding.

[Insert Table 9 here.]

4.3.4. Unfriendly sentiment towards Chinese in the workplace

Finally, We test if our finding of the under-performance of Asian female fund managers is primarily due to the conflicts between Chinese and non-Chinese fund managers within the management team during the pandemic as well as the escalating tension between the U.S. and China. Since on the street, Asians who "look like" Chinese face the same risk of hate-driven attacks, our hypothesis predicts that the productivity of both Chinese and non-Chinese Asian female managers is affected by the AAPI Hate. In the workplace, information about a manager's country origin is likely known. Therefore, a simple unfriendly sentiment towards Chinese in the workplace predicts that only Chinese female managers were affected by the AAPI Hate. Such a distinction allows us to separate the two causes. Among Asian females, we divide the group into Chinese and non-Chinese. As a result, $AsianFemale\_Chinese$ is the fraction of Chinese females in a fund's management team. We define a manager as Chinese by her last name and her first-generation status. We define a manager as a first-generation immigrant by the classification algorithm used in

Section 4.3.3. About 39.1% of the Asian female managers in our sample are from China.

Results in the third column of Table 9 indicate that both Chinese and non-Chinese Asian female managers exhibit significant performance deterioration during the pandemic, which is expected as non-Chinese Asian female managers could still "look like Chinese" on the street. Although the magnitude of the coefficient estimate of $AsianFemale\_Chinese \times Post$ is almost twice that of $AsianFemale\_NonChinese \times Post$, the difference is statistically insignificant. In addition, the results also confirm that "being Chinese" is not the source of stress but "looking like Chinese" is. Hence, the source of the stress is not due to the unfriendly sentiment towards Chinese in the workplace arising from COVID-19 and the tension between China and the US.

4.3.5. Placebo Test

During the AAPI Hate that started in 2020, Asians who could be perceived to be Chinese or of East and Southeast Asian descent were disproportionately targeted in the hate crimes (See Footnote 8). Such a specific targeting provides us a test involving non-Asian minority female managers (including Black, Hispanic, and South Asians) as the placebo group, which was exposed together with the Asian female managers to COVID-era xenophobia and racial discrimination. But only the latter group was the specific target of the AAPI Hate crimes.

To conduct such a test, we construct the variable $NonAsianMinorityFemale$ to be the fraction of "other" (i.e., not belong to $AsianFemale$ defined in Section 1) minority female managers in a fund's management team. Approximately, 11.0% of female managers are classified as non-Asian minority female managers in our sample. When we estimate the model of Equation (1) with additional interaction terms, we find that, as shown in Table 10 column (1), the coefficient estimate on $NonAsianMinorityFemale \times Post$ is indistinguishable from zero, economically and statistically. When we zoom into the subsample of South Asian managers (who are Asians by geography but are distinct from East and Southeast Asians in appearance and who were unlikely victims of the AAPI Hate crimes, see Footnote 8), results reported in column (2) are similarly null. Taken together, our main finding of deteriorating performance of Asian female fund managers during the AAPI Hate does not seem to be driven by the general heightened attention to xenophobia and racial discrimination during the COVID-era. The result again reinforces that it is one's "looking like Chinese" that matters for the vulnerability to the AAPI Hate.

[Insert Table 10 here.]

5. Sensitivity Checks

5.1. Alternative measures of fund performance

In Table IA.1 of the Internet Appendix, we employ three alternative measures of fund performance to check the robustness of the baseline findings in column (3) of Table 2. The first alternative is the annualized average monthly fund return in a quarter. Because we deploy year-by-quarter fixed effects, the variable is effectively broad market-adjusted returns. The second alternative is the annualized prospectus benchmark-adjusted return calculated as the average difference between the monthly fund return and the prospectus benchmark monthly return over a quarter. The third alternative measure is the alpha estimated from the Fama-French five-factor model (Fama and French, 2015). Our results are robust to these three alternative performance measures.

5.2. Alternative samples

We also examine the robustness of our baseline findings in Table 2 column (3) in two refined albeit smaller sub-samples. In column (1) of Table IA.3 of the Internet Appendix, we restrict the analysis to funds that were solely managed by female managers. In column (2), we restrict the sample to funds that were solo-managed by a female manager. The sub-sample in column (1) allows us to filter out the potential influence of male managers in the same female-present fund, while the sub-sample in column (2) further removes the difference between funds with different team size. Overall, the results reported in Table IA.2 are robust and the Hate effect is larger than that is observed in Table 2 column (3).

5.3. Pure Index Funds

In Table IA.3, we perform the second placebo test using pure index funds, which closely track pre-determined benchmarks and thus are unlikely subject to Asian managers' negative emotions induced by the AAPI Hate. Thus, we expect that the performance of Asian female-managed pure index funds should be largely indifferent to the Hate.

Pure index funds were identified based on fund names, as well as Morningstar (where the Morningstar index fund flag equals "Yes") and CRSP index fund identifiers (where the CRSP Index Fund Flag equals "D"). We follow the same procedure as in our primary analysis to obtain the gender and race identities of the managers who managed pure index funds during the sample period. Since Cremers, Petajisto, and Zitzewitz (2013) argue that the Fama-French-Carhart model, which is used in our main analyses, produces biased fund performance for index funds, we follow Crane and Crotty (2018) and measure fund performance of pure index funds using prospectus benchmark-adjusted return, which is calculated as the average difference between the monthly fund net return and the prospectus benchmark monthly return in a quarter. As expected, the results show that the coefficient estimate of $AsianFemaleSenior \times Post$ is close to zero and statistically insignificant.

5.4. Some further evidence on Asian male managers

In the second column of Table 2, we show that the performance of Asian male-managed funds, on average, is not affected by the AAPI Hate. We argue it is because males typically possess a greater physical ability to defend themselves compared to females and thus they are less vulnerable and targeted during the AAPI Hate. Results of news search discussed in Section 2.1 are consistent with this argument. However, we find that Asian male managers were not completely immune to the APPI Hate when the exposure to the anti-Asian animus is sufficiently high. Specifically, we first split Asian male managers into two mutually exclusive subgroups including those based in high- and low-animus states during the AAPI Hate. [16] We define high-animus states as those in the top decile of the proxy of anti-Asian animus among 50 U.S. states and the District of Columbia. The rest of the states are assigned to be low-animus states. Similar to the tests in Table 5, We use the number of FBI hate crime incidents and the number of racial tweets as the two proxies of anti-Asian animus. As a result, based on the two proxies, 52% and 55% of Asian male managers are assigned to the high animus group. We then re-estimate the baseline model in Equation (1) using the male-managed funds by replacing $AsianMale$ with $AsianMale\_HighAnimus$ and $AsianMale\_LowAnimus$. The results reported in columns (2) and (3) of Table IA.4 in the Internet Appendix show that the performance of Asian male managers is not responsive to the AAPI Hate in either the high- or low- animus group using a cutoff that assigns about half of the male managers into the high-animus group. However, it could be the case that Asian male managers require an even higher hurdle to be affected.

In columns (5) and (6), we, therefore, assign Asian male managers in the top two states ranked by local racial animus into the high-animus group and the rest into the low-animus group. This sorting assigns roughly one third of the Asian male managers into the high-animus group for both proxies. Consistent with our prediction that the performance of Asian male managers would respond to the Hate only when the local anti-Asian animus is sufficiently high, we find that the performance of Asian male managers who were based in the high-animus states proxied by the number of racial tweets declined significantly during the AAPI Hate. Moreover, the difference in the effect of the Hate between the high- and low- animus groups, $\beta_2 - \beta_3$, is statistically significant at the 5% level. We observe a similar pattern when the local anti-Asian animus is proxied by the number of hate crime incidents

[16] Due to the large number of male managers (over 2,500) in the male-managed sample, we do not have location information for all of them. As a result, we are unable to estimate a standard triple-differences model as in Table 5.

though the negative effect is not statistically significant at the conventional level (t-value = -1.45).

6. Conclusion

Racial animus has attracted significant research, most of which focuses on workplace (e.g., recruiting, promotion, political elections) and marketplace settings (e.g., credit access) as the finding has well-defined legal and policy implications. In contrast, race-based hostility or hate in a sociopolitical setting is often hard to quantify. This study explores the wave of hate crimes against Asian Americans and Pacific Islanders (AAPI) communities (AAPI Hate) since early 2020 as an exogenous shock to sociopolitical racial animus in the U.S, and uses the mutual fund industry as a laboratory given its clean and readily available performance measures. We find that, among funds with at least one female manager, funds with more East- and Southeast-Asian female managers exhibit worse return performance in 2020. The performance decline is more pronounced for funds whose Asian female managers are located in states with higher levels of anti-Asian animus, need to trade more often or more aggressively, or play a more influential role in fund management.

Further, neither workplace anti-Asian animus from fund investors nor heterogeneity in fund quality can explain the performance decline during the AAPI Hate. Importantly, our main results are not due to Asian female managers' greater childcare responsibilities, concerns for family members in their Asian countries of origin, unfriendly sentiment towards Chinese arising from the escalating tension between China and the U.S., or the heightened level of xenophobia against all minorities during the pandemic. Taken together, the evidence is consistent with vulnerability to the AAPI Hate crimes inducing distraction and stress and leading to impaired performance. Our study extends the sizable literature on detecting racial discrimination in various contexts by providing one of the first pieces of evidence that sociopolitical racial animus entails a significant economic cost and engenders a real effect on the group of people who are vulnerable to such animus. Second, this study also adds to the small yet growing literature on the obstacles faced by women in finance by showing vulnerability to violent racial hate crimes that can cause a stress to female professionals. While the study is based on an episode of the AAPI Hate and a setting of the mutual fund industry, we believe the lesson could be generalized that sociopolitical racial animus entails a significant economic and career cost on the group of people who are targets of such animus.

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Appendix

Variable Definitions

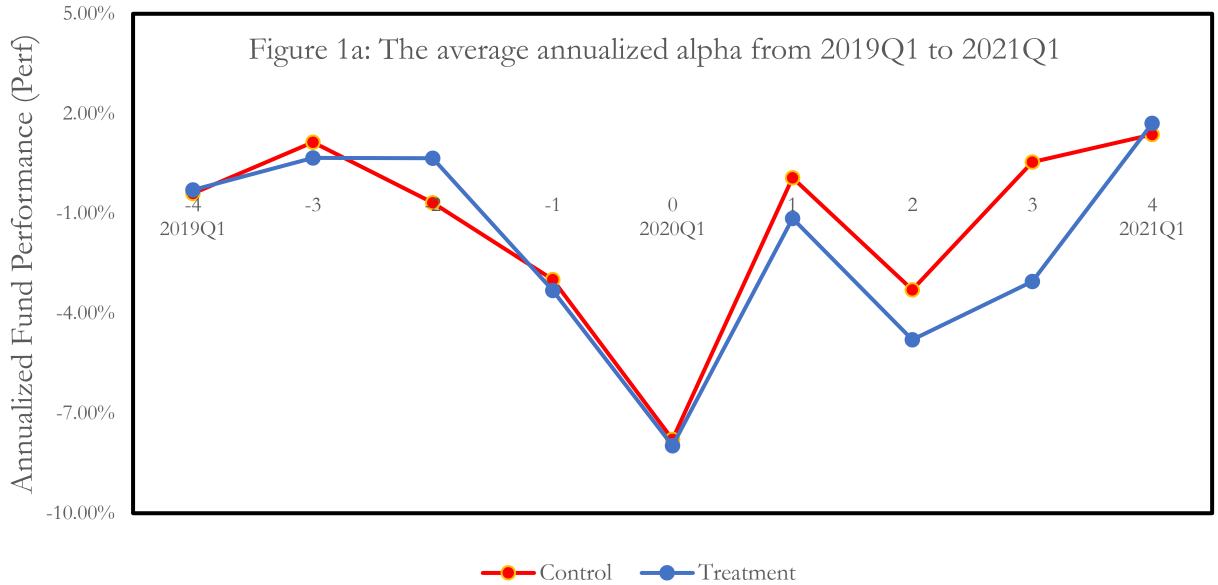
Variable	Definition
Perf	The annualized average monthly abnormal returns over a calendar quarter. For diversified equity funds including equity funds and allocation funds with more than 50% of AUM in U.S. equities, we estimate the alpha using the Fama and French (1993) and Carhart (1997) four-factor model. For corporate bond funds, we estimate the alpha using the four-factor model based on Elton, Gruber, and Blake (1995) and Cici and Gibson (2012). For sector funds, alternative funds, and allocation funds with less than 50% of AUM in U.S. equities, we estimate the alpha using a one-factor model, where the factor is constructed as the average return of peer funds in the same Morningstar category (Ma, Tang, and Gomez, 2019). Following Ain Tommar, Kolokolova, and Mura (2022), a fund's abnormal return during the testing period (from 2019 Q1 to 2021 Q1) is based on the factor loadings that are estimated from the 36 monthly fund returns prior to the first entry of the fund in the sample.
TNA	The total net assets of a fund at a quarter-end.
Expense	A fund's net expense ratio at a quarter-end.
VOL	The volatility of annualized monthly fund return (in excess of risk-free rate) over the last 12 months.
Turnover	A fund's turnover ratio reported at a quarter-end.
NumMgr	The number of managers in a fund's management team.

Variable	Definition
Asian	The fraction of Asian managers (i.e., managers have an appearance that could be construed as being of East and Southeast Asian descent) in a fund's management team.
AsianMale	The fraction of Asian male managers in a fund's management team.
AsianFemale	The fraction of Asian female managers in a fund's management team.
AsianFemale_Senior	The fraction of Asian female managers on a fund's management team when at least one Asian female manager is classified as a senior manager in a fund, and zero otherwise.
AsianFemale_Junior	The fraction of Asian female managers on a fund's management team when no Asian female manager is classified as a senior manager in the fund, and zero otherwise.
AsianFemale_HighCareBurden	The fraction of Asian female managers who were aged between 35 and 49 as of 2019 in a fund's management team (Kruger, Maturana, and Nickerson, 2022).
AsianFemale_LowCareBurden	The fraction of Asian female managers who are not classified as having high childcare burden on a fund's management team. We classify an Asian female manager as having a high childcare burden if she was aged between 35 and 49 in 2019.
AsianFemale_FirstGen	The fraction of Asian female managers who are classified as first-generation immigrants to the U.S. on a fund's management team.
AsianFemale_NonFirstGen	The fraction of Asian female managers who are not classified as first-generation immigrant to the U.S in a fund's management team.

Variable	Definition
AsianFemale_Chinese	The fraction of Asian female managers who are classified as Chinese female managers in a fund's management team. A manager is classified as Chinese if the manager has a last name spelled in Chinese phonetics and the manager is a first generation immigrant.
AsianFemale_NonChinese	The fraction of Asian female managers who are not classified as Chinese female managers in a fund's management team.
NonAsianMinorityFemale	The fraction of minority female managers who are not classified as Asian female managers on a fund's management team. The group of female managers includes Black, Hispanic, and South Asian managers.
SouthAsianFemale	The fraction of South Asian female managers on a fund's management team. The group includes managers of Bangladeshi, Indian, and Pakistani descent, as well as those from other South Asian countries.
HateCrimeNum	The number of hate crime incidents in a quarter-state. The data are sourced from the FBI's Uniform Crime Reporting (UCR) program.
AntiAsianTweet	The number of tweets that contain racial slurs against Asians in a quarter-state. The data are collected via Twitter's public timeline API for academic research.

Figure 1: The validity of parallel trend analysis for the female-present sample

Figure 1a plots the average fund performance of treatment and control funds in the female-present sample. Figure 1b plots the point estimates from Equation (2), the dynamic test on the effects of anti-Asian animus on fund performance of Asian-female-present funds. Marked confidence intervals are at the 95% confidence level, using robust standard errors that are clustered at the fund level.



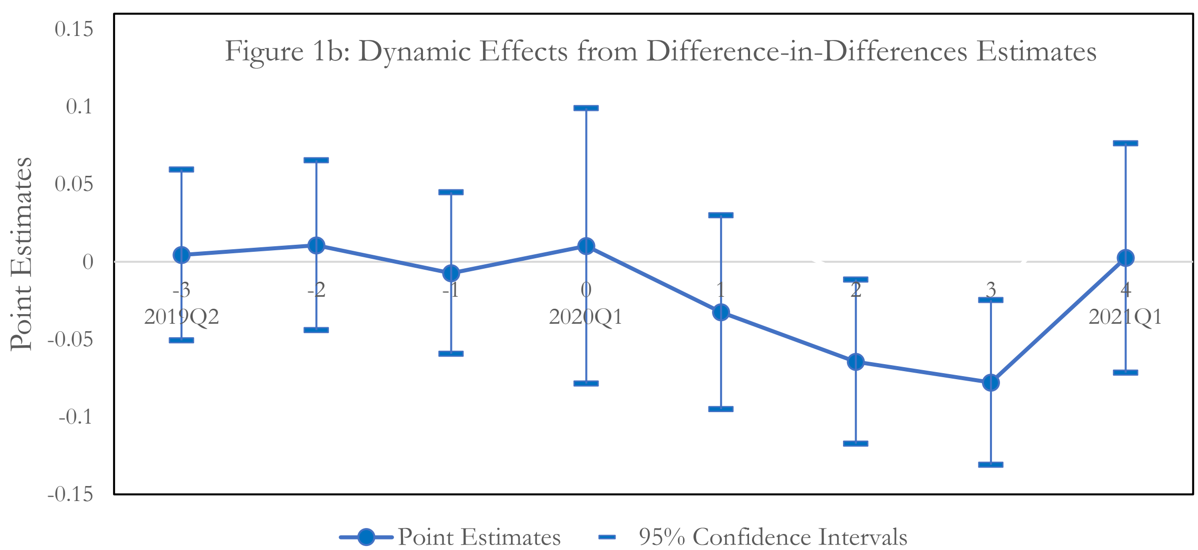


Table 1: Summary Statistics

This table presents the descriptive statistics of the main variables for the full sample, the male managed-sample, and the female-present sample. The full sample is the combination of male-managed and female-present sample. The male-managed sample includes funds that are solely managed by male managers. The female-present sample consists of funds that are managed by at least one female manager. The male-managed sample and female-present sample are mutually exclusive. Detailed variable definitions are provided in the Appendix. To mitigate the influence of outliers, *Perf*, *TNA*, *Expense*, *VOL*, and *Turnover* are winsorized at the 1st and 99th percentiles.

	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
	Full Sample			Funds solely managed by male manager			Funds managed by at least one female manager		
Perf	-0.001	0.109	16,543	0.001	0.111	13,628	-0.008	0.099	2,915
TNA	2,025.889	4,727.115	16,543	1,920.440	4,341.960	13,628	2,712.176	7,746.332	2,915
Expense	0.009	0.004	16,543	0.009	0.004	13,628	0.008	0.003	2,915
VOL	0.174	0.095	16,543	0.175	0.097	13,628	0.171	0.089	2,915
Turnover	0.828	1.143	16,543	0.861	1.207	13,628	0.660	0.670	2,915
NumMgr	2.655	1.690	16,543	2.484	1.434	13,628	3.455	2.413	2,915
Asian	0.050	0.161	16,543	0.034	0.128	13,628	0.124	0.251	2,915
AsianFemale	0.015	0.090	16,543	0.000	0.000	13,628	0.083	0.200	2,915
AsianMale	0.035	0.127	16,543	0.034	0.128	13,628	0.040	0.121	2,915

Table 2: The effect of anti-Asian animus on fund performance during the AAPI Hate

This table performs the difference-in-differences analysis examining the effect of anti-Asian animus on fund performance during the AAPI Hate. In column (1), we perform the analysis using the full sample, where the treatment funds are funds managed by at least one Asian manager. In column (2), we focus on the male-managed sample that consists of funds solely managed by male managers, where the treatment funds are funds managed by at least one Asian male manager. In column (3), we restrict the analysis to the female-present funds, where the treatment funds are funds managed by at least one Asian female manager. The full sample is the combination of the male-managed sample and female-present sample, which are mutually exclusive. Fund performance is *Perf*, measured as the annualized risk-adjusted monthly return averaged over a quarter. *Asian* is the fraction of Asian managers in a fund's management team. *AsianMale* is the fraction of Asian male managers in a fund's management team. *AsianFemale* is the fraction of Asian female managers in a fund's management team. *Post* is an indicator variable that equals one for the fund-quarter after the event quarter (i.e., 2020Q1). The event quarter is excluded from the analysis to avoid ambiguity. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =		*Perf*	
	Full Sample	Funds solely managed by male managers	Funds managed by at least one female manager
	(1)	(2)	(3)
Asian×Post	**-0.012**		
	(-1.164)		
AsianMale×Post		**0.002**	
		(0.133)	
AsianFemale×Post			**-0.049*** **
			(-3.414)
Log(TNA)	-0.046***	-0.047***	-0.042***
	(-8.557)	(-7.898)	(-3.650)
Expense	-1.744	-1.577	-2.054
	(-0.854)	(-0.714)	(-0.406)
VOL	-0.029	-0.005	-0.161
	(-0.567)	(-0.086)	(-1.345)
Turnover	0.001	-0.000	0.019**
	(0.370)	(-0.081)	(2.256)
Fund FEs	Yes	Yes	Yes
Style-by-Time FEs	Yes	Yes	Yes
Observations	16,543	13,628	2,915
Adjusted R-squared	0.159	0.165	0.139

Table 3: Test of the balance of covariates for the female-present funds

Table 3 conducts the test for the balance of covariates in the quarter prior to the event (i.e., 2019 Q4) between "treatment" (i.e., *AsianFemale* being positive) and control funds in the female-present sample that consists of funds managed by at least one female manager. The treatment funds include funds with at least one Asian female manager, while the control funds consist of funds without a Asian female manager. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Variables	Treatment funds (funds with at least one Asian female manager)	Control funds (funds without Asian female manager)	Difference in Mean (*t*-stat)
	Mean	Mean	
Perf	-0.033	-0.030	-0.347
Log(TNA)	6.276	6.528	-1.374
Expense	0.0078	0.0084	-1.397
VOL	0.107	0.109	-0.309
Turnover	0.701	0.621	0.914
NumMgr	3.325	3.722	-1.185
NumFemaleMgr	1.157	1.161	-0.097
Observations	83	353	

Table 4: Evidence from managerial actions for the female-present funds

This table examines the effect of the AAPI Hate on managerial actions by exploring quarterly holdings of diversified equity funds in the female-present sample that consists of funds managed by at least one female manager. In columns (1), the dependent variable is the return gap (Kacperczyk, Sialm, and Zheng, 2008). In columns (2), the dependent variable is the DGTW-Adjusted returns (Daniel et al., 1997). Specifically, the monthly DGTW-Adjusted return is the value-weighted monthly stock returns of the equity holdings as at the end of last quarter less the DGTW benchmark return based on value-weighted returns of 5×5×5 benchmark portfolios sorted on size, book-to-market, and momentum. The quarterly DGTW-Adjusted returns are then calculated as the average monthly DGTW-Adjusted returns over a quarter. All dependent variables are annualized by multiplying 12. Fixed effects are denoted in each column. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. T-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Return Gap*	*DGTW-Adjusted Return*
	(1)	(2)
AsianFemale×Post	**-0.019****	**-0.058****
	(-2.290)	**(-2.314)**
Controls in Table 2	Yes	Yes
Fund FEs	Yes	Yes
Style-by-Time FEs	Yes	Yes
Observations	1,540	1,421
Adjusted R-squared	0.134	0.007

Table 5: Cross-sectional tests based on the local anti-Asian animus for the female-present funds

This table explores the variations in local anti-Asian animus by estimating a nested fully interacted triple-difference regression model with the female-present sample. The female-present sample consists of funds that are managed by at least one female manager. Specifically, we interact *HighAnimus* with each of the variables in Equation (1) as well as the fund and style-by-time fixed effects. In each quarter, we split 50 U.S. states and the District of Columbia into two sub-samples: the top decile of states based on an anti-Asian animus proxy and the rest of the states. Since female managers are concentrated in a few large states (e.g., New York, California, and Massachusetts), empirically we find that the top decile cutoff of the sorting variable gives us a rather balanced fund-quarter level observations across the high- and low- subgroups. *HighAnimus* is an indicator variable that equals one if a state is in the top decile of the sorting variable on racial animus in a quarter and zero otherwise. We then assign each sample fund into High- or Low- animus states based on the office location of a fund's female managers. In column (1), the level of local anti-Asian animus is proxied by the number local hate crime incidents (*HateCrimeNum*). The state-level hate crime data are sourced from the FBI's UCR Program. In column (2), the level of local anti-Asian animus is proxied by the number of anti-Asian tweets (*AntiAsianTweet*) in a state-quarter. The state-level anti-Asian tweets data are collected via Twitter's public timeline API for Academic Research. To avoid ambiguity, we restrict to funds whose female managers are in the same state. We also eliminate from the analysis funds whose female managers are in foreign countries. Note that *AsianFemale*×*HighAnimus*, *Post*×*HighAnimus*, and *HighAnimus* are all absorbed when *HighAnimus* is interacted with fund and style-by-time fixed effects. In column (1), we eliminate observations in 2021 Q1 as the FBI data are subject to serious data issues due to the FBI transitioning into a new reporting system in 2021. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Perf*	
	HateCrimeNum	*AntiAsianTweet*
	(1)	(2)
AsianFemale×*Post*×*HighAnimus* (β_1)	**-0.080*****	**-0.083*****
	(-2.658)	**(-3.045)**
AsianFemale×*Post* (β_2)	-0.019	-0.007
	(-1.081)	(-0.347)
F-Test ($\beta_1 + \beta_2 = 0$)	**-0.099*****	**-0.090*****
(p-value)	**(0.000)**	**(0.000)**
Controls in Table 2	Yes	Yes
Fund FEs	Yes	Yes
Style-by-Time FEs	Yes	Yes
Observations	2,326	2,680
Adjusted R-squared	0.183	0.136

Table 6: Moderating effect from the heterogeneity in fund characteristics for the female-present funds

This table estimates a nested fully interacted triple-difference regression model to examine the moderating role of a fund's trading frequency, investment objective, and management team size in the female-present sample. The female-present sample consists of funds that are managed by at least one female manager. Specifically, we interact *HighTurnover*, *AgressiveInvest,* or *SmallTeam* with all the variables in Equation (1) as well as the fund and style-by-time fixed effects. *HighTurnover* is an indicator variable that equals one if a fund's pre-event turnover ratio is above the sample median value. A fund's pre-event turnover is calculated as the average turnover ratio over the five years (or as long as possible if fewer than five years) ending in 2019 Q4. *AgressiveInvest* is an indicator variable that equals one if a fund's prospectus investment objective is "Aggressive Growth" or "Corporate Bond - High Yield" or the fund's CRSP objective code is "EDYG" or "ICQY" in 2019 Q4. *SmallTeam* is an indicator variable that equals one if a fund's team size is below the sample median value in 2019 Q4. Note that the double-interaction terms between the sorting variables (i.e., *HighTurnover*, *AgressiveInvest*, , and *SmallTeam*) and *AsianFemale* and *Post* are all absorbed by the fund and style-by-time fixed effects. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =		*Perf*	
	(1)	(2)	(3)
AsianFemale×*Post*×*HighTurnover* (β_1)	**-0.077*****		
	(-2.774)		
AsianFemale×*Post*×*AgressiveInvest* (β_1)		**-0.098*****	
		(-2.951)	
AsianFemale×*Post*×*SmallTeam* (β_1)			**-0.152***
			(-1.937)
AsianFemale×*Post* (β_2)	0.008	-0.016	0.097
	(0.411)	(-0.906)	(1.258)
F-Test ($\beta_1 + \beta_2 = 0$)	**-0.069*****	**-0.114*****	**-0.055*****
(p-value)	**(0.000)**	**(0.000)**	**(0.000)**
Controls in Table 2	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Style-by-Time FEs	Yes	Yes	Yes
Observations	2,915	2,915	2,915
Adjusted R-squared	0.143	0.158	0.141

Table 7: Is the finding driven by large fund outflows or less-skilled managers in treatment funds?

This table examines whether the adverse effect of anti-Asian animus on the performance of funds managed by Asian females is driven by large fund outflows experienced by Asian-female-present funds during the AAPI hate or due to less-skilled managers in Asian-female-present funds. In column (1), we replace the dependent variable in Equation (1) with contemporaneous fund flow to directly examine the effect of AAPI Hate on fund flow. *FundFlow* is the contemporaneous monthly fund flow averaged over a quarter. In column (2), we perform a nested fully interacted triple-difference analysis to explore if fund flows influence the effect of the Hate on fund performance. *LargeOutFlow* is an indicator variable that equals one if a fund's average monthly outflow in the contemporaneous quarter is 5% or more and zero otherwise. In column (3), we perform a nested fully interacted triple-difference analysis to examine how pre-event fund performance influences the effect of the Hate on fund performance. *LowPerf* is an indicator variable that equals one if a fund's pre-event fund performance is below the sample median. A fund's pre-event fund performance is calculated as the average monthly fund performance over the past five years ending in 2019 Q4. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Note that the double-interaction terms between the sorting variables (i.e., *LargeOutFlow* and *LowPerf*) and *AsianFemale* and *Post* are all absorbed by the fund fixed effects or style-by-time fixed effects. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*FundFlow*	*Perf*	
	(1)	(2)	(3)
AsianFemale×*Post* (β_1)	**-0.005**	**-0.050*****	**-0.048****
	(-0.911)	**(-3.527)**	**(-2.124)**
AsianFemale×*Post*×*LargeOutFlow* (β_2)		**-0.024***	
		(-1.662)	
AsianFemale×*Post*×*LowPerf* (β_2)			**-0.006**
			(-0.193)
F-Test ($\beta_1 + \beta_2 = 0$)		**-0.074*****	**-0.053*****
(p-value)		**(0.000)**	**(0.005)**
Controls in Table 2	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Style-by-Time FEs	Yes	Yes	Yes
Observations	2,915	2,856	2,913
Adjusted R-squared	0.394	0.149	0.172

Table 8: The influence of Asian female managers in the management team

This table examines whether the adverse effect of anti-Asian animus on the performance of Asian female-present funds varies with the managerial role that the Asian female managers played in the fund's management team. Note that we only have information on managerial role for the Asian female managers and thus have a standard triple-differences analysis is not feasible. We divide *AsianFemale* into two mutually exclusive variables: *AsianFemale_Senior* and *AsianFemale_Junior*. *AsianFemale_Senior* is the fraction of Asian female managers when an Asian female manager plays a senior role in a fund's the management team, and zero otherwise. *AsianFemale_Junior* is the fraction of Asian female managers when no Asian female manager plays a senior role in the fund, and zero otherwise. We determine that an Asian female manager plays a senior role if the manager holds the title of the lead portfolio manager or is the only manager of the fund, if the manager's tenure in the fund is the longest in the team, if the manager is listed before other fund managers in the fund management section in the fund's prospectus in a non-alphabetic order. This is because we observe that fund companies usually list the name of the lead portfolio manager first when introducing the team in the prospectus. We collect managers' managerial role information from the fund's SEC filings at two data points: 2019 Q4 and the last entry of the fund in the sample. This allows us to ensure that managers' roles remain the same in the post-event period. To qualify for a senior manager, we require the Asian female manager's role to be senior at the two data points in the analysis. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Perf*
	(1)
AsianFemale_Senior×*Post* (β_1)	**-0.063*****
	(-4.253)
AsianFemale_Junior×*Post* (β_2)	**-0.014**
	(-0.483)
F-Test ($\beta_1 - \beta_2 = 0$)	**-0.049***
(p-value)	**(0.098)**
Controls in Table 2	Yes
Fund FEs	Yes
Style-by-Time FEs	Yes
Observations	2,915
Adjusted R-squared	0.139

Table 9: Alternative explanations

This table examines alternative explanations for the performance decline effect, including increased childcare burden during the pandemic (Barber et al., 2021; Ain Tommar, Kolokolova, and Mura, 2022), Asian managers' extra concerns for their families in their home countries, or the potential presence of unfriendly sentiment towards Chinese in the workplace under the crossfire of COVID-19 and souring relations between the U.S. and China. In column (1), we divide Asian female managers into two mutually exclusive groups: Asian female managers with a likely high childcare burden and the rest. *AsianFemale_HighCareBurden* is the fraction of Asian female managers with potential high childcare burden, while *AsianFemale_LowCareBurden* is the fraction of Asian female managers who are not classified as having a high childcare burden. We classify an Asian female manager to have a high childcare burden if she was aged between 35 and 49 in 2019 (Kruger, Maturana, and Nickerson, 2022). We code the indicator variable based on managers' date of birth, first-degree graduation year, or the number of years in the industry. We obtained the data from various sources including fund company website, Morningstar Direct database, and LinkedIn. In column (2), we divide Asian female managers into two mutually exclusive groups: first-generation Asian female managers and the rest. First-generation managers are expected to face both the stress sourced from the anti-Asian animus in the U.S. and the stress sourced from worries about the effects of the COVID-19 waves on their extended family members in their home countries. *AsianFemale_FirstGen* is the fraction of first-generation-immigrant Asian female managers, while *NotAsianFemale_NonFirstGen* is the fraction of Asian female managers who are not classified as first-generation-immigrant Asian female managers. We determine a manager to have first-generation immigration status if one of the following conditions is satisfied: (1) the manager has her first name spelled in Asian phonetics (i.e., a ``non-Anglicised" name); (2) the manager received her bachelor's degree in an Asian country according to biographic information; and (3) the manager's mother tongue is an Asian language according to information from LinkedIn. In column (3), we divide Asian female managers into two mutually exclusive groups: Chinese female and non-Chinese female managers. *AsianFemale_Chinese* is the fraction of Chinese females in a fund's management team, while *AsianFemale_NonChinese* is the fraction of non-Chinese Asian female managers in a fund's management team. We define a manager as Chinese by her last name and by her first-generation immigration status. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Perf*		
	(1)	(2)	(3)
AsianFemale_HighCareBurden×Post (β_1)	**-0.036****		
	(-2.069)		
AsianFemale_LowCareBurden×Post (β_2)	**-0.075*****		
	(-2.732)		
AsianFemale_FirstGen×Post (β_1)		**-0.077*****	
		(-3.085)	
AsianFemale_NonFirstGen×Post (β_2)		**-0.040*****	
		(-2.688)	
AsianFemale_Chinese×Post (β_1)			**-0.079*****
			(-3.160)
AsianFemale_NonChinese×Post (β_2)			**-0.042*****
			(-2.883)
F-Test (β_1 - β_2 = 0)	**0.039**	**-0.037**	**-0.037**
(p-value)	**(0.190)**	**(0.156)**	**(0.151)**
Controls in Table 2	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Style-by-Time FEs	Yes	Yes	Yes
Observations	2,840	2,893	2,915
Adjusted R-squared	0.139	0.142	0.140

Table 10: Placebo Tests

This table presents two placebo tests that contrast the effect of the AAPI Hate on Asian female managers with that on non-Asian minority female managers and on South Asian female managers. In column (1), we augment the baseline model in Equation (1) by including the interaction term, *NonAsianMinorityFemale*×*Post*. *NonAsianMinorityFemale* is the fraction of minority female managers who do not have a Chinese-looking appearance (including Black, Hispanic, and South Asian female managers). The control group in column (1) comprises of funds without minority-looking female managers. In column (2), we zoom into South Asian female managers who are Asians but are distinct from East Asians in appearance and who were unlikely victims of AAPI hate crimes. *SouthAsianFemale* is the fraction of South Asian-looking female managers including Indians and Pakistan. The control group in column (2) comprises funds without any Chinese-looking Asian female manager or South Asian-looking female manager. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Perf*	
	(1)	(2)
AsianFemale×*Post* (β_1)	**-0.049*** **	**-0.049*** **
	(-3.348)	**(-3.359)**
NonAsianMinorityFemale×*Post* (β_2)	**0.005**	
	(0.331)	
SouthAsianFemale×*Post* (β_2)		**0.011**
		(0.562)
F-Test (β_1 - β_2 = 0)	**-0.054*****	**-0.060*****
(p-value)	**(0.000)**	**(0.000)**
Controls in Table 2	Yes	Yes
Fund FEs	Yes	Yes
Style-by-Time FEs	Yes	Yes
Observations	2,915	2,915
Adjusted R-squared	0.139	0.139

Internet Appendix For

The Real Effect of Sociopolitical Racial Animus:

Mutual Fund Manager Performance during the AAPI Hate

Table IA.1: Alternative measures of fund performance for the female-present funds

This table tests the robustness of the baseline regression results in Table 2 column (3) using three alternative measures of fund performance. The dependent variable is the average monthly fund raw return, the prospectus benchmark-adjusted monthly return, and the fund performance estimated from the Fama-Fench five-factor model (Fama and French, 2015) for equity funds. All alternative measures are calculated as the annualized average monthly values over a quarter. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Average Monthly Raw Return*	*Prospectus Benchmark-adjusted Return*	*Fama-French 5-factor Perf*
	(1)	(2)	(3)
AsianFemale×Post	**-0.083*****	**-0.074*****	**-0.052*****
	(-2.805)	**(-3.889)**	**(-3.449)**
Controls in Table 2	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Style-by-Time FEs	Yes	Yes	Yes
Observations	2,915	2,734	2,915
Adjusted R-squared	0.739	0.283	0.123

Table IA.2: The alternative female-present sample

This table re-estimates the baseline regression model in Table 2 column (3) using the sample of funds that are solely managed by female managers (column (1)) and solo-managed funds by female managers (column (2)). *Perf* is the annualized risk-adjusted fund performance. *AsianFemale* is the fraction of Asian female managers in the fund. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Perf*	
	Funds that are solely managed by female managers	Funds that are solo-managed by female managers
	(1)	(2)
AsianFemale×*Post*	**-0.093*** **	**-0.066** **
	(-3.143)	**(-2.261)**
Fund FEs	Yes	Yes
Style-by-Time FEs	Yes	Yes
Observations	302	225
Adjusted R-squared	0.142	0.148

Table IA.3: Placebo test with pure index funds

This table re-estimates the baseline regression model in Table 2 column (3) using pure index funds. Pure index funds are identified based on fund names as well as Morningstar (the index fund flag equals "Yes") and CRSP index fund identifiers (Index Fund Flag equals "D"). Fund performance is measured as the annualized monthly Benchmark-adjusted returns averaged over a quarter. *AsianFemale* is the fraction of Asian female managers in a fund's management team. *Post* is an indicator variable if the fund-quarter is after the event quarter. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =	*Benchmark-adjusted Return*
AsianFemale×*Post*	**0.005**
	(0.369)
Fund FEs	Yes
Time FEs	Yes
Observations	538
Adjusted R-squared	0.177

Table IA.4: Some further evidence on Asian male managers

This table explores the variations in local anti-Asian animus in the male-managed sample that consists of funds that are solely managed by male managers. In column (1), we report the average effect of the AAPI Hate on Asian male-present funds copied from Table 2 column (2) for the convenience of comparison. In columns (2)-(5), we divide *AsianMale* into two mutually exclusive variables: *AsianMale_HighAnimus* and *AsianMale_LowAnimus*. *AsianMale_HighAnimus* is the fraction of Asian male managers who were based in states with a high level of anti-Asian animus. *AsianMale_LowAnimus* is the fraction of Asian male managers who were based in states with low level of anti-Asian animus. In columns (2) and (3), we split the 50 U.S. states and the District of Columbia into two subsamples consisting of the top decile of the proxy of anti-Asian animus at the state-quarter level and the rest in each quarter. We choose top decile of the sorting variable as the cutoff to enable us to obtain a roughly balanced number of Asian male managers across the high- and low- subgroups. The states in the top decile are classified as high-animus states, while the rest are defined as low-animus states. In columns (4) and (5), we assign the top two states ranked by the local anti-Asian animus among 50 U.S. states and the District of Columbia to the high anti-Asian animus group and the rest are assigned to the low-animus group. As a result, roughly one third of Asian male managers are assigned into the high-animus group. We then assign each sample fund to one of the two groups based on the office location of a fund's Asian male managers. In columns (2) and (4), the level of local anti-Asian animus is proxied by the number local hate crime incidents (*HateCrimeNum*). The state-level hate crime data are sourced from the FBI's UCR Program. In columns (3) and (5), the level of local anti-Asian animus is proxied by the number of anti-Asian tweets (*AntiAsianTweet*). The state-level anti-Asian tweets data are collected via Twitter's public timeline API for Academic Research. In columns (2)-(5), we eliminate funds from the analysis if their Asian male manager's location information is missing or Asian male managers were based in a foreign country. In columns (2) and (4), we eliminate observations in 2021 Q1 as the FBI data are subject to serious data issues due to the FBI transitioning into a new reporting system in 2021. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. *T*-statistics are reported in parentheses. The event quarter [0] (i.e., 2020 Q1) is excluded from the analysis to avoid ambiguity. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable =		*Perf*			
		HateCrimeNum	*AntiAsianTweet*	*HateCrimeNum*	*AntiAsianTweet*
		Top Decile and Rest		Top 2 states and Rest	
	(1)	(2)	(3)	(4)	(5)
AsianMale (β_1)	**0.002**				
	(0.133)				
AsianMale_HighAnimus×Post (β_2)		**-0.012**	**0.021**	**-0.043**	**-0.065****
		(-0.461)	**(0.769)**	**(-1.448)**	**(-2.132)**
AsianMale_LowAnimus×Post (β_3)		0.004	-0.023	0.016	0.020
		(0.193)	(-1.205)	(0.725)	(0.985)
F-Test ($\beta_2 - \beta_3 = 0$)		**-0.016**	**0.044**	**-0.059**	**-0.085****
(p-value)		**(0.566)**	**(0.168)**	**(0.105)**	**(0.018)**
Controls in Table 2	Yes	Yes	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes	Yes	Yes
Style-by-Time FEs	Yes	Yes	Yes	Yes	Yes
Observations	13,628	12,023	13,546	12,023	13,546
Adjusted R-squared	0.165	0.174	0.165	0.174	0.165

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