The Real Effect of Sociopolitical Racial/Ethnic Animus: Mutual Fund Manager Performance During AAPI Hate ☆

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Abstract

During the unexpected 2020-2021 "AAPI Hate," mutual funds with female managers perceived as of East Asian descent (the primary targets) experienced performance deterioration relative to other female managers. The impact intensified in states with higher anti-Asian crime rates or sentiment, among more actively managed portfolios, and when these managers play leadership roles. We address alternative hypotheses, including investor redemption, workplace animus, childcare challenges, and concerns for families overseas during the pandemic. Performance deterioration manifests itself mainly in stock picking. Our study highlights the negative productivity impact of racial-ethnic animosity even when it arises outside the workplace and the labor market.

JEL classification: G23, J150

Keywords: Ethnic Animus, Mutual Fund Performance, AAPI Hate, Asian Female Managers

1. Introduction

Ethnicity-based bias undermines equality, justice, and potentially reduces economic efficiency. Although there is growing research, mainly on documenting the existence of ethnic animus in the workplace (e.g., employment) (Hsieh et al., 2019; Huber, Lindenthal, and Waldinger, 2021; Kline, Rose, and Walters, 2022) and in the marketplace (for example, access to credit and to quality service) (Bayer, Ferreira, and Ross, 2018; Bartlett et al., 2022; Butler, Mayer, and Weston, 2022; Hayes et al., 2023), there is limited evidence on the economic consequences of ethnic animus in broader social spheres. Our study extends this literature by examining the effect of a distinct wave of incidences of sociopolitical ethnic animosity, "AAPI (Asian American and Pacific Islander) Hate" during the COVID-19 pandemic, on the productivity of target groups.

AAPI Hate (hereafter "Hate" for brevity) began in early 2020 and persisted until 2021. Hate emerged from a confluence of factors, including perception of the origin of the virus, anti-Asian sentiment, xenophobia, economic stress, and social biases. Acts of discrimination, violence, and scapegoating were directed at Asian Americans and Pacific Islanders (AAPI), and disproportionately targeted women who have an appearance that could be perceived as being of East, Southeast, and Central Asian descent. A distinct feature of Hate was that it was aimed at what people "look like."[1] President Biden summarized the severity of the situation in March 2021 that "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

[1]Following the outbreak of COVID-19, people were perceived as being Chinese became the first group of targets of hate crimes and negative attitudes. Michelle Tran, a 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).

attacked, blamed, scapegoated, and harassed. They've been verbally assaulted, physically assaulted, and killed."[2]

The persistent safety threats in daily life, combined with ethnicity-based animosity, can cause fear, anxiety, stress, and/or anger, thereby undermining the productivity of its targets, even in the absence of workplace discrimination. Although psychology theory has long established that fear and anxiety impair productivity and decision making,[3] empirical evidence is scarce due to the challenge of pairing a well-defined animus shock with accurately measured productivity outside an experimental setting. In this study, we focus on mutual fund managers, as they are a group of professionals whose performance can be objectively measured and compared, whose actions can be observed and evaluated, and whose decision-making abilities are crucial to fund performance. AAPI Hate is an ideal setting for making causal inferences about performance changes due to the following key features.

First, the sudden surge in anti-Asian animus was triggered by the pandemic, which was not anticipated by the population. The Federal Bureau of Investigation (FBI) shows that the number of anti-Asian incidents in 2020 reached 2.5 times the average number of anti-Asian incidents over the last decade (from 2010 to 2019). Both the unexpected nature and the magnitude of the backlash make Hate a plausible exogenous shock. Second, the hate wave offers a unique identification by itself. Before the recent AAPI Hate, there was little cohesion among people in the AAPI designation, as it consists of culturally and economically heterogeneous groups of people. Due to the attribution of the origin of

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

[3]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) present the theory of attention control, which suggests that anxiety can lead to decreased cognitive performance in regulating focus and concentration. 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.

the pandemic, all AAPI people (especially women) became common targets of hate crimes simply because they could "look Chinese" to a hater. Given this unique setting, we are able to classify a "treated" group consisting of funds with at least one manager of East Asian, Southeast Asian, and Central Asian descent (and whose appearance could be construed as being Chinese by the haters). For simplicity and when there is no risk of confusion, we shall henceforth refer to this group as Asian managers.

To get down to a sample of mutual fund managers that include "treated" and control groups, we start with all actively managed US mutual funds from 2019 Q1 to 2021 Q1 (the "full sample"), which covers four quarters before the COVID-19 outbreak in the US and four quarters afterward. Due to compelling evidence from the existing literature regarding a disparate effect along the gender line of COVID-19 on work productivity (e.g., Barber et al., 2021; Ain Tommar, Kolokolova, and Mura, 2022) and the fact that Hate disproportionately targeted Asian women (Jeung et al., 2021; Kaur, 2022), we also construct a key sub-sample of mutual funds with at least one female portfolio manager ("female-managed funds" or "funds with female managers"). This sub-sample allows us to isolate the impact on Asian women (the primary targets of Hate), in relation to other non-Asian female portfolio managers so that the comparison is not confounded with the gender effect established in the literature. The remaining subset of the full sample consists of the funds managed by all-male teams.

In the full sample, we find that Asian managers experience a negative but not statistically significant performance deterioration. Once we restrict our analyses to the sub-sample of funds with female managers who were primary targets of Hate, we find that performance of the "treated" funds (i.e., funds with at least one Asian female manager) worsened significantly after 2020 Q1, the onset of Hate. The effect comes from

a difference-in-differences framework comparing the treated funds with control funds (i.e., funds managed by women from other racial/ethnicity groups) and comparing post- with pre-COVID period. Moreover, the comparison includes fund fixed effects and style-by-time fixed effects to absorb time-invariant unobserved heterogeneity at the fund level and time-varying common return shocks to funds in a given category, respectively. When comparing a fund with 50% of managers being Asian women with a fund having female managers but no Asian women, the former performance shortfall amounts to 0.2 percentage points in monthly risk-adjusted returns. Importantly, the divergence in performance materializes after a complete parallel trend all the way until 2020 Q1 before converging in 2021 Q1 after the availability of potent vaccines and community and legislative support. The treated funds and the control funds share similar characteristics in Q4 of 2019 and the result is robust to using a matched sample. This constitutes preliminary but informative evidence that Hate caused fear, anxiety, stress, and/or anger, thereby levying a toll on fund managers from the demographic group being the primary targets.

We conduct further tests to tighten up the association between Hate and fund manager performance. 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. 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 require more frequent and demanding investment decisions that are particularly sensitive to negative emotions such as stress, anxiety, and anger. Third, the decline in fund performance was concentrated in funds when Asian female managers played a more influential role in decision making, such as being on a small team or assuming a senior role.

Given the concurrence of AAPI Hate and the pandemic, it is imperative that we isolate the effect of the former from the profound socioeconomic impacts brought by the latter. Several cross-sectional tests based on the institutional settings unique to Hate enable us to achieve the separation. First, Asian women managers aged 35 to 49 years, who are presumed to carry a high burden on childcare, did not perform worse than their younger or older Asian women counterparts during a period when family care services were largely unavailable. The null result rules out the burden of family care during the pandemic as a driving force of our results. Second, Asian female managers who are recent immigrants could be stressed about their families and relatives in their countries of origin that were devastated by COVID-19. Using a combination of first names and biographical information, we are able to single out first-generation Americans among the treated managers and discover that they experienced similar performance setbacks as Asian women who are more rooted in the US, ruling out another COVID-related explanation. The fact that AAPI Hate targeted Asians (especially women) who "look like Chinese" instead of being driven by actual nationality, and the fact that the animus mostly spared South Asians, provide us with clean tests to differentiate from 'sinophobia' in the workplace (a distinct branch of xenophobia due to both the COVID pandemic and the escalated US-China tension) and the ongoing ethnic disparity concerning minorities. We discover a performance setback for female fund managers of Chinese origin and those who might "look like them" similar to a bystander on the street, ruling out possible sinophobia in the workplace (where people's country origins are usually known). The fact that South Asian, as well as other minority, female managers appeared to be performing on par with White female managers further singles out the source of AAPI Hate.

We also show that the underperformance of treated funds was not due to fund investors discriminating funds with managers with Asian names by withdrawing their

investments. The combined positive tests (which connect performance setback to an element in Hate) and negative tests (which refute alternative explanations, especially the confounding factors stemming from the pandemic) lend more credence to the sociopolitical ethnic animus as the leading explanation for the performance setback of the treated group. In particular, our results are consistent with the findings that more than 60% of Asian professionals in the Coqual survey and more than 70% of Asian women in the NAPAWF survey suffered from anxiety and stress due to Hate (see Section 2.1 for details).

Lastly, we verify that performance deterioration can be explained by actions and decision making in portfolio management. We find that the negative alpha of the treated funds is of an order of magnitude consistent with that of the "return gap" (Kacperczyk, Sialm, and Zheng, 2008), generated by "hidden actions" of portfolio managers that could improve performance beyond a buy-and-hold strategy. Treated fund managers did not slow down their work of initiating new positions, but the quality of these initiations (as measured by post-initiation benchmark-adjusted returns) were significantly subpar. Examining "churn rate" (Yan and Zhang, 2009) and "active share" (Cremers and Petajisto, 2009) yield similar inferences. In general, the treated fund managers did not appear to retreat from work, but their stock selection became less informed, consistent with an impairment in decision making.[4]

Our study expands existing research on racial and ethnic animus and discrimination that has focused primarily on unequal career opportunities and market transactions for minority groups (e.g., Stephens-Davidowitz, 2014; Hsieh et al., 2019; Kumar, Niessen-

[4]According to the 2021 Stop AAPI Hate Mental Health Report, individuals may encounter various psychological responses to racism, including, but not limited to, depression, intrusive thoughts, anger, heightened vigilance, somatic symptoms and physiological reactions, diminished self-esteem, and tendencies towards avoidance or emotional numbing. Zhou, Banawa, and Oh (2023) document severe anxiety and depression among Asian Pacific Islander students during the pandemic.

Ruenzi, and Spalt, 2015; Kline, Rose, and Walters, 2022; Bartlett et al., 2022; Butler, Mayer, and Weston, 2022; Dougal et al., 2019). Our study explores the ethnic animus beyond the workplace and the marketplace. Despite a rich and growing literature on ethnic discrimination, quantifying the economic consequences of discrimination is difficult in a social context (as opposed to labor market frictions[5]) due to challenges in both isolating a discrete episode and measuring the economic outcome. Our study fills in this void by combining a distinct wave of ethnic animus and a sample of mutual fund managers with heterogeneous exposures to Hate in a setting where performance can be objectively measured.

A concurrent paper by Qiao, Xu, and Zhang (2023) shows that anti-Asian hate impaired the forecast quality of East Asian sell-side analysts. Our paper examines the effect of AAPI Hate on mutual fund managers whose productivity can be captured by fund 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 exploit the heterogeneous treatment effect and carefully rule out numerous alternative explanations using rich microlevel data. Overall, 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 ethnic animus on work performance of the most targeted groups.

Our study is related to, but distinct from, the literature that examines 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,

[5]Hsieh et al. (2019) find that the improved allocation of talented women and Black men contributed to the growth in the aggregate market output per person in the US. Huber, Lindenthal, and Waldinger (2021) show that the expulsions of Jewish managers in Nazi Germany reduced the market value of German firms.

2020; Cuculiza et al., 2021), and natural disasters (Bernile, Bhagwat, and Rau, 2017; Hanaoka, Shigeoka, and Watanabe, 2018; Alok, Kumar, and Wermers, 2020) on the economic behavior of individuals. In contrast to these studies that focus on changes in preferences, such as risk tolerance following negative experiences, our study highlights loss of productivity due to impaired decision-making ability. Importantly, the working mechanism in our study does not rely on Asian women's actual experience of hate violence, but on perceived threat of such violence. Furthermore, these previous studies have focused on shocks that created vulnerable groups based on characteristics related to economic outcomes (e.g., investors in stocks, childhood hardship, and residents in disaster zones). In contrast, 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.

Finally, our study is also relevant to the literature that examines the effect of disruptions or distractions caused by events in the market or personal lives, for example, marriage and divorce (Roussanov and Savor, 2014; Lu, Ray, and Teo, 2016), major illness (Masulis and Zhang, 2019), busy professional life (Falato, Kadyrzhanova, and Lel, 2014), and information influx originating from firm-specific events (Schmidt, 2019) or industry-specific events (Kempf, Manconi, and Spalt, 2017) on an agent's performance and economic behavior. Unlike these studies, we explore an unprecedented and unanticipated sociopolitical event that targeted the treatment population merely by its appearance in relation to race and ethnicity. Our goal is not to show that fund managers matter for fund performance–which was the stated goal of papers such as Bennedsen, Pérez-González, and Wolfenzon (2020) that demonstrate that "CEOs matter" using hospitalization events, but to highlight the real effects of racial-ethnic animus. In a world that continues to grapple with a multitude of hatred and bigotry based on ethnicity, religion, and social background, our

study underscores the imperative to comprehend and address these issues in contemporary society.

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 ethnic animus on fund performance. Section 4 filters out confounding factors and examines alternative hypotheses. Section 5 is on sensitivity checks. Section 6 investigates the potential mechanisms behind the performance deterioration of funds affected by ethnic animus. Section 7 concludes.

2. Data Sources, Variable Construction, and Sample Overview

2.1. Episodes of AAPI Hate

The event window of our study begins in the initial quarter of 2020 (2020 Q1), when COVID-19 cases started to be reported in the United States, quickly escalating into a full-fledged pandemic. 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. The same quarter also marked the onset of a surge in AAPI Hate crimes (Lu and Sheng, 2022), largely fueled by the stigma surrounding the presumed origin of COVID-19. Some people blamed the Asian (especially the Chinese) community and used it as an excuse to target and discriminate against individuals of Asian descent. Our sample period from Q1 2019 to Q1 2021 covers a heightened wave of anti-Asian crimes. 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 or their families and friends. Asians of all socioeconomic backgrounds, including highly accomplished professionals, were targeted for simply what

they look like.[6]

One distinct feature of Hate wave was that Asian women were disproportionately targeted by AAPI Hate relative to their male counterparts, contrary to the norm that women are less likely victims of violent crimes than men. Women reported 2.3 times Hate incidences as men from March 2020 to February 2021 (Jeung et al., 2021). According to a survey conducted in 2022 by the National Asian Pacific American Women's Forum (the "NAPAWF survey") , 74% of AAPI women report personal experience of racism and/or discrimination and 71% report feeling anxious or stressed due to fear of discrimination, violence, etc. Our Factiva news search also 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. In addition, women were overrepresented among victims of violent crimes, including deadly hate crimes (Kaur, 2022).[7]

While Hate incidences remained low-probability events for individuals, the perceived threat to safety to Asian women could be further amplified by psychological and cognitive factors, including the "availability heuristic" (the likelihood assessed of an event based on how easily examples come to mind, see Tversky and Kahneman (1973)), media coverage (Logan and Walker, 2021), emotional impact, and the nature of the crime perceived as unpredictable and beyond one's control (Warr, 1994). For this reason, we expect Asian female fund managers to be more likely to suffer a productivity decline during Hate and to constitute the key "treated" group of our main analyses.

[6] A survey by a global leading think tank Coqual (the "Coqual survey") 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 include the Atlanta spa shooting in 2021 and the murder of a female business executive in a New York City subway in 2022.

2.2. Sample of mutual funds and fund managers

Our sample construction starts with all open-ended, actively managed funds in the US that primarily invest in US securities and are covered by the Morningstar Direct database. This leaves us with diversified US equity funds, corporate bond funds, sector funds, allocation funds, and alternative strategy funds, excluding index funds identified by fund names, as well as Morningstar and CRSP index fund identifiers. The characteristics of the fund, obtained from the Morningstar Direct database, include total net assets, turnover ratio, expense ratio, and fund style. Following Niessen-Ruenzi and Ruenzi (2019), we combine data from CRSP and Morningstar, as the first database contains high-quality data on fund performance, while Morningstar is considered to have more accurate information on manager names (Massa, Reuter, and Zitzewitz, 2010). The quarterly holding data for mutual funds are obtained from the CRSP mutual fund holdings database. 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 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 possible incubation bias (Evans, 2010). To avoid the confounding effects of managers' turnover on fund performance, including communication cost within ethnically diversified mutual fund teams (Evans and Young, 2022), we only include fund observations under the same management team. Given our difference-in-difference setting, we require that a management team has at least one observation before and one after the shock to be included in the sample.[8] With such

[8]We check the attrition rates and ensure that the attrition rates are comparable economically and statistically between sub-samples of funds with and without at least one Asian manager, and sub-samples

filtering, fund fixed effects and manager fixed effects coincide in the difference-in-difference analysis.

As we explained in Section 2.1, anti-Asian sentiment fueled by the COVID-19 pandemic targeted people who "look like" Chinese, and the threat was extended to anyone who could be perceived as of East Asian descent. Because attacks on the street are based on how people "look" (instead of their true nationality or ethnicity), the target group includes East Asians, most Southeast Asians, and some Central Asians. According to a 2021 report from the Stop AAPI Hate Reporting Center, East Asians account for 74.2% of the victims of reported anti-Asian hate incidents, and Southeast Asians make up 23.5%.[9]

The distribution of hate victims guides our classification of the "treated" group of fund managers. We start by identifying the gender of the fund managers according to a multistep procedure. First, we follow Niessen-Ruenzi and Ruenzi (2019) and match portfolio managers' given names obtained from the Morningstar Direct database with the super-set of the lists of the top 200 most popular names for each gender for the last ten decades from the 1920s to the 2010s published by the US Social Security Administration.[10] Second, for given names that are not matched to the list because they are not among the most popular or are gender neutral, we resort to the algorithm published by the website gender API to estimate gender probability scores. We classify a manager as female if the probability value is 95% or greater. Finally, we manually classify the remaining ambiguous cases by searching managers' biographies in the Morningstar Direct database or sources on the Internet, such as fund prospectuses. We classify a manager as female only where there is affirmative information for gender (e.g., pronouns and photos).

of female-managed funds with and without at least one female Asian manager.

[9]The small remaining percentages were taken up by South Asians, Pacific Islanders, and others.

[10]For further information, see https://www.ssa.gov/oact/babynames/decades/index.html (accessed March 21, 2023).

We start with the *ethnicolr* Python program that calculates a probability score for four groups based on family names: Asian, Black, Hispanic, and White.[11] Next, for all male managers with at least 5% probability (which is meant to be a conservative threshold) of being Asian by their names and all female managers regardless of their names,[12] we search for photographs of fund managers on the internet, starting from LinkedIn and fund company websites, to determine whether a manager has an appearance that could be perceived as being of East, Southeast, and Central Asian descent. For a small number of names without photographs from public sources, we also treat them as Asians because their given names and family names are unambiguously Asian names.

Gender plays a potentially important role for two quite different reasons. First, Asian women were disproportionately victimized by hate crime (see the discussion in Section 2.1), and women generally exhibit a higher level of fear of violent crimes (Johansson and Haandrikman, 2021). Second, recent work has documented a gender-asymmetric effect of the COVID-19 pandemic on work productivity (Barber et al., 2021; Ain Tommar, Kolokolova, and Mura, 2022; Du, 2023). Both factors affect our assessment of Hate (which was concurrent with COVID-19) on productivity. We thus divide the full sample into two mutually exclusive sub-samples: funds with at least one female manager (18.83% of all funds) and those funds that are solely managed by male managers. Bifurcating the sample enables us to isolate the effect of Hate from other gendered effects during the COVID era, by, for example, comparing performances within the same gender groups.

Because Hate crimes and sentiment were not evenly distributed throughout the

[11] Although name-based race prediction algorithms using Bayesian methods such as *ethnicolr* tend to misclassify Black and Hispanic as White, they generally achieve fairly accurate predictions for Asian names that are more distinctive than names of Black and Hispanic (Chernenko and Scharfstein, 2023).

[12] Affirming Asian ethnicity by photo images for all female fund managers allows the identification of Asian women with non-Asian family names, usually via marriage.

nation, the regional variation helps with causal inferences. Therefore, we collect information on the office locations of fund managers 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 primary sources are not available, we resort to B2B data providers (e.g., ZoomInfo, RocketReach, and SignalHire). For the remaining managers, we use the location of their co-managers if all co-managers with available location information are located in the same state.

In the end, our full sample includes 16,543 fund-quarter observations for 2,316 unique funds from 2019 Q1 to 2021 Q1 (excluding 2020 Q1 to avoid the ambiguity about the treatment of the quarter as pre- or post-shock). The sample of funds solely managed by men includes 13,628 fund-quarter observations for 1,880 unique funds; and the remaining 2,915 fund-quarter observations for 436 unique funds belong to funds that were managed by at least one female manager.

The Appendix at the end of this paper lists the definitions of the main variables. Table 1 reports their summary statistics. We provide details on the construction of the variables when they first appear in the discussion of our empirical analyses.

[Insert Table 1 here.]

3. Fund Performance during AAPI Hate

3.1. Underperformance of Asian fund managers during AAPI Hate

Anti-Asian discrimination and bigotry have a long history and have taken different forms in the past. However, the surge and the expressions of AAPI Hate incidents in early 2020 were unexpected. This shock allows us to trace its impact in a difference-in-differences (DiD) framework that analyzes the performance of fund managers. More specifically, we

start with the following baseline regression at the fund (i)-quarter (t) level:

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

In the above equation, the dependent variable *Perf* stands for fund performance. The default measure is the monthly risk-adjusted abnormal return (alpha) averaged over a quarter, defined as follows. For diversified equity funds including equity funds and allocation funds with more than 50% AUM in US equities, we estimate the alpha using the four-factor model by Fama and French (1993) and Carhart (1997). 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 the rest of the funds, mostly sector funds, alternative funds, and allocation funds with less than 50% AUM in US equities or bonds, 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), the abnormal return of a fund 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 the first entry of a fund into our sample.[13]

An Asian identity is a direct measure of the fund management team's exposure to Hate. We replace *Asian* with *AsianMale* and *AsianFemale* when we conduct sub-sample analyses using the funds solely managed by men and the funds with at least one female manager, respectively. The variable *Asian* is constructed to be the fraction of managers in a given fund who could be perceived as of East Asian decent, which includes some Southeast Asians and Central Asians. *AsianMale* and *AsianFemale* are analogously

[13]We find a similar performance decline effect if we estimate alphas using dynamic factor loadings.

defined. All three variables range between 0 and 1. Asian managers are present in 11.8% of the observations in the entire sample, Asian male managers are in 8.6% of the observations associated with the funds managed exclusively by men, and Asian female managers are in 18.9% of the funds with at least one female manager. $Post_t$ 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 to avoid ambiguity in assigning the quarter relative to the event period. $X_{i,t-1}$ denotes a set of time-varying fund characteristics lagged by one quarter, including fund size or total net assets in logarithm (*Log(TNA)*), expense ratio (*Expense*), volatility of the monthly return over the last 12 months(*VOL*), and fund turnover ratio (*Turnover*).[14] Finally, fund fixed effects (θ_i) absorb time-invariant unobserved heterogeneity at the fund level, and style-by-time fixed effects ($\delta_{s,t}$) filter out time-varying common return shocks to funds in a given category. The fixed effects subsume $Asian_i$ and $Post_t$, leaving $Asian_i \times Post_t$ the key variable of interest.

Table 2 reports the regression results for the difference-in-differences estimation of Equation (1). In column (1) which incorporates all sample funds, we find that the coefficient of $Asian_i \times Post_t$ is negative but statistically insignificant, suggesting that Asian managers in general do not suffer significant performance deterioration during AAPI Hate. When we separate managers by gender, an asymmetric pattern emerges. In column (2), we restrict the analysis to the sub-sample of funds that were solely managed by male managers, and confirm the insignificant result as in the full sample. In column (3), we focus on the sub-sample of funds that were managed by at least one female manager. This time, the coefficient of $AsianFemale_i \times Post_t$ is negative and statistically significant at the 1% level.

[14] Our baseline results remain robust if we do not control for fund characteristics or when we replace lagged fund characteristics with those measured in 2019Q4 interacted with *Post* to allow funds with different pre-event characteristics to follow a different path during AAPI Hate.

Comparing a fund with 50% of its managers being Asian women with another non-Asian female managed fund, we learn that the former's performance shortfall amounts to about 0.2 percentage point ($= -0.408 \times 50\%$) for monthly risk-adjusted abnormal returns.[15]

Note that because the funds in the control sample were also managed by women, the effect of COVID-19 on women's productivity cannot explain the incremental effect experienced by female Asian fund managers. In column (4), we use the full sample to test the difference in the effect of AAPI Hate on fund performance between Asian male managers and Asian female managers by including both $AsianFemale_i \times Post_t$ and $AsianMale_i \times Post_t$ in the same model. The results in column (4) confirm the different results shown in the sub-sample analyses of columns (2) and (3).

[Insert Table 2 here.]

To put economic significance into perspective, a comparison could be made to the literature showing performance setbacks of corporate and fund managers due to "distractions," while recognizing that stress originating from ethnic bias is distinct from the more commonplace distractions encountered in the workplace. For example, Lu, Ray, and Teo (2016) report that divorce is associated with a 4.3% reduction in hedge fund managers' annual performance. Schmidt (2019) finds that a one standard-deviation increase in distraction due to earnings announcement of portfolio stocks decreases the average post-trade profitability by 0.24 percentage points over the following four weeks. This magnitude is similar to the monthly underperformance of 0.2 percentage points associated with a fund with 50% of managers being Asian women. Falato, Kadyrzhanova, and Lel (2014)

[15] In untabulated analyses, we also show that the results are robust to the inclusion of state-by-time fixed effects, which account for the heterogeneous effects of COVID-19 across different states where female managers are located. We do not include such state-by-time fixed effects as standard controls in the regression model because we only have information on the location of Asian female managers.

document that the death of a director or a CEO is associated with a −0.79 percentage point abnormal return over a four-day event window among directors-interlocked firms. Finally, Bennedsen, Pérez-González, and Wolfenzon (2020) show that a 10-day hospital stay by the company's CEO reduces the firm's operating profitability by 0.5 percentage points.

Taken together, the findings presented in Table 2 align with the prediction that the professional performance of Asian women was adversely affected by the surge in AAPI Hate crimes that mainly targeted their demographic group. This impact could be attributed to stress, anxiety, and anger arising from ethnic animus and racially motivated criminal acts. The fact that Asian women, but not Asian men, experienced performance setbacks could be attributed to several factors: Asian women faced more than double the probability of being victimized by these hate crimes (Jeung et al., 2021), women in general are more physically vulnerable when encountering violent crimes (Kaur, 2022), and women tend to perceive greater danger from and exhibit greater fear of violent crimes (Logan and Walker, 2021) (for more details, see Section 2.1). Given the evidence from Table 2 and the underlying rationale, our subsequent analyses will concentrate on the sub-sample of mutual funds that are managed by at least one woman.

3.2. Affirming the connection between fund performance and AAPI Hate

Although the previous section establishes a significant correlation between AAPI Hate and the performance shortfall of mutual funds managed by Asian women (the primary targets of Hate), making an attribution requires additional tests aimed at causal inferences, which we explore in this section.

3.2.1. Parallel pre-trends and dynamic effects

A first premise for a DiD analysis to provide causal inference is the assumption of parallel trend, that is, in the absence of the treatment being studied, the treated and control

groups would have followed a similar path over time. A testable form of this assumption is the ex-ante similarity of treated and control funds, i.e., similarity of the two groups along observable dimensions and a pre-event parallel trend leading to the shock. First, Table 3 confirms that the two groups of funds were indistinguishable from each other along all observable dimensions of the characteristics of the fund before the event quarter.

[Insert Table 3 here.]

Next, Figure 1 shows the parallel trend. A formal regression helps formalize and quantify both the pre-event parallel trend as well as the post-event dynamic effects. Specifically, we estimate the following regression, which is an extension of Equation (1) and conditional on the sample of mutual funds with at least one female portfolio manager:

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

In the equation above, $Quarter_k$ is an indicator variable that equals one if the quarter t is k a quarter (s) away from the quarter 0 ($k = 0$), i.e., the quarter when Hate began. We then visualize the key coefficients, $\hat{\beta}_k$, for $-3 \leq k \leq +4$, in Figure 1 including the 95% confidence intervals. The figure affirms a clear pre-event parallel trend; more importantly, it also shows that the difference in performance between the two groups became statistically significant in 2020 Q2 and 2020 Q3. The two groups converged again in Q1 of 2021, which could be explained by individual adaptability (psychological coping, increasing awareness, and changes in behavior to reduce the probability of victimization), the availability of potent vaccines in the late 2020 and community and legislative support, such as the "COVID-19 Hate Crimes Act" that President Biden signed in May 2021.

[Insert Figure 1 here.]

3.2.2. Underperformance sorted by the intensity of AAPI Hate

If the performance deterioration we have documented in the previous sections was caused by AAPI Hate, then the effect should be more pronounced among funds located in regions with higher intensity of AAPI Hate. To test this hypothesis, we estimate a nested 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 intensity of anti-Asian animus, *HighAnimus*, with all the variables in the baseline regression model in Equation (1) including fund fixed effects and style-by-time fixed effects.[16] In each quarter, we split all the 50 US states and the District of Columbia into two sub-samples including the top-decile states and the rest of the states, based on two sorting variables. The first sorting variable for the intensity of 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 of the FBI. The UCR program generates comprehensive statistics on law enforcement and is considered the most reliable information for criminal justice research, the media, and the public.[17]

The second sorting variable is based on the number of anti-Asian tweets posted in

[16] Notethat*AsianFemale*×*HighAnimus*, *Post*×*HighAnimus*, and *HighAnimus* are all absorbed when *HighAnimus* is interacted with fund and style-by-time fixed effects.

[17] 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 renders 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 US, which is different from the prevailing observations and common belief.

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 ethnic animus in an area. We define anti-Asian tweets (*AntiAsianTweet*) at the state-quarter level as those containing ethnic 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 the locations of Twitter users based on their real-time geolocations or the location information they have 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.[18]

Empirically, we find that the top-decile cutoff of the sorting variable gives us a roughly balanced fund-quarter level observations across the high- and low- subgroups due to the overrepresentation of a few large states. *HighAnimus* is an indicator variable that equals one if a state is in the top decile of ethnic animus in a given 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 and potentially dangerous environment with a higher level of anti-Asian animus. Table 4 reports the results.

[Insert Table 4 here.]

[18]The sample becomes smaller with both sorting variables when we exclude 35 funds with female managers who are located in multiple states, live in foreign countries, or that have missing location information.

The coefficients associated with *AsianFemale*×*Post*×*HighAnimus* are negative and statistically significant at the 1% level using both sorting variables, while those of *AsianFemale*×*Post* are negative but statistically insignificant. The findings suggest that notable underperformance is more profound among Asian female fund managers located in areas where anti-Asian animus (manifesting as street-level harassment/crimes and animosity expressed on Twitter) ran rampant. The magnitude is also quite striking: the performance effect associated with Hate in columns (1) and (2) is about 101% and 83% larger than that in the baseline test (i.e., Table 2 column (3)). A correspondence between the magnitude of the performance deterioration and the level of the intensity of Hate supports a potential causal impact.[19]

3.2.3. Underperformance sorted by the importance of decision making

If ethnic animus impairs the productivity of the targeted group, then the effect should be stronger when decision-making is more crucial for performance. We test this hypothesis based on the extent of active portfolio management and the role played by Asian female managers.

First, we perform a triple difference test similar to that of Equation (3) except replacing *HighAnimus* with *HighTurnover*. *HighTurnover* is an indicator variable that equals one if a fund's five-year (or as long as possible if the available data are fewer than five years) pre-event portfolio turnover ratio is above the sample median value (about 49% annually). The results, presented in column (1) of Table 5 Panel A, confirm that Asian

[19] One may argue that the observed underperformance of funds with Asian female managers is merely due to Asian females' greater vulnerability to COVID-19. There is no anecdotal evidence supporting this speculation. We are unable to directly incorporate COVID severity in a triple-difference framework because in the pre-event period COVID-19 cases were always zero. However, we find that the local intensity of COVID-19 measured by the number of newly confirmed cases is only weakly correlated with *HateCrimeNum* (the Pearson correlation coefficient is 0.31); its correlation with *AntiAsianTweet* is 0.69. In general, we argue that our results are unlikely to be driven by the vulnerability of Asian women to COVID-19. In Section 4.1.1, we consider the merits of several additional factors related to COVID-19.

women managing high-turnover portfolios experienced significantly (at the 1% level) worse performance, compared to the performance of high-turnover funds managed by non-Asian women, or to that of low-turnover funds managed by members of the treated group. In other words, when timely decision making is more important, the effect associated with AAPI Hate loomed larger.

A similar logic could apply to active portfolio management based on funds' investment objective. We define an *AggresiveInvest* category to include any fund that is an aggressive growth fund or a high-yield bond fund in Q4 of 2019. These funds typically require a higher level of focus and involve more demanding investment decisions. The results, reported in column (2) of Table 5 Panel A, again support the hypothesis with a significant coefficient (at the 1% level) on the triple term $AsianFemale \times Post \times AggressiveInvest$.

Finally, we expect performance to decline more among funds as Asian famle managers take on greater responsibilities. In a small team, each individual manager's input could be material to the investment process, and thereby performance. As a result, the loss of team productivity due to "treated members" (Asian female managers) in smaller teams is expected to be more significant compared to that in larger teams. The last column of Table 5 Panel A confirms that the sorting variable *SmallTeam* (an indicator variable that equals one if the size of a fund management team does not exceed the sample median value, 3, in 2019 Q4) generates the expected contrast.

In a similar vein, we expect the impact to be stronger if Asian female managers assume a more senior role in the team and thus are more likely to be decision makers in portfolio management. To test this hypothesis, we hand-collect information about the managerial role of each treated manager from the fund's SEC filings (Form 485BPOS or Form 497K) right before 2020. We determine that a manager plays a senior role if one

of the following conditions is satisfied: (1) the manager holds the title of "lead portfolio manager;" (2) she is the only manager of a fund; (3) the manager commands the longest tenure with the fund on the team when information is not available for both (1) and (2); or (4) the manager is the first-listed manager against an alphabetical order in the fund management section of a fund's prospectus when information is not available for both (1) and (2).[20] To qualify as a senior manager, the manager needs to have her senior status at both the end of 2019 and the last entry of the fund in our sample.

We then decompose *AsianFemale* into two mutually exclusive variables:*AsianFemale_Senior* and *AsianFemale_Junior*.[21] *AsianFemale_Senior* is the fraction of Asian female managers who play a senior role in a fund's management team, and *AsianFemale_Junior* is the fraction of Asian female managers who do not play a senior role in a fund's management team. The results are reported in Table 5 Panel B. The interaction terms $AsianFemale_Senior \times Post$ and $AsianFemale_Junior \times Post$ show asymmetry. 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. Furthermore, the difference in performance deterioration between the two sub-samples is statistically significant at the 10% level. The contrast supports the hypothesis that AAPI Hate was more detrimental when the targeted members were important decision makers.

[Insert Table 5 here.]

[20] 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.

[21] Whenever the sorting variable is hand-collected information about the fund manager's demographic characteristics, we only collect such information for the treated sample. Given that the purpose is to explore the potential heterogeneous treatment effect, the information about the control sample does not contribute to the estimation with our saturated fixed effects. For this reason, we do not collect information on the control sample, and, for that reason, we are unable to run triple-difference regressions.

3.2.4. Minority managers who "do not look Chinese"

During AAPI Hate that started in 2020, Asians who could be perceived as Chinese or of East and Southeast Asian descent were the focal targets in hate crimes (see Section 2.2). Such an appearance-based targeting provides us with a test involving non-Asian (Black and non-White Hispanic) and South Asian minority female managers as the placebo group, which shared with Asian female managers the minority status, but were not the specific targets of AAPI Hate crimes.

To develop such a test, we construct the variable *NonAsianMinorityFemale* to be the fraction of "other" (i.e., not belonging to *AsianFemale* defined in Section 3.1) minority female managers in the management team of a fund. Approximately 11.0% of female managers are classified as non-Asian minority female managers in our sample. When we estimate Equation (1) with additional interaction terms, we find that, as shown in Table 6 column (1), the coefficient estimate on $NonAsianMinorityFemale \times Post$ is indistinguishable from zero, economically and statistically, suggesting that minority female managers who were not targeted by AAPI Hate did not experience performance deterioration. More telling is the sub-sample of South Asian managers (who are Asians by geography, but are distinct from East, Southeast, and Central Asians in appearance and who were not among the victims of AAPI hate crimes; see Footnote 9). The results reported in column (2) are similarly null. Taken together, our main finding of deterioration of the performance of Asian female fund managers during AAPI Hate does not appear to be driven by heightened xenophobia during the COVID era or general ethnic discrimination. The result again reinforces that having a Chinese-like appearance was what mattered for the vulnerability to AAPI Hate.

[Insert Table 6 here.]

4. Addressing confounding factors and alternative hypotheses

AAPI Hate was incited by the outbreak of a pandemic that disrupted many aspects ranging from macroeconomic to individuals' daily routines. Given this background, it becomes imperative for us to address the pivotal confounding factors and consider alternative hypotheses with care. This section is dedicated to such a critical examination.

4.1. Other COVID-era productivity shocks

4.1.1. Lack of childcare during the pandemic period

The lack of support services (especially childcare and other family care services) for an extended period of time in states devastated by the pandemic has been shown to be a negative productivity shock, especially for professional women (Barber et al., 2021; Li and Wang, 2021; Ain Tommar, Kolokolova, and Mura, 2022). Recall that our main sample was already restricted to funds that have at least one female manager and therefore should have muted the general gender effect of COVID-19 on productivity. There could still be an argument that there was a differential impact on Asians due to their unique family culture, a possibility that we test in this section.

Following Kruger, Maturana, and Nickerson (2022), we classify a female manager as having a high childcare burden if her age is between 35 and 49 in 2019.[22] We infer a manager's age based on the year 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 with the graduation year information retrieved from the Morningstar Direct database. When this information is missing, we supplement it with information from managers' LinkedIn profile pages (if any). If information is still missing, we classify

[22] Our results are similar if we classify a female manager as having a high childcare burden using a wider age range (i.e., 30-49).

managers with more than 28 years of work experience in 2019 as the low-childcare burden group. Managers' working experience information is collected from the Morningstar Direct database or LinkedIn profile pages. We then decompose *AsianFemale* into two mutually exclusive variables:*AsianFemale_HighCareBurden* and *AsianFemale_LowCareBurden*. The former is the fraction of Asian female managers who were between 35 and 49 years old in 2019 in a fund, and the latter is the fraction of Asian female managers who were under 35 years of age or over 49 years of age in 2019.

We then expand 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 7. 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 regardless of the potential childcare burden of managers during the pandemic. The magnitude of the estimate of $AsianFemale_HighCareBurden \times Post$ is, in fact, slightly smaller than that of $AsianFemale_LowCareBurden \times Post$.[23] It is important to note that this result does not dismiss the negative impact of the lack of family care services on productivity, and especially concerning professional women. Note that our results speak only of a relative effect because sample funds have been restricted to those managed by women. This test indicates that the main finding on the performance deterioration of Asian female managers could not be explained by an important alternative COVID-era productivity shock, namely a lack of family care services.

[Insert Table 7 here.]

[23]This could be because Asian female managers facing low childcare burden are more likely to assume a senior role in their funds.

4.1.2. Pandemic concerns about families at home countries

Asian countries were among the first batch of countries to reach the pandemic situation, and many experienced waves of devastation. Because Asian professionals in the US are more likely to be recent immigrants compared to other race groups,[24] they may experience additional stress due to concerns about their extended families in their original home countries, especially when the latter entered the peak phases of the COVID-19 waves. Under this hypothesis, we expect Asian female managers who are first-generation immigrants to endure more stress in relation to their family and relatives in their home countries, compared to managers who were born or grew up in the US. On the other hand, both groups face the same risk of becoming targets of anti-Asian hate crimes.

To test this hypothesis, we construct a new variable *AsianFemale_FirstGen* to be the fraction of Asian female managers in a fund that are classified as first-generation Americans. 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-Anglicized" name);[25] (2) the manager received her bachelor's degree in an Asian country according to biographical information; and (3) the manager's mother tongue is an Asian language according to LinkedIn information (if any).

With this information, we expand the baseline model in Equation (1) by decomposing *AsianFemale* into *AsianFemale_FirstGen* and *AsianFemale_NonFirstGen*. The results are reported in column (2) of Table 7. The coefficient estimates of

[24] 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.

[25] American-born Asians take anglicized names as part of integration. Asian immigrants often anglicize their names for a variety of reasons, including to avoid racism and xenophobia and to facilitate pronunciation and assimilation (Yeung, 2021). Hence, a non-Anglicized name is a relatively sufficient but far from necessary condition for the first-generation classification.

AsianFemale_FirstGen×*Post* and *AsianFemale_NonFirstGen*×*Post* are both negative and statistically significant at the 1% level. Consistent with the expectation that Asian female managers who are first-generation immigrants can experience additional stress due to worries about their families in their countries of origin, the magnitude of the coefficient estimate of *AsianFemale_FirstGen*×*Post* is notably higher but the difference is not statistically significant. Importantly, the fact that both groups of managers classified by immigration status experience a significant deterioration in performance suggests that concerns for families and relatives in Asian countries of origin do not drive our main finding.

4.2. Possible discrimination in professional settings

4.2.1. COVID-stigma induced marketplace discrimination: Fund outflows

This section addresses the possible concurrence (with AAPI Hate) of discrimination in the business setting that could be related to COVID-19. In a similar setting and 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 explanation of our main finding could be marketplace hostility in the form of investors' redemption from Asian-managed funds due to the association with the stigma of the coronavirus. Prior literature (e.g., Edelen, 1999; Coval and Stafford, 2007; Simutin, 2014) shows that large redemptions hurt fund performance for remaining shareholders, as liquidity-motivated trades tend to occur at unfavorable prices or even at a fire-sale discount. Furthermore, due to the negative spillover to remaining shareholders, anticipation of redemption of some investors may trigger redemption by other investors (Chen, Goldstein, and Jiang, 2010). Needless to say, this hypothesis, even true, still supports the hypothesis that the ethnic animus of the COVID era impacted manager performance. We believe that such a test is still valuable in that it separates discrimination in the business setting from an animus in the broad social context, one of the key features

that distinguishes our study from previous work.

We start with a test by replacing the dependent variable in Equation (1) to be *FundFlow* to directly examine the effect of AAPI hate on fund flows (*FundFlow*), which is defined as the return-adjusted change in a fund's total net assets (TNA) following the standard practice in the literature pioneered by Chevalier and Ellison (1997) and Sirri and Tufano (1998). Since fund investors rely mainly on managers' names to infer their ethnicity (Kumar, Niessen-Ruenzi, and Spalt, 2015), we focus on Asian managers with a typical Chinese family name in column (1) and Asian female managers with a typical Chinese family name in column (2), respectively. We perform the fund flow test using the sample of funds with at least one female manager, which is the primary sample in our other tables. We include the lagged fund return (average monthly raw return in percentage) as a control for performance in addition to the control variables in Table 2. Columns (1) and (2) of Table 8 show that funds with at least one Asian manager or at least one Asian female manager who has a typical Chinese family name did not experience significantly greater fund outflow compared to other funds. Therefore, there is no evidence of marketplace discrimination against funds managed by managers with Asian names. This null result in fund flows suggests that our finding of underperformance of funds with at least one Asian female manager during the pandemic was not driven by their larger fund outflows.

Nevertheless, this does not mean that a larger fund outflow does not hurt performance, which we show in column (3) where we sort the sample into a *HighOutFlow* sub-sample, defined as monthly outflow averaged within the contemporaneous quarter to be 5% or more. When we interact *HighOutFlow* with $AsianFemale \times Post$ in a triple difference regression model, we find that the coefficient associated with $AsianFemale \times Post \times HighOutFlow$ is indeed negative and marginally significant (at the 10% level),

consistent with the broad literature showing a negative impact of large redemption on fund performance. Importantly, however, the coefficient on $AsianFemale \times Post$ is more significant, both economically and statistically, suggesting that the sub-sample of funds managed by Asian women that did not experience substantial redemption still suffered in productivity, in a magnitude similar to that in our baseline analysis (see Table 2). In general, market place discrimination in the form of large investor redemption does not explain our main findings.

[Insert Table 8 here.]

4.2.2. COVID-stigma induced discrimination in the workplace

At the core of anti-Asian racism during the early stage of the pandemic was "sinophobia," linked to the early wave in the city of Wuhan in China and further intensified by the escalating tensions between the US and China in a similar time frame. As the virus spread worldwide, the animus targeted people of Asian descent, especially East Asians. This section delves into whether workplace animus played a role in this context. This analysis is facilitated by the distinct targeting mechanisms. On the streets, Asians who bear physical resemblance to Chinese individuals face similar risks of hate-driven attacks. Consequently, this animus is expected to hit managers of East Asian, Southeast, and Central Asian heritage, regardless of their Chinese origin. In contrast, in a workplace setting, information about a manager's country of origin is usually known. Therefore, an unfriendly sentiment towards Chinese individuals within the workplace predicts that only Chinese female managers would experience a decrease in productivity.

Among our sample of Asian female managers, we are able to divide the group into managers of Chinese origin and the rest. A new variable $AsianFemale_Chinese$ measures the fraction of female managers of Chinese origin in the management team of a fund. We

define a manager as Chinese by her family name and her first-generation status. We define a manager as a first-generation immigrant by the classification algorithm used in Section 4.1.2. About 39.1% of the Asian female managers in our sample are from China. The results in the fourth column of Table 8 indicate that both Chinese and non-Chinese Asian female managers exhibit significant performance deterioration during the pandemic, which is expected under the AAPI Hate hypothesis because non-Chinese Asian female managers could still "look like Chinese" on the street and become targets of Hate violence. There is a notable difference in the magnitude of the two coefficients, but the difference is statistically insignificant.

In general, the results confirm that non-Chinese who "look like Chinese" were negatively impacted, which can be explained by the animus in the social context, instead of the unfriendly sentiment toward Chinese on the job arising from COVID-19 and the tension between China and the US.

4.3. Heterogeneity in fund quality

Although we tested parallel trends and balanced covariates before the event, there is still a possibility that among the "treated" funds (i.e., funds with at least one Asian female manager), lower quality managers faced an even greater challenge in portfolio management when COVID-19 triggered economic downturns, driving down the performance of the "treated" group. To address this issue in one further step, we re-estimate the triple difference regression model in Equation (3) with *LowPerf* to be the interaction variable. *LowPerf* is an indicator variable that equals one if a fund's pre-event fund performance is below the sample median value, where a fund's pre-event performance is calculated as the average fund performance over the five years prior to the event. Table IA.1 shows that $AsianFemale \times Post$ remains negative and statistically significant (at the level 5%), and

the term of triple interaction, which captures the incremental experience of managers who underperformed during the pre-event period, is statistically insignificant. Overall, there is little support for the hypothesis that our main finding is driven by Asian female managers who were underperforming to start with.

5. Sensitivity checks

5.1. Alternative measures of fund performance

In Table IA.2 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 average monthly fund return in a quarter. The second alternative is the 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 using these three alternative performance measures.

5.2. Alternative samples

In Table 3, we have shown that the treated funds and the control funds have comparable fund characteristics. Nevertheless, we further employ both propensity score matching and entropy balance matching strategies to check the robustness of our key finding. The matching variables include all the control variables in Table 2 and both matching techniques are performed in the quarter before the shock (that is, Q4 2019). In column (1) of Table IA.3 of the Internet Appendix, we match the one-to-one nearest neighbor propensity score with replacement and a caliper of 0.1. In column (2), we present the results from using entropy balance matching that balances both the first- and second-moments of the covariates between the treated funds and control funds without losing the

sample size. The DiD results reported in columns (1) and (2) of Table IA.3 are robust and exhibit an economic magnitude similar to that reported in column (2) of Table 2.

Another concern is that our key finding might be due to the unobserved differences in funds' team management structure between treated funds and control funds. We conducted two tests to mitigate this concern. First, in column (3) of Table IA.3, we repeat the baseline analysis (i.e., column (3) of Table 2) with funds that were managed solely by female managers. This can help further alleviate the effect of gender differences (e.g., household responsibilities) and the potential effects of Asian male managers on fund performance. The results are robust and have a larger economic magnitude than what is reported in column (2) of Table 2. In column (4), we provide the strongest test by restricting the sample to funds that were solo-managed by a female manager. This test not only filters out the potential influence of male managers in the funds with at least one female manager, but also removes the difference in the size of the management team. However, an understandable but unavoidable caveat of this approach is the very small sample size. Nevertheless, we find affirmative results in column (4).

In general, the results reported in Table IA.3 rule out the concern that the observed effect of the AAPI on the performance of funds with Asian female managers is driven by the unobserved differences between treated funds and control funds.

6. Verifying the mechanisms of performance deterioration

6.1. Stock-picking related performance measures

Although the results in the previous sections confirm the performance decline effect of AAPI Hate, it remains to be verified that performance deterioration could be attributed to managerial actions or strategies that are associated with a lower quality in portfolio management. We address this question by resorting to several well-established measures

in the literature. We analyze these "action-related variables," placing them as dependent variables in Equation (1). The results are reported in Table 9.

[Insert Table 9 here.]

The first measure is the "return gap" developed by Kacperczyk, Sialm, and Zheng (2008), which, according to the authors, captures "hidden actions" by portfolio managers that could enhance performance beyond a buy-and-hold strategy. *Return Gap* is calculated as the difference between a fund's actual return in a quarter and the buy-and-hold quarterly return that would be earned by the funds' disclosed holdings at the closest previous quarter end. Following the earlier work, we restrict the regression sample to funds with 75% or more assets in US equities and with non-missing holdings data from the CRSP Mutual Fund Holdings Database. We also exclude "alternative" funds, as they often have significant positions (such as derivatives) that are not reported in the standard holdings database. To avoid stale information, we also require that the interval between the calendar quarter end and the previous holdings disclosure month be three months or shorter. The results, reported in the first column of Table 9, indicate that the return gap of the treated funds, with 50% of the managers being Asian women, decreased by 0.08 percentage points ($= 0.16 * 50\%$) monthly during AAPI Hate, compared to a fund run by non-Asian female managers.

Second, we employ "DGTW-adjusted return" (Daniel et al., 1997) measures to analyze the quality of stock picking, especially the quality of position initiation and termination decisions. The "DGTW-adjusted return" is calculated as the difference between the value-weighted returns of the equity holdings held at the end of the last quarter and a benchmark return based on value-weighted returns of $5\times5\times5$ benchmark portfolios sorted on size, book-to-market, and momentum. We learn from column (2) of Table 9 that

the monthly DGTW-adjusted returns decreased by 0.24 percentage points ($= 0.483 * 50\%$) during the post-event period for a fund with 50% of managers being Asian female relative to funds with only non-Asian female managers.

With the DGTW measure, we can assess initiation and termination decisions. In column (3), the dependent variable is calculated as the value-weighted DGTW-adjusted return of the initiation portfolio. For the pre-event quarters, the initiation portfolio consists of stock buys initiated during the period from 2019 Q1 to 2019 Q4. For the post-event quarters, the initiation portfolio includes stock buys initiated from 2020 Q2 to 2021 Q1. The initiated positions are identified by comparing the holdings of a fund in two consecutive quarters (i.e., t and t-1). An initiated stock in the previous quarter will be carried forward into the next quarter until the pre-event period ends or the post-event period ends or until the position is reversed, whichever is earlier. The coefficient estimate of $AsianFemale \times Post$ in column (3) is negative and statistically significant at the 1% level. Furthermore, the magnitude of the coefficient estimate is almost three times the coefficient estimate in column (2), suggesting that the lowered quality of the initiation actions is a driving force of performance degradation during AAPI hate.

Column (4) applies the same analysis to the termination portfolio with necessary adjustments. To isolate discrete material portfolio decisions, we focus on termination (i.e., a reduction of holdings to zero) excluding partial reductions in holdings. The coefficient estimate of $AsianFemale \times Post$ in column (4) is positive (which represents negative performance for termination decisions) but statistically insignificant. The asymmetry is not surprising given that prior literature (e.g., Pinnuck, 2003; Fang, Peress, and Zheng, 2014) has found that position termination is not as informed as initiation because of analysts' bias towards buy recommendations, bad news incorporating slower than good news in stock

prices (Hong, Lim, and Stein, 2000), and higher search costs for buys compared to sells (managers can buy a stock from the entire universe but can only sell from their portfolio due to short-sale constraints).

6.2. Portfolio activeness

The next two measures for which the results are reported in Table 9 Panel B capture the degree of active portfolio management. The first is *ChurnRate*, a holdings-based portfolio turnover measure developed in Yan and Zhang (2009);[26] the second is *ActiveShare*, proposed by Cremers and Petajisto (2009) to measure the extent to which a fund's portfolio deviates from its prospectus benchmark. The insignificant coefficient of $AsianFemale \times Post$ for both measures suggests that Asian female portfolio managers did not seem to "slow down" their active portfolio management, but it is of lower quality, as shown in Panel A of the same table.[27] Such a pattern exhibits differences from the effect induced by distraction or stress. For example, Schmidt (2019) finds that fund managers distracted by the arrival of earnings announcements tend to reduce trading; on the contrary, Gambetti and Giusberti (2012) show that anger increases the propensity to trade.

7. Conclusion

Existing research has focused primarily on assessing the existence of racial and ethnic animus within workplaces and marketplaces, shaped by legal and policy considerations. This study delves into the wave of hate crimes targeting AAPI communities during 2020, using this surge as a catalyst to explore the underlying sociopolitical ethnic animus. To facilitate this exploration, the mutual fund industry is employed as a laboratory,

[26] Our results are similar if we use the churn rate proposed in Gaspar, Massa, and Matos (2005).
[27] Consistent with the findings in Liu et al. (2023), the model in column (2) of Table 9 has a high adjusted R-squared, likely due to the little variation in active share after the inclusion of fund fixed effects.

characterized by its objective and measurable performance metrics and managerial actions. Our study demonstrates that funds managed by East Asian and Southeast Asian female managers exhibited a significant decline in performance after the identified shock. This decline was particularly pronounced in states marked by heightened anti-Asian animus, in funds engaging in more active management, following a more aggressive fund style, and where Asian female managers play a more important decision-making role. The observed effect cannot be explained by other concurrent factors such as lack of childcare during the pandemic, marketplace and workplace discrimination, pandemic-induced xenophobia (unrelated to Hate), and disparities in fund quality. The underperformance of funds with Asian female managers is mainly due to the lowered stock picking ability, especially the quality of stock initiation positions during AAPI Hate rather than their reduced activeness in managing their portfolios.

What emerges from the analysis is a compelling case for the causal impact of AAPI Hate on productivity loss through hate-induced anxiety and stress in the primary target group. Although the study is rooted in the AAPI Hate episode and the mutual fund sector, the research serves as a stark reminder of the far-reaching consequences of ethnic hatred and discrimination, even as explicit forms of bigotry have been outlawed in employment and market activities.

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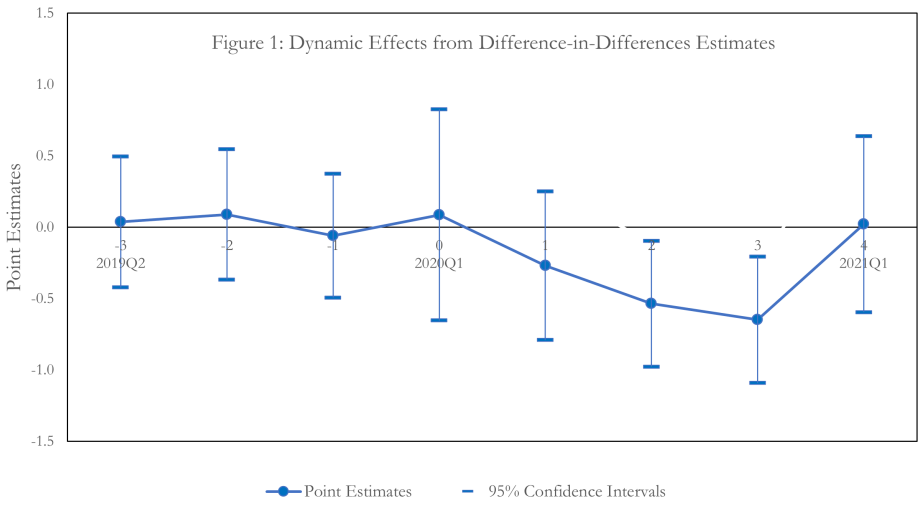
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Figure 1: The parallel trend analysis for the female-managed fund sample

Figure 1 plots the point estimates from Equation (2), the dynamic DiD test on the effects of anti-Asian animus on the performance of funds with at least one Asian female manager. Marked confidence intervals are at the 95% confidence level, using robust standard errors that are clustered at the fund level.



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Table 1: Summary Statistics

This table presents the descriptive statistics of the main variables for the full sample, the all-male-managed fund sample, and the female-managed fund sample. The full sample is the combination of all-male-managed and female-managed fund sample. The all male-managed sample includes funds that are solely managed by male managers. The female-managed fund sample consists of funds that are managed by at least one female manager. The all-male-managed fund sample and female-managed fund 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.	N	Mean	Std.	N	Mean	Std.	N
	Full Sample			Funds solely managed by male managers			Funds managed by at least one female manager		
Perf (%)	−0.008	0.908	16,543	0.006	0.928	13,628	−0.067	0.823	2,915
TNA	2,025.9	4,727.1	16,543	1,920.4	4,342.0	13,628	2,712.2	7,746.3	2,915
Expense	0.009	0.004	16,543	0.009	0.004	13,628	0.008	0.003	2,915
VOL (%)	5.025	2.755	16,543	5.043	2.795	13,628	4.946	2.563	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
AsianMale	0.035	0.127	16,543	0.034	0.128	13,628	0.040	0.121	2,915
AsianFemale	0.015	0.090	16,543	0.000	0.000	13,628	0.083	0.200	2,915
Asian(0/1)	0.118	0.322	16,543	0.086	0.280	13,628	0.267	0.443	2,915
AsianMale(0/1)	0.093	0.290	16,543	0.086	0.280	13,628	0.126	0.331	2,915
AsianFemale(0/1)	0.033	0.179	16,543	0.000	0.000	13,628	0.189	0.391	2,915

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Table 2: Anti-Asian animus on fund performance during AAPI Hate

This table performs the difference-in-differences analysis of the effect of anti-Asian animus on fund performance during AAPI Hate. In column (1), we perform the analysis using the full sample, where the treated funds are funds managed by at least one Asian manager. In column (2), we focus on the all-male-managed sample that consists of funds solely managed by male managers, where the treated funds are funds managed by at least one Asian male manager. In column (3), we restrict the analysis to the funds with at least one female manager, where the treated funds are funds managed by at least one Asian female manager. In column (4), we utilize the full sample to test the difference in the effect of Asian male managers and Asian female managers. The full sample is the combination of the all-male-managed fund sample and female-managed fund sample, which are mutually exclusive. Fund performance is *Perf*, measured as the risk-adjusted percentage 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., 2020 Q1). The event quarter is excluded from the analysis to avoid ambiguity. Detailed variable definitions are provided in the Appendix. Estimates are based on OLS regressions with robust standard errors that are clustered at the fund level. T-statistics are reported in parentheses. ***, **, 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	Full Sample
	(1)	(2)	(3)	(4)
Asian×Post	**−0.103**			
	(−1.164)			
AsianMale×Post (β_1)		**0.018**		**0.022**
		(0.133)		**(0.171)**
AsianFemale×Post (β_2)			**−0.408*** **	**−0.339*** **
			(−3.414)	**(−3.397)**
Log(TNA)	−0.384***	−0.396***	−0.352***	−0.385***
	(−8.557)	(−7.898)	(−3.650)	(−8.602)
Expense	−14.533	−13.140	−17.115	−13.791
	(−0.854)	(−0.714)	(−0.406)	(−0.811)
VOL (%)	−0.008	−0.001	−0.046	−0.008
	(−0.567)	(−0.086)	(−1.345)	(−0.541)
Turnover	0.011	−0.003	0.155**	0.011
	(0.370)	(−0.081)	(2.256)	(0.395)
F-Test ($\beta_1 - \beta_2 = 0$)				**−0.361** **
(p-value)				**(0.043)**
Fund FE	Yes	Yes	Yes	Yes
Style-by-Time FE	Yes	Yes	Yes	Yes
Observations	16,543	13,628	2,915	16,543
Adjusted R-squared	0.159	0.165	0.139	0.159

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Table 3: Test of covariate balance between the treated and control funds

This table reports covariate balance checks in the quarter prior to the event (i.e., 2019 Q4) between the treated funds and control funds. The treated funds include funds with at least one Asian female manager, while the control funds consist of funds with at least one female manager but having no Asian female managers. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Variables	Treated funds (funds with at least one Asian female manager)	Control funds (funds with at least one female manager but having no Asian female managers)	Difference in Mean
	Mean	Mean	T-stat
	(1)	(2)	(3)
Perf (%)	−0.276	−0.248	−0.347
Log(TNA)	6.276	6.528	−1.374
Expense	0.0078	0.0084	−1.397
VOL (%)	3.091	3.153	−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	

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Table 4: Underperformance sorted by the intensity of AAPI Hate

This table explores the variations in local anti-Asian animus by estimating a nested fully interacted triple-difference regression model using the female-managed fund sample. 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 US 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 ethnic 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. *Perf* is measured as the risk-adjusted percentage monthly return averaged over a quarter. In column (1), the level of local anti-Asian animus is proxied by the number of 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* is absorbed by the interactions between *HighAnimus* and Fund FE; *AsianFemale* is absorbed by Fund FE; *Post*×*HighAnimus* and *HighAnimus* are absorbed by the interactions between *HighAnimus* and Style-by-Time FE; *Post* is absorbed by Style-by-Time FE. In column (1), we eliminate observations in 2021 Q1 as the FBI data are subject to serious data issues due to the transition into a new reporting system in 2021 (Grawert and Kim, 2022; Li and Ricard, 2023). 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* (%)	
	HateCrimeNum	*AntiAsianTweet*
	(1)	(2)
AsianFemale×*Post*×*HighAnimus* (β_1)	**−0.667*** **	**−0.689*** **
	(−2.658)	**(−3.045)**
AsianFemale×*Post* (β_2)	−0.155	−0.057
	(−1.081)	(−0.347)
F-Test ($\beta_1 + \beta_2 = 0$)	**−0.822*** **	**−0.746*** **
(p-value)	**(0.000)**	**(0.000)**
Controls in Table 2	Yes	Yes
Fund FE	Yes	Yes
Style-by-Time FE	Yes	Yes
Observations	2,326	2,680
Adjusted R-squared	0.183	0.136

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Table 5: Underperformance sorted by the importance of decision making

Panel A explores the heterogeneity in the importance of decision making sorted by fund characteristics using a nested fully interacted triple-difference regression. The analysis is restricted to funds that are managed by at least one female manager. *Perf* is measured as the risk-adjusted percentage monthly return averaged over a quarter. 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 the available data are 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 interactions between the sorting variables (i.e., *HighTurnover*, *AgressiveInvest*, and *SmallTeam*) and *AsianFemale* are absorbed by the interactions between the sorting variables and the fund FE. The interactions between the sorting variables and *Post* are absorbed by the interactions between the sorting variables and the style-by-time FE. Panel B examines the heterogeneous effects of AAPI Hate sorted by splitting Asian female managers into two mutually exclusive groups based on their seniority status. Specifically, we divide *AsianFemale* into two mutually exclusive variables: *AsianFemale_Senior* and *AsianFemale_Junior*. We split *AsianFemale* in this way rather than doing a simple interaction because we only have seniority information for Asian female managers. *AsianFemale_Senior* is the fraction of Asian female managers who play a senior role in a fund's management team. *AsianFemale_Junior* is the fraction of Asian female managers who do not play a senior role in a fund's management team. 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, or if the manager is the first-listed manager against an alphabetical order in the fund management section of a fund's prospectus. 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 points in time: 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 these 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.

Panel A: Sorting by fund characteristics			
Dependent Variable =	*Perf* (%)		
	(1)	(2)	(3)
AsianFemale×*Post*×*HighTurnover* (β_1)	**−0.645***** **(−2.774)**		
AsianFemale×*Post*×*AgressiveInvest* (β_1)		**−0.818***** **(−2.951)**	
AsianFemale×*Post*×*SmallTeam* (β_1)			**−1.270*** **(−1.937)**
AsianFemale×*Post* (β_2)	0.067 (0.411)	−0.133 (−0.906)	0.811 (1.258)
F-Test ($\beta_1 + \beta_2 = 0$) (p-value)	**−0.578***** **(0.001)**	**−0.950***** **(0.000)**	**−0.459***** **0.000**
Controls in Table 2	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Style-by-Time FE	Yes	Yes	Yes
Observations	2,915	2,915	2,915
Adjusted R-squared	0.143	0.158	0.141

Panel B: Sorting by the managerial role of Asian female managers	
Dependent Variable =	*Perf* (%)
	(1)
AsianFemale_Senior×*Post* (β_1)	**−0.524***** **(−4.253)**
AsianFemale_Junior×*Post* (β_2)	**−0.114** **(−0.483)**
F-Test ($\beta_1 - \beta_2 = 0$) (p-value)	**−0.410*** **(0.098)**
Controls in Table 2	Yes
Fund FE	Yes
Style-by-Time FE	Yes
Observations	2,915
Adjusted R-squared	0.139

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Table 6: Minority managers who "do not look Chinese"

This table contrasts the effect of AAPI Hate on Asian female managers with that on non-Asian minority female managers and on South Asian female managers. The analysis is restricted to funds that are managed by at least one female manager. *Perf* is measured as the risk-adjusted percentage monthly return averaged over a quarter. In column (1), we augment the baseline model by including the interaction term, $NonAsianMinorityFemale \times Post$. *NonAsianMinorityFemale* is the fraction of minority female managers who do not have a Chinese-looking appearance (including Black, non-White Hispanic, and South Asian female managers). The control group in column (1) comprises of funds whose female managers do not look like a Black, non-White Hispanic, or South Asian. 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 female managers of Bangladeshi, Indian, and Pakistani descent, as well as those from other South Asian countries. 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)	**−0.407*** **	**−0.405*** **
	(−3.366)	**(−3.359)**
NonAsianMinorityFemale×*Post* (β_2)	**0.018**	
	(0.130)	
SouthAsianFemale×*Post* (β_2)		**0.091**
		(0.562)
F-Test ($\beta_1 - \beta_2 = 0$)	**−0.425*** **	**−0.496*** **
(p-value)	**(0.008)**	**(0.006)**
Controls in Table 2	Yes	Yes
Fund FE	Yes	Yes
Style-by-Time FE	Yes	Yes
Observations	2,915	2,915
Adjusted R-squared	0.139	0.139

(Go back to section)

Table 7: Other COVID-era productivity shocks

This table examines alternative explanations related to other COVID-era shocks that concurred with AAPI Hate. The analysis is restricted to funds that are managed by at least one female manager. *Perf* is measured as the risk-adjusted percentage monthly return averaged over a quarter. 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 a 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. 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 US and the stress sourced from worries about the effects of 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 *AsianFemale_NonFirstGen* is the fraction of Asian female managers who are not classified as first-generation-immigrant Asian female managers. We determine that a manager has the 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 biographical information; and (3) the manager's mother tongue is an Asian language according to information from LinkedIn. 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_HighCareBurden×*Post* (β_1)	**−0.299****	
	(−2.069)	
AsianFemale_LowCareBurden×*Post* (β_2)	**−0.627*****	
	(−2.732)	
AsianFemale_FirstGen×*Post* (β_1)		**−0.639*****
		(−3.085)
AsianFemale_NonFirstGen×*Post* (β_2)		**−0.330*****
		(−2.688)
F-Test ($\beta_1 - \beta_2 = 0$)	**0.327**	**−0.309**
(p-value)	**(0.190)**	**(0.156)**
Controls in Table 2	Yes	Yes
Fund FE	Yes	Yes
Style-by-Time FE	Yes	Yes
Observations	2,840	2,893
Adjusted R-squared	0.139	0.142

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Table 8: Possible discrimination in professional settings

This table rules out alternative discrimination in two professional settings: marketplace discrimination and workplace discrimination. The analysis is restricted to funds that are managed by at least one female manager. In columns (1) and (2), we replace the dependent variable in Equation (1) with fund flow to directly examine the effect of AAPI Hate on fund flows. *FundFlow* is the contemporaneous monthly fund flow averaged over a quarter. Since fund investors infer managers' ethnicity from their names (Kumar, Niessen-Ruenzi, and Spalt, 2015), we focus on Asian managers with a typical Chinese family name in column (1) and Asian female managers with a typical Chinese family name in column (2). The variables of interest are *Asian_ChineseName×Post* in column (1) and *AsianFemale_ChineseName×Post* in column (2). *Asian_ChineseName* is the fraction of Asian managers with a typical Chinese family name, while *AsianFemale_ChineseName* is the fraction of Asian female managers with a typical Chinese family name. We include lagged fund return (average monthly raw return expressed as a percentage) as an additional control variable when the dependent variable is fund flow. In columns (3) and (4), the dependent variable is *Perf*, measured as the risk-adjusted percentage monthly return averaged over a quarter. In column (3), we perform a nested fully interacted triple-difference analysis to explore if fund flows influence the effect of Hate on fund performance. *HighOutFlow* is an indicator variable that equals one if a fund's average monthly outflow in a quarter is 5% or more and zero otherwise. Note that *AsianFemale×HighOutFlow* is absorbed by the interactions between *HighOutFlow* and Fund FE; *AsianFemale* is absorbed by Fund FE; *Post×HighOutFlow* and *HighOutFlow* are absorbed by the interactions between *HighOutFlow* and Style-by-Time FE; *Post* is absorbed by Style-by-Time FE. In column (4), 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 family 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 =	*FundFlow*		*Perf* (%)	
	(1)	(2)	(3)	(4)
Asian_ChineseName×*Post* (β_1)	**0.008**			
	(0.977)			
AsianFemale_ChineseName×*Post* (β_1)		**0.011**		
		(1.093)		
AsianFemale×*Post* (β_1)			**−0.418*** **	
			(3.527)	
AsianFemale×*Post*×*HighOutFlow* (β_2)			**−0.197***	
			(−1.662)	
AsianFemale_Chinese×*Post* (β_1)				**−0.659*** **
				(−3.160)
AsianFemale_NonChinese×*Post* (β_2)				**−0.346*** **
				(−2.883)
F-Test ($\beta_1 + \beta_2 = 0$)			**−0.615*** **	
(p-value)			**(0.000)**	
F-Test ($\beta_1 - \beta_2 = 0$)				**−0.312**
(p-value)				**(0.151)**
Controls in Table 2	Yes	Yes	Yes	Yes
Lagged Fund Return	Yes	Yes	No	No
Fund FE	Yes	Yes	Yes	Yes
Style-by-Time FE	Yes	Yes	Yes	Yes
Observations	2,915	2,915	2,856	2,915
Adjusted R-squared	0.411	0.410	0.149	0.140

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Table 9: Verifying the mechanisms of performance deterioration

This table examines the effect of AAPI Hate on managerial actions by exploring quarterly holdings of equity funds in the sample. The analysis is restricted to funds that are managed by at least one female manager. In Panel A, we focus on stock-picking related performance measures. The dependent variable is the return gap expressed in percentage (Kacperczyk, Sialm, and Zheng, 2008) in column (1) and the DGTW-adjusted returns expressed in percentage (Daniel et al., 1997) in column (2). We first construct the monthly DGTW adjusted return defined as the difference between the value-weighted monthly stock returns of the equity holdings held at the last quarter-end and 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 returns are then calculated as the average monthly DGTW adjusted returns over a quarter. In column (3), we re-estimate the model in column (2) by focusing on newly initiated equity holdings. Specifically, the dependent variable in column (3) is calculated as the value-weighted DGTW-adjusted return of the initiation portfolio. For the pre-event quarters, the initiation portfolio consists of initiated stocks from 2019 Q1 to 2019 Q4. For the post-event quarters, the initiation portfolio consists of initiated stocks from 2020 Q2 to 2021 Q1. The initiated stocks are identified by comparing a fund's holdings in the current quarter and the holdings in the previous quarter. An initiated stock in the last quarter is carried forward to the next quarter until the pre-event period end or the post-event period end unless it is terminated. In column (4), we re-estimate the model in column (2) by focusing on newly terminated equity holdings. The dependent variable in column (4) is calculated as the value-weighted DGTW-adjusted return of the terminated portfolio. For the pre-event quarters, the terminated portfolio consists of terminated stocks from 2019 Q1 to 2019 Q4. For the post-event quarters, the terminated portfolio consists of terminated stocks from 2020 Q2 to 2021 Q1. The terminated stocks are identified by comparing the fund's holdings in the current quarter and the holdings in the previous quarter. A terminated stock in the last quarter is carried forward to the terminated portfolio in the next quarter until the end of the pre-event period or the end of the post-event period unless it is later bought back. We exclude the terminated stocks that experienced holding-reduction in the prior quarter because stocks that were gradually sold out are likely inherently different from those that were unexpectedly terminated. In Panel B, we examine the impact of Hate on managerial activeness. The dependent variable in columns (1) and (2) is *ChurnRate*, a holdings-based portfolio turnover measure proposed in Yan and Zhang (2009) and *ActiveShare*, which measures the extent to which a fund's portfolio deviates from its prospectus benchmark in Cremers and Petajisto (2009), respectively. Estimates are based on OLS regressions with robust standard errors 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.

Panel A: Stock-picking related performance measures				
Dependent Variable =	*Return Gap*	*DGTW*	*DGTW_Initi*	*DGTW_Termi*
	(1)	(2)	(3)	(4)
AsianFemale×Post (β_1)	**−0.160****	**−0.483****	**−1.403*****	**0.608**
	(−2.290)	**(−2.325)**	**(−2.999)**	**(1.120)**
Controls in Table 2	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Style-by-Time FE	Yes	Yes	Yes	Yes
Observations	1,540	1,421	1,334	1,199
Adjusted R-squared	0.134	0.008	0.047	−0.024

Panel B: Portfolio activeness		
Dependent Variable =	*ChurnRate*	*ActiveShare*
	(1)	(2)
AsianFemale×Post	**0.024**	**−0.003**
	(1.323)	**(−0.251)**
Controls in Table 2	Yes	Yes
Fund FE	Yes	Yes
Style-by-Time FE	Yes	Yes
Observations	1,437	1,056
Adjusted R-squared	0.738	0.985

Appendix

Variable	Definition
Perf	Monthly abnormal percentage returns averaged over a calendar quarter. For diversified equity funds including equity funds and allocation funds with more than 50% of AUM in US 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 US 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 aggregated across share classes at a quarter end.
Expense	A fund's net expense ratio weight-averaged across share classes at a quarter end.
VOL	The standard deviation of percentage monthly fund return (in excess of risk-free rate) over the last 12 months.
Turnover	A fund's turnover ratio weight-averaged across share classes at a quarter-end.
NumMgr	The number of managers in a fund's management team.
Asian	The fraction of Asian managers (i.e., managers having an appearance that could be construed as being of East, Southeast, and Central 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.
Asian(0/1)	An indicator variable that equals one if a fund has at least one Asian manager in its management team.

Variable	Definition
AsianFemale(0/1)	An indicator variable that equals one if a fund has at least one Asian female manager in its management team.
AsianMale(0/1)	An indicator variable that equals one if a fund has at least one Asian male manager in its management team.
AsianFemale_Senior	The fraction of Asian female managers who play a senior role in a fund's management team.
AsianFemale_Junior	The fraction of Asian female managers who do not play a senior role in a fund's management team.
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 in 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 US in a fund's management team.
AsianFemale_NonFirstGen	The fraction of Asian female managers who are not classified as first-generation immigrant to the US in a fund's management team.
Asian_ChineseName	The fraction of Asian managers with a typical Chinese family name in a fund's management team.
AsianFemale_ChineseName	The fraction of Asian female managers with a typical Chinese family name in a fund's management team.
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 a Chinese if the manager has a family 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 - i.e., do not have an appearance that could be construed as being of East, Southeast, and Central Asian in a fund's management team. The group of female managers include Black, non-White Hispanic, and South Asian managers.

Variable	Definition
SouthAsianFemale	The fraction of South Asian female managers in a fund's management team. The group of managers include 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 ethnic slurs against Asians for each state every quarter. The data are collected via Twitter's public timeline API for academic research.

Internet Appendix

for The Real Effect of Sociopolitical Racial/Ethnic Animus: Mutual Fund Manager Performance during AAPI Hate

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Table IA.1: Heterogeneity in fund quality

This table examines whether the adverse effect of anti-Asian animus on the performance of funds managed by Asian female managers is due to the heterogeneity in fund quality. The analysis is restricted to funds that are managed by at least one female manager. We perform a nested fully interacted triple-difference analysis to examine how pre-event fund performance influences the effect of Hate on fund performance during the pandemic. *Perf* is measured as the risk-adjusted monthly return averaged over a quarter and expressed as a percentage. *LowPerf* is an indicator variable that equals one if a fund's pre-event fund performance is below the sample median of the variable in the same period. 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 two-way interaction terms between the sorting variable *LowPerf* and *AsianFemale* and *Post* are all absorbed by the interactions with 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 =	*Perf* (%)
	(1)
AsianFemale×*Post* (β_1)	**−0.396****
	(−2.124)
AsianFemale×*Post*×*LowPerf* (β_2)	**−0.047**
	(−0.193)
F-Test ($\beta_1 + \beta_2 = 0$)	**−0.443*****
(p-value)	**(0.005)**
Controls in Table 2	Yes
Fund FE	Yes
Style-by-Time FE	Yes
Observations	2,913
Adjusted R-squared	0.172

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Table IA.2: Robustness checks with alternative measures of fund performance

This table tests the robustness of the baseline regression results in Table 2 column (3) using three alternative measures of fund performance. In columns (1) to (3), the dependent variable is the monthly fund raw return, prospectus benchmark-adjusted monthly return, and the fund performance estimated from the Fama-French five-factor model (Fama and French, 2015) for equity funds, respectively. All alternative measures are calculated as the monthly percentage values averaged 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	**−0.692*** **	**−0.613*** **	**−0.436*** **
	(−2.805)	**(−3.889)**	**(−3.449)**
Controls in Table 2	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Style-by-Time FE	Yes	Yes	Yes
Observations	2,915	2,734	2,915
Adjusted R-squared	0.739	0.283	0.123

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Table IA.3: Robustness checks with alternative samples

This table re-estimates the baseline regression model in Table 2 column (3) using four alternative samples. In column (1), we perform the one-to-one nearest neighbor propensity score matching with replacement and a caliper of 0.1. We use all the control variables included in Table 2 as covariates in matching. In column (2), we present the results from using entropy balance matching that balances both the first- and second- moments of the covariates. Both matching techniques are performed in 2019 Q4 before the event. Columns (3) and (4) employ the sample of funds that are solely managed by female managers and the sample of funds that are solo-managed by a female manager. *Perf* is measured as the risk-adjusted monthly percentage return averaged over a quarter. *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* (%)			
	Propensity -matched sample	Entropy -balanced sample	Funds solely managed by female managers	Funds solo-managed by a female manager
	(1)	(2)	(3)	(4)
AsianFemale×*Post*	**−0.439*** (−2.620)**	**−0.371*** (−3.265)**	**−0.774*** (−3.143)**	**−0.550** (−2.261)**
Controls in Table 2	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Style-by-Time FE	Yes	Yes	Yes	Yes
Observations	991	2,915	302	225
Adjusted R-squared	0.154	0.138	0.142	0.148