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DID VIOLENCE AGAINST ASIAN-AMERICANS RISE IN 2020? EVIDENCE FROM A NOVEL APPROACH TO MEASURING POTENTIALLY RACIALLY-MOTIVATED ATTACKS

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ABSTRACT

Did anti-Asian violence rise after the onset of the COVID-19 pandemic? Efforts to answer this question are compromised by the inherent difficulty of measuring racially-motivated crimes as well as concerns that reporting of racially-motivated hate crimes may have changed due to their increased salience during the pandemic. We pursue an alternative approach to studying whether anti-Asian violence rose after March 2020 that addresses each of these concerns. Using data from the FBI's National Incident-Based Reporting System, we study inter-race violence occurring in public spaces. While public violence declined among all Americans after March 2020, the share of public violence directed at Asian-Americans by people who were previously unknown to them – or were acquaintances – rose more than it did for other Americans. While this relationship did not hold among an auxiliary sample of large US cities, the national evidence is consistent with a modest increase in racially- motivated violence directed towards Asian-Americans.

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1 Introduction

In March 2020 then U.S. President Donald J. Trump declared the COVID-19 pandemic to be a national emergency and, soon after, he began to refer to the novel coronavirus in public commentary as the "Chinese virus."[1] Throughout the early months of the pandemic, other stigmatizing terms such as the "Wuhan flu" generated public concern that anti-Asian violence might rise as a result of the increasingly widespread and casual use of disparaging language (Costello et al., 2021). Numerous media outlets have reported, based on anecdotal stories as well as analyses of official hate crime data, that racially-motivated attacks may have become considerably more common as Asian-Americans became convenient scapegoats for people seeking to assign blame for the pandemic's presumed geographic origin in East Asia (Hassanin et al., 2021).

To what extent did racially-motivated violence against Asian-Americans, in fact, rise with the pandemic? There have been a number of papers on this topic in the nearly four years since the beginning of the pandemic, including research by Gover et al. (2020), Tessler et al. (2020), Han et al. (2023), Kim and Tummala-Narra (2022), Lantz and Wenger (2022) and Cao et al. (2023). The available research has generally found that anti-Asian hate crimes, officially-defined, rose in 2020. However, the extent to which *racially-motivated* violence against Asian-Americans rose during the pandemic is surprisingly difficult to assess definitively given the quality and availability of existing data.

The primary national measure of racially-motivated crimes in the United States is derived from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program which records microdata on "hate crimes," offenses which were determined by the police to be motivated, at least in part, by bias towards the targeted group. These data have been widely analyzed to study crimes motivated by religious hatred (Ratcliff & Schwadel, 2023; Walfield et al., 2017) as well as by a victim's perceived sexual identity (Coston, 2018; Stotzer, 2010) and race (King, 2007; Torres, 1999). While the official hate crimes data have been used extensively, it is widely acknowledged that the data are unlikely to provide reliable counts of racially-motivated crimes. This is true for several reasons. First, there is much variation in the processes and thresholds used to class a crime as a hate crime across the nearly 20,000 U.S. law enforcement agencies that report data

[1] The first time that President Trump used the term "Chinese virus" was March 16, 2020.

to the FBI. Second, offenders do not always indicate why a particular victim was selected for a violent attack. While some attackers make their motivations clear through the use of racial epithets or other hate-driven language, a great deal of violence may be motivated, in part, by a victim's background or identity even if the attacker does not reveal his or her precise motivations – or reveals them in a legally ambiguous way.

A second source of national data on racially-motivated crimes in the United States is the U.S. National Crime Victimization Survey (NCVS), an annual survey of approximately 240,000 people living in the United States conducted by the U.S. Census Bureau which asks members of the public whether they were the victim of a crime in the six months preceding the survey. While a survey is, in principle, an ideal tool for measuring racially motivated attacks, the NCVS has considerable limitations which constrain our ability to understand whether anti-Asian hate crimes increased in 2020. As a general matter, survey responses tend to be highly sensitive to the salience of the information being collected. In our context, we might be concerned that Asian-Americans became more likely to report hate crimes to authorities as well as to survey collectors in 2020 due to the greater prominence of anti-Asian violence in the context of the COVID-19 pandemic. An even more fundamental problem with the NCVS is that the survey quickly runs into a foundational data limitation when it is used to understand the prevalence of a relatively rare crime committed against a small population group. Of the 15,985 Asian respondents to the NCVS in 2019, only 40 reported being the victim of a violent crime that occurred in the previous year. Of these individuals, only three respondents thought that the crime was a hate crime, with not a single one of these respondents indicating that they reported the crime to the police. These sample sizes are too small to draw meaningful conclusions about the prevalence of hate crimes against Asian-Americans, let alone trends in hate crime victimization, which require even more data to be able to identify with confidence.[2]

In this paper we propose an alternative way to measure changes in race-specific exposure to violence, using data on a broader set of violent crimes that are *potentially* motivated by racial

[2] In the context of the pandemic, scholars have turned to community reporting sites to study increases in hate crimes against Asians (Cao et al., 2023; Dipoppa et al., 2023). In the US, 4,409 anti-Asian hate incidents were reported to the platform STOP AAPI Hate in 2020 (STOP AAPI HATE, 2023). These platforms are extraordinarily valuable but they face their own problems. They often capture hate-motivated incidents like verbal harassment or shunning (deliberate avoidance) which, while deeply upsetting, are often legal. Moreover, we lack historical data from these platforms, making it impossible to understand whether these incidents became more common after the onset of the COVID-19 pandemic.

animus. Leveraging the latent stigma generated by the apparent East Asian origin of the COVID-19 virus, we study whether violence against Asian-Americans rose in the months after the onset of the pandemic. We use data from the FBI's National Incident-Based Reporting System, alongside microdata from several tactically selected cities, and focus on violence perpetrated against Asian victims by non-Asian strangers – and acquaintances – in public spaces like city streets or businesses open to the public. We focus on public violence committed by strangers of a different race for two reasons. First, criminologists have long recognized that this sort of violence generates outsize fear among members of the public (Ferraro, 1995; Lupton, 1999; Scott, 2003; Timrots & Rand, 1987).[3] Second, given that violence committed by friends and family of the victim typically has a motive other than racial animus, racially motivated attacks will tend to be concentrated among perpetrators who the victim did not know – or at least did not know well – prior to the attack.[4]

The pandemic is unlikely to have been timed in accordance with underlying race-specific crime trends in stranger victimization, a feature which provides a unique opportunity to causally identify changes in violence that was driven by changes in animus against Asian-Americans. Nevertheless, there are three potential threats to causal identification that we must address. First, the pandemic induced many changes to public life, most notably a dramatic increase in the practice of working from home, a decline in public transit ridership and a dramatic reduction in social activities. In the spring and summer of 2020, Americans spent far more time at home than they did previously, an outcome which had the effect of reducing victimization in public spaces (Massenkoff & Chalfin, 2022). As we illustrate, Asian-Americans appear to have spent less time outside their homes than other Americans in response to the pandemic, a finding that is likely to confound cross-race comparisons that are based on the prevalence of violence. To account for such race-specific changes in the risk of public violence due to shifts in the amount of time spent outside one's home, we study changes in the *share of public attacks* with an Asian victim and a non-Asian offender that were committed by a stranger (or, in some models, an acquaintance). We thus assess whether, among people who were attacked in public by a person who was of a different race, the share of

[3]In 1987 the Bureau of Justice Statistics (BJS) issued a special report on Violent Crime by Strangers and Nonstrangers. In the opening of the report, the then-director of the BJS explains that part of the motivation for the report is that "the fear of crime is largely a fear of strangers" (Timrots & Rand, 1987).

[4]NCVS data for 2015-2019 suggest that more than half of perpetrators of hate crimes were unknown to the victim at the time of the attack (Kena et al., 2021). Recognizing that acquaintances – individuals who were known to the victim but were not a friend or a family member – can also be a source of racially motivated attacks, we consider these offender-victim relationships as well.

stranger offenders increased after the onset of the pandemic.

A second threat to identification that is not addressed by the innovation discussed above is race-specific selection with respect to *who* is spending time in public. Irrespective of race, characteristics like age, gender, and income have long been known to be correlated with the risk of victimization (Hindelang et al., 1978). To the extent that shifts in time spent away from home shortly after the pandemic were different among Asian-Americans (e.g., young Asian-Americans stayed home relatively more often during the pandemic than other young Americans), we might be concerned that our identification strategy could lead to biased estimates. To address this concern, we turn to data from the American Time Use Survey (ATUS) and study whether race-specific shifts in time spent in public are correlated with key characteristics that predict stranger victimization. Using the ATUS data, we do not observe evidence of race-specific selection on individual characteristics in time spent in public spaces at the time of the COVID-19 pandemic. Given the importance of selection and its potential to confound our estimates, we nevertheless take a cautious approach and control for these variables in our preferred specifications.

A final issue concerns whether there is race-specific bias in which offenders show up in our arrest data. This is potentially a first-order threat to our identification strategy as our interest in offenders and victims who are of a different race requires an explicit focus on crimes with a known perpetrator which is a minority of all crimes known to law enforcement. Our estimates could be compromised if police became differentially more or less likely to solve crimes with an Asian-American victim in 2020. To address this possibility, we regress an indicator for whether a case was cleared by an arrest on our variables of interest using a broader set of crime incidents, and confirm that there was no race-specific selection along these lines on or around the time of the COVID-19 pandemic.

We report two main findings. First, overall public violent victimization of Asian-Americans *fell* shortly after the COVID-19 pandemic, in line with the fact that Asian-Americans spent more time at home during the early months of the pandemic. Second, focusing on incidents of inter-race public violence, there is evidence that, relative to other Americans, Asian-Americans became more likely to be victimized by both strangers and acquaintances as opposed to perpetrators who were family members or friends, after the pandemic began. This finding is consistent with the presence of more racially-motivated violence against Asian-Americans after the beginning of the COVID-19 pandemic, accounting for reductions in time spent in public.

The remainder of the paper is organized as follows. In Section 2 we provide a brief review of the literature on hate crimes and racially-motivated attacks with a focus on violence against Asian-Americans. In Section 3 we discuss our data and empirical models. Section 4 presents results and Section 5 concludes.

2 Setting and Prior Literature

2.1 The Prevalence of Hate Crimes in the United States

The principal source of data on hate crimes in the United States comes from the FBI's Uniform Crime Reporting program. For a crime to be considered a hate crime under the FBI's definition, there must be some evidence that the crime is motivated, at least in part, by bias against an individual or group based on a characteristic protected by law, such as race or nationality.[5] Official FBI hate crime data thus captures only the subset of crimes motivated by racial animus in which bias motivation was apparent to both the victim of the crime and law enforcement officials.[6]

In the decade before the COVID-19 pandemic, an average of 6,363 hate crimes were captured by law enforcement each year, which works out to roughly 2 hate crimes per 100,000 U.S. residents annually.[7] However, this is almost surely a dramatic underestimate of the true number of hate crimes as the lion's share of law enforcement agencies – including many large police departments – report zero hate crimes, or do not participate in the Hate Crime Statistics program at all (Kaplan, 2023a; Smith, 2021). Indeed, commentary on this issue by Balboni and McDevitt (2001), McDevitt and Iwama (2016) and Kaplan (2022) among others, has highlighted that the official FBI hate crimes data are biased and incomplete to the point of being unsuitable for use in certain types of academic scholarship. To illustrate this point, taking the official data at face value would suggest that only two of the over one million Asian-American residents of New York City experienced a

[5] As established by the Hate Crime Statistics Act of 1990 (28 U.S.C. § 534.). Hate crime laws can vary by state, but almost always include the victim's perceived or actual race or skin color, and, at the federal level, national origin.

[6] As with all index crimes, hate crimes data represent how a crime was classified by a local law enforcement agency at the time or shortly after the crime was committed. Accordingly, the data do not necessarily capture how the subsequent legal process unfolded and whether the crime resulted in a hate crime conviction.

[7] Authors' calculations based on a statistical brief on officially recorded hate crimes in 2010–2019 (Smith, 2021).

hate crime in 2019. In the same year, California, home to nearly six million residents of Asian origin, recorded the highest number of anti-Asian hate crimes in the United States at *43*, fewer than one hate crime per 100,000 Asian residents. While every state – and Washington DC – had at least one agency submit hate crime data, twenty states reported zero anti-Asian hate crimes while only five states recorded 10 or more. Nationally, the FBI's hate crime data recorded only *216* instances of anti-Asian hate crimes in 2019 in a country with nearly 20 million people of Asian origin. One interpretation of these statistics is that racial violence against Asian-Americans is exceedingly rare in the United States. However, even a casual cross-referencing of news articles – as well as survey data – against the official data suggests that the true incidence of anti-Asian hate crimes is likely to be much higher.

A secondary source of data on hate crimes comes from the National Crime Victimization Survey, a nationally representative survey of U.S. residents which is intended to capture, among many other types of crime, crimes that victims perceive as motivated by the offender's bias towards them. Crimes are classified as hate crimes in the NCVS when evidence of bias is apparent in the form of hateful language, hate-related signs or symbols, or if the victim indicates that the police investigated the crime as a hate crime. An NCVS report covering 2010-2019 shows that the rate of hate crime victimizations per year for persons age 12 or older averaged to over 80 per 100,000 (Kena et al., 2021).[8]Among Asian-Americans, the rate was approximately 40 per 100,000 – lower than that for the average American but 20 times higher than the rate implied in the FBI hate crimes data.

A major advantage of the NCVS is that it captures crimes that are unreported to law enforcement as well as crimes that are not ultimately classified as hate crimes. Unfortunately the NCVS also quickly runs up to a data limitation with small population groups and a relatively rare crime. This greatly diminishes the survey's usefulness in measuring changes in the number of racially-motivated crimes in the United States. We use an example to illustrate this point. Of the 14,671 Asian respondents to the NCVS in 2020, only three respondents reported being the victim of a violent hate crime. After adjusting for survey weights, the projected individual-level rate of violent hate crime victimization is 40.58 per 100K Asians in 2020. A similar calculation

[8]The rate for 2010-2019 was 80 per 100,000 for violent hate crimes. During this period, 9 out of 10 hate crime victimizations were violent crimes (Kena et al., 2021). The rate including non-violent crimes will be slightly higher than 80.

for 2019 resulted in a rate of 10.06 per 100K, even though the number of Asian respondents who reported a violent hate crime (3) was the same. This seemingly 4-fold increase results solely from the differences in survey weighting even when the underlying number of respondents is the same and very small. As such, while the NCVS serves as a useful bookend on the prevalence of racially-motivated crime, the survey's sample size limitations mean that it cannot be used to identify anything other than very large year-to-year changes in racially-motivated victimization – especially for a relatively small sub-population like Asian-Americans.

2.2 Hate Crimes During the COVID-19 Pandemic

Despite the attendant limitations in tracking levels and trends in the prevalence of hate crimes, the extant literature from the United States and other countries around the world provides some insight into how the COVID-19 pandemic might have affected racially-motivated attacks. Historically, most hate crime research has been cross-sectional or has focused on long-term changes in social, economic, or political conditions (Green & Spry, 2014). One theoretical hypothesis underlying much research on hate crimes is that such crimes are a reaction to real or perceived threats by subaltern social groups, and that these threats can be perceived to heighten when existing hierarchies between groups are upset, for example, because economic relationships between groups change (Sharma, 2015), or when subaltern groups gain political power. More recent academic scholarship has examined the effects of shorter-term "shocks" that affect inter-group perceptions of threat, including salient events and changes in political rhetoric. Studies on the aftermath of 9/11 and other terror attacks show that these threatening events can lead to race-specific increases in hate crimes (Disha et al., 2011; Frey, 2020; Hanes & Machin, 2014; Ivandic et al., 2019). Hate crimes also appear to rise in the wake of political events that might have heightened racial tensions, such as the election of Donald Trump in the United States (Rushin & Edwards, 2018) and the Brexit referendum in the UK (Albornoz et al., 2020; Devine, 2021). Others have shown a relationship between negative government statements about specific groups and hate crimes against those groups (Dugan & Chenoweth, 2020; Jäckle & König, 2018). These studies provide some support for the hypothesis that the news cycle can embolden others to commit hate crimes by generating, legitimating or validating biases.

Given the existing research on triggering events and political rhetoric, it is perhaps of little surprise that the outbreak of the COVID-19 pandemic raised alarm bells about potential increases in hate crimes.[9] Indeed, as Dipoppa et al. (2023) have argued, disease outbreaks are arguably another type of "threatening event", triggering the types of emotional responses that might translate into violence directed at an out-group. References to the "Wuhan flu" and the "Chinese virus" by prominent politicians provided the type of stigmatizing language that may have clarified who to target frustration or anger at. Scholars have already convincingly shown that in the initial weeks and months after the onset of COVID-19, written and verbal expressions of anti-Asian animus increased sharply (Cao et al., 2023; Costello et al., 2021; Darling-Hammond et al., 2020; He et al., 2021; Hswen et al., 2021; R. Lu & Yanying Sheng, 2022; Ruiz et al., 2020; Schild et al., 2021).[10] A Pew survey in June 2020 also showed that Asian-Americans were more likely than any other group to report negative experiences, such as being subject to slurs or jokes, than any other group in the US since the outbreak of the virus (Ruiz et al., 2020). Extant research thus points to increases in stigmatization and prejudicial attitudes against Asian Americans after the outbreak of the pandemic, yet it is less clear from prior research whether those attitudinal changes also translated into an increase in racially-motivated crimes during the COVID-19 pandemic (Dipoppa et al., 2023).

The question, then, is whether increases in anti-Asian *animus* translated into increases in anti-Asian *crimes* in 2020. A descriptive analysis of official data cannot answer that question but it is a reasonable place to begin our inquiry. UCR data show that hate crimes increased by 13% (7,314 to 8,052) in the United States in 2020 as compared to 2019 (FBI, 2023), the largest increase in hate crimes since 2001, when anti-Muslim hate crimes spiked after the 9/11 terror attack (Farrell & Lockwood, 2023). NCVS data, however, shows a 39% *decrease* in violent hate crime victimizations between 2019 and 2020, in line with the overall reduction in public victimizations in 2020 (Morgan & Thompson, 2021).[11] Both UCR data and NCVS data suggest that anti-Asian hate crimes rose

[9]The impact of the COVID-19 pandemic is multifaceted. In addition to social and political implications, it also involved an economic shock. The literature on the effects of economic conditions in industrialized countries on hate crimes in recent periods is mixed (Anderson et al., 2020; Dipoppa et al., 2023). However, recent quasi-experimental literature has shown that areas harder hit by welfare cuts (Bray et al., 2022), and that were harder hit by the Great Recessions (Anderson et al., 2020), experienced greater increases in hate crimes.

[10]In a vignette study, Y. Lu et al. (2021) also show that priming COVID-19 salience increases both anti-Asian prejudice and discriminatory intent.

[11]NCVS figures in this paragraph are based on authors' calculations. We calculate the annual national estimate of the number of violent hate crime victimizations in 2019 and 2020 using series weights.

from 2019-2010, by 77% and 319% respectively. Note, however, that the NCVS figure is more reflective of an exceptionally low estimate for 2019 than it reflects a high hate crime estimate for 2020. Anti-Asian hate crime victimizations were, in fact, *lower* in 2020 than in three out of the five preceding years.

Beyond the limitations of the NCVS and the UCR in documenting hate crime prevalence in any given year, there are several reasons why official statistics do not give us a good grip on *changes* in hate crimes in 2020. First, hate crimes are particularly vulnerable to changes in the reporting dispositions of both victims and police officers. Several police departments launched task forces and/or invested in (raising awareness of) reporting platforms which is likely to have affected how and when hate crimes were reported.[12] Second, as Kaplan (2022) has highlighted, agencies that report hate crime data to the UCR are not random nor is reporting consistent over time, with agencies reporting one year often not reporting in a subsequent year, a problem which makes it difficult to track trends. The fact that 452 fewer agencies reported hate crime statistics in 2020 than in 2019 is a case in point. Finally, Americans also spent far more time at home during the spring and summer of 2020 than they did previously, reducing absolute levels of victimization in public (Massenkoff & Chalfin, 2022). The fact that Asian-Americans had an especially high rate of public health compliance in 2020 further complicates efforts to understand changes in violence against this group (Dickinson et al., 2021).

To our knowledge, only one other study has directly examined whether anti-Asian hate crimes in the US rose during the pandemic. An analysis by Han et al. (2023) based on data for hate crimes and hate incidents from four major police departments revealed no significant increases in anti-Asian hate crime in the year after March 16th, 2020, except during the first week after March 16th.[13] This finding is perhaps not surprising as analyses based on the raw number of Asian-American hate crimes during the pandemic will reflect reductions in time spent outside. This paper builds upon the important paper by Han et al. (2023), but takes a different approach to measuring changes in anti-Asian hate crimes that addresses concerns about shifts in post-pandemic

[12]For example, the NYPD deployed plain-clothed officers to neighborhoods with large Asian populations, distributed informational fliers, and made available investigators of Asian descent to reduce language barriers.

[13]Outside of the US, Dipoppa et al. (2023) use data from the NGO Lunaria, and leverage variation across Italian municipalities, to show that hate crimes against Asians increased substantially at the start of the pandemic.Cao et al. (2023) answer a related question but do not directly answer the question of whether anti-Asian hate crime increased. They show that reports of anti-Asian incidents to the program "Stop AAPI HATE" increased more in Trump-supporting counties relative to Clinton-supporting counties.

time use.

3 Data and Methods

3.1 Empirical Approach

In this paper, we focus on inter-race violence occurring in public spaces. We focus on these crimes because seemingly random attacks in public inspire the most fear among potential victims (Ferraro, 1995; Lupton, 1999; Scott, 2003; Timrots & Rand, 1987) and have taken up most space in the public discussion of anti-Asian hate crimes during the pandemic. Our empirical strategy is motivated by the premise that if the COVID-19 pandemic compromised the safety of Asian-Americans by raising the degree of racial animus directed towards the Asian population in the United States, we would expect to observe race-specific changes in violent victimization for the types of crimes in which racial animus is especially likely to play a role: attacks by a stranger – or potentially by an acquaintance.[14]

We focus on violent crimes to the exclusion of property crimes for several reasons. First, though violent crimes are comparatively rare, they drive an outsize share of the social costs of crime in the United States (Chalfin & McCrary, 2017). Second, our analysis hinges on studying crimes with known victim-offender relationships and we are much more likely to have information on the offender and his or her relationship to the crime's victim when the crime involved violence than when it did not. This is because violent crimes have victims who can inform police about the characteristics of the assailant while most property crimes are committed outside the presence of the victim and therefore make it more difficult to identify the perpetrator.[15] Finally, it is unclear if property offenders know who they are committing a crime against. An offender who steals a bicycle or breaks into a car is unlikely to know if their victim is White, Black, or Asian – whereas offenders in violent crimes can see and select their victim. While some share of intra-Asian violence may

[14]Naturally many – even most – stranger attacks will not be motivated by racial animus and therefore will not be hate crimes under existing legislation. However, perpetrators of hate crimes are more likely to be strangers relative to the perpetrators of non-hate crimes. Official data sources suggest that, among violent hate crimes, 46% and 56% were committed by a stranger during 2011-2015 and 2015-2019 respectively. These rates were 37.2% and 36.9% for violent non-hate crimes (Kena et al., 2021; Masucci, 2017).

[15]For larceny, the identification approach used in this paper would be particularly problematic as the target is often a business and so it is potentially unclear what the racial identity of the business is.

itself be motivated by ethnic hatred (e.g., a crime in which a perpetrator is Japanese-American and an offender is Chinese-American), we limit our analysis to inter-race crimes in order to focus on the subset of violent crimes which are disproportionately likely to be driven by racial animus.[16]

To identify the effect of the pandemic on the victimization of Asian-Americans, we must address several potential threats to causal identification. First, in the spring and summer of 2020, Americans spent far more time at home than they did previously, an outcome which had the effect of reducing victimization in public spaces (Massenkoff & Chalfin, 2022). To the extent that these behavioral shifts differed across race groups, this would confound estimates of the prevalence of Asian-American victimization during the pandemic relative to other racial groups. Consider Figure 1 which plots the number of public violent victimizations in 2019 and 2020 for White, Black, and Asian-Americans as well as American Indians in the NIBRS. In line with the findings of Massenkoff and Chalfin (2022), the figures show that public violent victimizations fell for Americans generally at the start of the pandemic, most notably in April 2020 when people responded to the risk of disease and public advisories by staying indoors. It is important to note that Asian-Americans are no exception to this trend – indeed violent public victimizations *fell more* for Asian-American victims between February and April 2020 than for any other group (by over one-third for Asian-Americans as compared to approximately 20% for White and Black-Americans).

It is instructive to compare this figure with a second figure, Figure 2, which, using data from the American Time Use Survey (ATUS), plots the amount of time that people living in the United States spent in public during this same period, separately by year. There is a gap in the 2020 series because the ATUS surveys were suspended in April 2020. Nevertheless, the figure illustrates that the share of time spent at home fell during this time for White, Black, and Asian-Americans.[17] Among Black Americans, the share of time spent in public fell from approximately 74% in March 2020 to approximately 55% in May 2020. Among White Americans, the share of time spent in public fell from approximately 70% to 55% during the same period. Among Asian-Americans,

[16]There is a further practical reason to focus on inter-race crimes: COVID-19 may have induced a shift in offending that varied across races. This is of concern because an offender of your own race is less likely to be a stranger to you than an offender of a different race. Race-specific shifts in offending, then, could be driving race-specific changes in the nature of victim-offender relationships. For example, if non-Asians offended relatively more after the onset of the pandemic, then non-Asians would have become more likely to be victimized by people they know. We would consequently observe an increase in Asian victimization by strangers.

[17]For American Indians, the trends are less certain, which may be driven by the small sample size.

76% of time was spent in public during February 2020. By March 2020, this share had fallen to 53% and the share had fallen further — to 48% in May 2020. The data thus indicate that Asian-Americans responded earlier and with greater intensity to news about the COVID-19 pandemic and subsequent stay-at-home orders issued by state and local governments.[18]

To the extent that a shift in the amount of time spent outdoors differed across races – and the evidence, as we have seen, suggests that Asian-Americans spent less time outside their homes than other Americans in response to the pandemic – this will contaminate cross-race comparisons that are based on the prevalence of violence. In other words, violence against Asian-Americans may have fallen but this does not account for the time that Asian-Americans were at risk of being the victim of this sort of public attack. To account for race-specific changes in the risk of public violence due to shifts in the amount of time spent outside one's home, we study changes in the *share* of attacks that were committed by strangers. Our models assess whether, among people who were attacked in public by a person who was of a different race, the share of random attacks by perpetrators unknown to the victim increased after the onset of the pandemic. Recognizing that racially-motivated attacks can also be committed by acquaintances such as neighbors and co-workers who the victim might vaguely know, we estimate separate models for violence perpetrated by strangers and acquaintances.

We plot descriptive trends in our stranger variable separately by race in Figure 3. For Asian-Americans, there is evidence that the share of public violence that was committed by a stranger did, in fact, rise shortly after March 2020. Whereas the stranger share of public violence in 2019 oscillated between 40% and 47%, in 2020, the share exceeded 50% most months, reaching 60% by the end of year. On the other hand, the acquaintance share of violence fell in 2020. These trends could represent the signature of an increase in random violence against Asian-Americans but the descriptive trends for White and Black Americans urge some caution as both of these groups experienced similar trends, albeit to a slightly lesser degree.

Our subsequent regression analysis relies crucially on the assumption that the pandemic did not affect victim-offender relationships in violent crimes in ways that differed by race. Two issues remain that may be cause for concern. First, we might be concerned about race-specific selection

[18]Note that we are making no specific claim about the reasons for this differential response which include cultural explanations, differences in the types of jobs individuals are employed in as well as geographic differences in the locations of Asian-American populations.

with respect to *who* was spending time in public during the COVID-19 pandemic. To the extent that shifts in time spent away from home shortly after the pandemic were different among Asian-Americans in a way that is correlated with the likelihood that an attacker is a stranger, our identification strategy could lead to biased estimates. To address this issue, we turn to data from the American Time Use Survey and study whether race-specific shifts in time spent outdoors are correlated with key factors that predict stranger victimization. Second, race-specific bias in which offenders show up in the NIBRS arrest data would be a first-order threat to our identification strategy as our interest in offenders and victims who are of a different race requires an explicit focus on crimes with *a known perpetrator*.[19] Our estimates would be compromised if police became differentially less likely to solve crimes with an Asian victim in 2020.[20] To examine this possibility, we regress an indicator for whether a case was cleared by an arrest on our variables of interest to test whether there was race-specific selection along these lines.

3.2 Data

3.2.1 Crime data

We obtain incident-level crime data for our 2017-2020 study period from the FBI's National Incident-Based Reporting System (NIBRS).[21] For each crime, the NIBRS contains information on the date, time, and location details of the crime, the type of crime that occurred, whether an arrest was made and the age, race, and gender of the victim. The NIBRS also contains the age, gender, and race of the perpetrator(s) if information was reported by the victim and recorded by the police.

Because NIBRS contains incident-level data, it is far richer than the annual counts of crime traditionally available from the FBI's Uniform Crime Reports and allows us to identify violent attacks occurring in public which has an Asian victim and a non-Asian perpetrator or perpetrators. However, while the UCR has excellent coverage within the United States, especially among mid

[19] Our identification strategy relies on crime incidents for which the offender's race and relationship to the victim are known. It does not require the exact identity of the offender to be known. For example, an incident would be retained if we know that the offender was a White stranger or a Black neighbor. Nevertheless, data in our sample disproportionately represent crime incidents that were cleared.

[20] A recent paper by Roberts (2023) found that Asian-American victims experience similar crime clearance rates as White victims but a higher crime clearance rate than Black victims.

[21] Specifically, we use Jacob Kaplan's Concatenated Files (Kaplan, 2023b).

to large-sized cities, NIBRS coverage is not as expansive. Overall, 49% of agencies – 8,842 out of 17,985 – reported to the NIBRS in 2020. These agencies cover 46% of the US population (see Figure A.2 for a map of agencies reporting data to NIBRS). Unfortunately, the largest cities in the United States – including NYC, Los Angeles, and Chicago – were not among the agencies reporting to NIBRS during our study period. To augment our NIBRS data with a large city sample, we submitted FOIA requests to ten cities in the US with among the largest Asian populations. We obtained suitable incident-level data with location information, as well as data on the victim, offender, and the relationship between the victim and the offender from San Jose CA, San Francisco CA, Los Angeles CA, and Chicago IL.[22]

We code victim-offender relationships into four categories: family (which includes all relatives and romantic partners including ex-partners), friends, acquaintances (those that the individual may know by sight only, such as a neighbor, colleague or customer whom one has seen before but may never have spoken to at any length), and strangers. For most of the analyses reported in the paper, we restrict our sample to incidents of public violence – violent crimes committed in a known non-residential location.[23] We retain only incidents with victims whose age and sex are known. We also limit our sample to violent crimes in which the victim and offender(s) were not of the same race and where the relationship of the offender(s) to the victim is known. We retain incidents with multiple offenders as long as all offenders are of the same race and are related to the victim in the same way.[24] Note that restricting our sample to victim-offender pairs of different races for which the victim-offender relationship is known means that we are working with a small subset of all reported violent victimization events; this is because the large majority of public violent crimes are by an offender of the same race, and most crimes are not cleared. Finally, a couple of additional data restrictions apply to our NIBRS data. We drop agencies that did not report to NIBRS in any one of the years 2017-2020, and agencies that did not report at least one Asian

[22] We also submitted FOIA requests to New York NY, San Diego CA, Philadelphia PA, Oakland CA, Houston TX, and Irvine CA, but received no response and/or did not receive suitable data.

[23] We classify crimes as being committed at a non-residential location when they occurred entirely at a non-residential location. If a crime description occurred partially at a residential location and partially elsewhere, the incident remains in our dataset.

[24] For example, an incident with an Asian victim and two White strangers would be retained in the dataset but an incident with an Asian victim and two strangers, one White and one Black, would be removed from the data. We likewise remove multiple offender incidents in which one offender is a stranger and the other is a friend or family member.

victim by an offender of a different race.[25] A detailed overview of all the above-mentioned sample restrictions for each crime dataset can be found in Annex A.1. Our final sample consists of 12% of all public violent victimizations in the NIBRS and 6 to 14% of all public violent victimizations from city-level datasets in 2017-2020.[26]

The nature of our data constrains the analysis discussed below in two ways. First, the datasets used in this study differed from each other with respect to what race and ethnicity information was available. Specifically, our NIBRS dataset did not contain data on the ethnicity of offenders. Conversely, some of the city datasets included a combined race-ethnicity variable which did not allow us to back out the race of the victim or offenders. Therefore, our NIBRS analyses are conducted using a race variable, and analyses with city data are conducted using a combined race-ethnicity variable.[27] Given that this study specifically focuses on victim-offender pairs of different races, we estimate our models separately for NIBRS and pooled city datasets. Second, our data did not allow us to distinguish between the many different cultural and ethnic backgrounds of Asian-American victims.[28] Individuals who trace their roots to China or other countries in East Asia, who make up about 2 out of every 5 American Asians, may have been more vulnerable to racial violence during the pandemic than South Asians who were less likely to be identified with the presumed geographic origins of the pandemic. South Asians, with origins in India, Pakistan, Bangladesh, and Sri Lanka, are presumably less likely to be mistaken for someone of Chinese origin than an individual from a country in East Asia that is more proximate to China.[29,30] Given that we are unable to disambiguate between South and East Asians, an unfortunate limitation of our approach – or any approach using national data – it is possible that treatment effects could be $\frac{1}{0.4} = 2.5$ times larger than those reported in subsequent analyses. We discuss this possibility in

[25] Making this restriction ensures that our summary statistics correspond to the sample over which we produce our estimates.

[26] See Annex Tables A.1, A.2, A.3, A.4 and A.5 for detailed overviews of the magnitude of each restriction in each of our samples.

[27] That is, NIBRS analyses include a variable for whether victims and offenders were Asian, White, Black, Indian American, regardless of ethnicity. Analyses with city data include a variables for whether victims and offenders were Non-Hispanic (NH) Asian, NH White, NH Black, NH Indian American, and Hispanic.

[28] Data for Los Angeles and San Jose included national subcategories in addition to a generic 'Asian' race category. However, most individuals were assigned to the generic 'Asian' category, making more granular analyses not feasible.

[29] A Pew Research Center Analysis of 2015 American Community Survey 1-year Estimates suggests that 23% of the Asian population trace their roots to China or Taiwan, 7% to Japan, 9% to Korea, 1% to Laos and less than 1% to Mongolia (Kennedy & Ruiz, 2020).

[30] Crime data generally includes people from East and South Asia as 'Asian' and counts people from Western Asia as White.

our presentation of the results and note that, if anything, our findings are likely to be conservative.

3.2.2 Supplementary datasets: NCVS and ATUS

In our descriptive analyses, we also draw on The American Time Use Survey (ATUS) (Bureau of Justice Statistics, 2021) and the National Crime Victimization Survey (NCVS) (Bureau Of Justice Statistics, 2021), which are both random samples of U.S. households. We use survey data from the American Time Use Survey (ATUS) for 2019 and 2020 to better understand how outdoor activity changed after the onset of the pandemic. We use person- and incident-level data from the NCVS data for 2015-2019.[31]

3.3 Empirical Model

We study whether the share of public violence that was committed by strangers and/or acquaintances rose for Asians relative to non-Asians in the United States using a victim-level dataset where each row represents a given victim in a crime incident known to law enforcement. We focus on the subset of crimes that occurred in public spaces and for which there is a known offender-victim relationship. We estimate variants of the following differences-in-differences specification:

$$Y_{itjg} = \psi_g + \beta_1 POST_t + \beta_2 POST_t \times ASIAN_g + X_i^{'}\alpha + \lambda_j + \epsilon_{ij} \tag{1}$$

In (1), Y_{itjg} is a binary variable that takes on the value of 1 if the offender(s) involved in crime incident i on day t in city j is a stranger or acquaintance to the victim of race, g, and zero if otherwise.[32] To capture time-invariant differences in victimization patterns across racial groups, we include fixed effects for victim race (ψ_g), thus allowing Asian, Black, White, and American Indian victims to have their own race-specific intercept.[33] The indicator variable $POST_t$ takes on a value of 1 if $t \geq$ March 1st, 2020, so that β_1 identifies whether the probability that an offense

[31] While the NCVS asks respondents to identify the type of location in which they were victimized, we use all NCVS data because sample sizes get extremely small when we subset to public victimizations only.

[32] g is a combined race-ethnicity indicator in models that use our city-level datasets.

[33] In models that use our pooled city data, this fixed effect allows Non-Hispanic Asian, Non-Hispanic Black, non-Hispanic White, non-Hispanic American Indian and Hispanic victims to have their own race-ethnicity specific intercept.

was committed by a stranger rose after March 2020.[34] The indicator variable $ASIAN_g$ takes on the value of 1 if $g =$ Asian American. β_2 tells us whether the change in the likelihood of stranger victimization for Asian-Americans was different from that same change for non-Asian-Americans. If $\beta_2 \geq 0$, this would indicate that stranger victimization became more likely for Asian-Americans after the pandemic began, relative to other Americans. In order to understand if effects are driven by strangers or acquaintances, we vary the dependent variable in supplementary models. In these models, we drop strangers or acquaintances from the analysis, leaving comparisons between strangers and family/friends, and acquaintances and family/friends.

X_i represents a matrix of victim-level control variables, including victim sex, age, and age squared. These control variables account for race-specific compositional changes in the population of crime victims after March 2020. λ_j denotes law enforcement agency fixed effects which allows us to compare Asian and non-Asian victimizations *within the same jurisdiction*. These fixed effects are critical because they ensure that we are not comparing Asian-American victims and White victims who are living in different parts of the United States or in different types of municipalities. We additionally interact λ_j with $POST_t$ in order to capture time-varying changes in the crime environment in each jurisdiction. We further interact our control variables with $POST_t$ to allow pandemic-induced changes in the risk of victimization by a stranger across age and sex. Finally, we include month-by-year and hour-by-day fixed effects to account for seasonality and time-of-day effects, and likewise interact these fixed effects with victim race. These interactions allow us to control for race-specific shifts in public time use which might predispose a given group to be more or less vulnerable to stranger victimization. In all models, we cluster our errors at the agency level to account for the serial correlation of the error terms within a given city.

In addition, we estimate several auxiliary models that are intended to address the possibility of selection. We use ATUS data to identify if race-specific shifts in time spent outdoors are correlated with key factors that predict stranger/acquaintance victimization, employing a regression of the following form:

[34] Note that we set our COVID variable to one on the first day of the month for ease of interpretation of our plots, and for consistency with our monthly descriptive statistics. However, concern about the virus was arguably already real when the Chinese authorities locked down Wuhan on January 23rd, 2020. Alternatively, some might argue that March 13th is a more appropriate date, when Trump declared the COVID-19 pandemic a national emergency, or March 16th, when Trump posts his first 'Chinese virus tweet'. We vary when we turn our COVID variable "on" in the robustness check section.

$$
\begin{aligned}
Y_{itg} = X_i'\alpha + \beta_1 POST_t + \beta_2 ASIAN_g + \\
\beta_3 POST_t X_i' + \beta_4 POST_t ASIAN_g + \beta_5 ASIAN_g X_i' + \\
\beta_6 POST_t ASIAN_g X_i' + \epsilon_i
\end{aligned}
\tag{2}
$$

In (2), Y_{itg} is a continuous variable that captures the share of time respondents spent in public, and X_i' is a vector of respondent characteristics, including their age, sex, education, and income. The indicator variables $POST$ and $ASIAN$ are as described above. The coefficient vector represented by β_6 tells us whether the change in time spent in public for Asians with particular characteristics post-COVID was different from that same change for non-Asians with these characteristics. If $\beta_6 \neq 0$ for any of the characteristics that predict stranger victimization, this would indicate that the characteristics of Asian-Americans who spent time in public post-COVID made them differentially likely to have a stranger for their attacker relative to other groups. This would compromise our estimates as it would indicate that race-specific selection into outdoor activity may be driving our results.

Finally, to test whether the police became differentially less likely to solve crimes with an Asian victim in 2020, we re-run specification 1 on a larger dataset that includes all crimes, including those where no offender information is known. We change the dependent variable to be a binary variable that takes on the value of 1 if crime incident i on day t in city j with a victim of race g resulted in at least one arrest, and zero if otherwise. All other variables are as described in Equation 1. If the coefficient on β_2 is different from zero, it would suggest that there might be race-specific selection in which crimes show up in our data which could bias our estimates.

4 Results

4.1 Descriptive Statistics

Tables 1 and 2 describe the victims in our NIBRS and pooled city-data respectively for our full study period (2017-2020). In both tables, Column 2 ("Analytic Dataset") is based on the data sample described in Section 3.2 that we use for our main regression. As we noted above, for most crimes, the offender and victim are of the same race. By restricting our sample to different-race victim-offender pairs, we are working with a small and somewhat unusual subset of all reported public violent victimization events. To illustrate how this affects the observations in our sample, column 1 ("Overall") includes all public violent victimization events, including those with same-race victim-offender pairs.[35] A few things stand out: First, the offender is more likely to be a stranger in our sample compared to the overall census of public violent victimizations. This reflects the fact that individuals' social networks predominantly consist of people of their own race, and an attacker of a different race is thus more likely to be a stranger to the victim. Second, relative to victims of all public violent crimes, victims in our sample are several times more likely to be Asian, which likely reflects both low offending rates among Asian-Americans (Mauer & King, 2007) and the fact that small minority groups will mechanically encounter more potential offenders that are not of their own race.

Column 2 shows that individuals in the NIBRS data are a victim of a stranger 45% of the time, and a victim of an acquaintance 39% of the time. In our pooled city sample, victims of public violence were attacked by a stranger 73% of the time, with 18% of attacks committed by acquaintances. This difference between the NIBRS and city data likely reflects differences in the reporting of crimes and data management, with city data capturing calls/offense reports that might be held to lower reporting standards than the information police agencies submit to NIBRS. Overall, 5% (NIBRS) and 8% (Cities) of the victims in our data are Asian. Hispanic victims in our pooled city-level dataset make up 41% of all victims, which is additional evidence of why it is important to preserve this category and separate out analysis by NIBRS and selected cities. Among all public violent victimizations, 45% (NIBRS) and 67% (cities) occurred in outdoor public spaces like city streets. Most other victimizations occurred in indoor public spaces like stores and businesses, with the remainder split between schools and other locations. The majority of the individuals in our sample were victims of simple and aggravated assaults, with the remainder split between robberies, intimidation, sexual offenses, and murders.

The columns to the right of column 2 divide our analytic sample among all victim-offender pairs in our data. That is, column 3 describes all observations in our data with an Asian victim

[35] The only difference between columns 1 and 2 is that column 2 includes victim-offender pairs of the same race. All other sample restrictions made in our core sample (column 2) have also been made in column 1.

and one or multiple non-Asian offenders, column 4 describes all observations in our data with a White victim and one or multiple non-White offenders, etc. This highlights that Asian victims in our sample were attacked by a stranger more often than victims of other racial groups, in 58% (NIBRS) and 81% (cities) of cases respectively. They are also somewhat more likely to be victim of robberies, and less likely to be women, in both NIBRS and city-data.

4.2 Main Results

Table 3 presents our main results, separately for the NIBRS sample (Panel A) and our pooled city sample (Panel B). Each model corresponds with equation (1) and coefficients therefore measure the post-pandemic change in the probability that an Asian-American victim who was assaulted in public was attacked by a stranger or an acquaintance (or, in some models, either a stranger or an acquaintance). A relative increase in the share of stranger and acquaintance assaults after March 2020 would be consistent with evidence that a greater share of Asian-American victims were the victim of a racially-motivated attack compared to other Americans. In Columns (1) to (3), the dependent variable takes the value of 1 when the offender was either a stranger or an acquaintance. Column (1) presents estimates for all victims in our data, and columns (2) and (3) present estimates for victims attacked by White offenders and Black perpetrators respectively. Columns (4) to (6) shed light on stranger effects separately by dropping all acquaintances from the data. Columns (7) to (9) shed light on acquaintance effects by dropping strangers from the model. Our comparison group – family and friends – remains the same in all models.

We begin with our NIBRS results. The result in column (1) suggests that Asian-Americans who fell victim to a violent attack were 2.5 percentage points more likely to be attacked by a stranger or acquaintance than other Americans, relative to a pre-period mean of 84.7%. Estimates that examine victims attacked by White and Black offenders separately provide inconclusive evidence that this result was driven disproportionately by either group of offenders. Results in columns (4) and (7) suggest that both stranger attacks and acquaintance attacks rose significantly. The increase was larger for acquaintance attacks than stranger attacks, although the confidence intervals for these estimates overlap. The direction and the relative magnitude of the coefficients across columns in our pooled city sample are qualitatively similar, yet coefficients are smaller and are not statistically significant. While this might be the result of insufficient power to identify changes this small – our pooled city-level dataset is more than four times smaller than our NIBRS dataset – the estimates may also point to a qualitatively different pattern in larger cities with a sizable Asian-American population. The city-level results also potentially suggest a different pattern for victims of White offenders and for Black offenders. However, in full-sample regressions interacted with the race of the offender, this difference is statistically insignificant.

Differences-in-differences estimates are identified in the presence of common trends. Figure A.1 presents event study separately for strangers and acquaintances which corresponds with our primary model. We observe little evidence of differential pre-trends for any of our models, a finding which is consistent with the presumed exogeneity of the timing of the pandemic. With respect to the post-treatment period, we do not observe clear evidence of a temporal pattern in the estimates though statistical power naturally becomes more limited when the post-period is divided into smaller windows.

4.3 Selection Concerns

Our analysis crucially relies on the assumption that the pandemic did not affect victim-offender relationships in violent crimes in ways that differed by race. In this section, we therefore examine the two potential concerns about the validity of our identifying assumption discussed in section 3.1. First, we examine if the characteristics of Asian-Americans who spent time in public post-COVID made them differentially likely to have a stranger for their attacker relative to other groups. Results from regressions using ATUS data (equation 2), presented in Table 4 suggest that there is little evidence of race-specific selection with respect to spending time in public after March 2020. The p-value on the joint F-test on the triple interaction terms is 0.51, showing that the inclusion of these terms do not significantly improve the model, and thus that race-specific changes in the amount of time spent in public are not correlated with key predictors of public stranger victimization.[36] Given the salience of selection and its potential to confound our estimates, we

[36] Race-specific shifts in time spent outdoors during the pandemic would have been particularly problematic if the characteristics of Asian individuals selecting into public activities would make them particularly likely or unlikely to have a stranger for their attacker, relative to people of other races who spent time in public. For details on the individual characteristics that predict stranger victimization, see Annex Tables A.10 and A.11. These tables show results from regressions that model the probability of stranger and acquaintance victimization given victim characteristics. Results from these regressions show that victims of violent crimes are more likely to have been attacked by a stranger if they were male, between the ages of 50-64, or had an annual income between \$30K and \$75K. Female, young people between the ages of 12-24, and those with an income of \$75K-\$100K are more likely

nevertheless take a cautious approach and control for these variables in our preferred specifications using NIBRS data.

Second, if police became more or less likely to solve crimes with an Asian victim in 2020 than crimes with victims of different races, our key identifying assumption might not hold because of a shift in the types of offenders that appear in our data. We therefore re-run specification 1 on a larger dataset that includes all crimes, including those where no offender information is known. We change the dependent variable to be a binary variable that takes on the value of 1 if a crime incident resulted in at least one arrest. Estimates are presented in Table 5 for the same nine specifications employed in our main results. Across all specifications, there is no evidence to suggest that crimes with an Asian victim are differentially likely to be cleared by arrest after March 2020.

4.4 Heterogeneity

Tables 6 and 7 disaggregate the main specification from the first column of Table 3 according to four demographic subgroups defined by gender (male, female) and age (those of the median age of 33 and older, and those younger than 33), for our acquaintance and stranger models respectively. The first column in each table replicates the full sample results from Table 3.[37] The next four columns consider victimizations of older females (column 2), younger females (column 3), older males (column 4) and younger males (column 5). For the NIBRS sample, we observe evidence that Asian-American females older than 33 were more likely to be attacked in public by strangers of a different race compared to non-Asian American women of similar age, with a share of stranger attacks growing by six percentage points after the beginning of the pandemic. However, this does not hold for our large city sample, where if anything, older women are less likely to be attacked by strangers. In our large city sample, we observe that older men are 1.4% less likely to be attacked by strangers, a result which is significant.

to be attacked by a stranger.

[37] That is, column (4) in Table 3 provides the same information as column (1) in Table 6 and Column (7) in Table 3 provides the same information as column (1) in Table 7.

4.5 Robustness

In this research, we made a number of modeling and data pre-processing decisions. While the decisions we made were based on theory and empirical knowledge about racially-motivated crimes, many of our analytic decisions are arbitrary in the sense that they are not "more or less defensible" than potential alternative specifications (Simonsohn et al., 2020). In order to provide some assurance that our results do not hinge on some of these choices, we employ specification-curve analysis (Simonsohn et al., 2020) to estimate a range of models that we consider would have been reasonable alternative estimations.

Specifically, we vary the following definitional choices and pre-processing decisions. First, in our core specification, we choose March 1st as the start date of the pandemic. However, concern about the virus was arguably already real when the Chinese authorities locked down Wuhan on January 23rd, 2020. Alternatively, some might argue that March 13th is a more appropriate date because this is when Trump declared the COVID-19 pandemic a national emergency. We therefore vary when we turn our COVID variable "on", using both March 13th and January 23rd as alternative dates. Second, because we have missing race information in our large city datasets, and missing ethnicity information in NIBRS, we have employed a differently-coded race variable across the two specifications. In our large-city samples, as many as 42% of our victims are Hispanic. In our specification analysis, we estimate a model in which we drop Hispanics from our large city samples, to assess the extent to which differences between our large city and NIBRS results might be driven by Hispanic victims. Third, we vary our definition of public spaces, restricting our sample to 'truly' public spaces and 'semi' public spaces. The former are mostly outdoor spaces that are often continuously accessible (such as streets, roads, parking lots, sidewalks, transportation locations, gas stations, and playgrounds), whereas the latter are mostly indoor places that are generally accessible to the public during certain hours of the day but are watched over by a guardian that may regulate access (such as restaurants, stores, bars, and hotels).

We estimate all possible combinations of the above choices, which results in a total of 81 estimations. Figure 4 plots 81 regression coefficients for our quantity of interest (the pandemic change in the share of stranger or acquaintance offenders in public violent attacks by offenders of a different race) and the associated 95% confidence intervals. Coefficients are sorted by magnitude, enabling a visual inspection of a range of "reasonable" models. The plot illustrates how our effect size varies with specific modeling and pre-processing decisions. By way of visual aid, all coefficients in red are positive and statistically significant. The plot is accompanied by a "dashboard chart" where the reader can trace each coefficient and confidence interval to a specific combination of choices.

Across all 81 specifications, zero return significantly negative effects, and 27 specifications yield statistically significant positive estimates, suggesting that Asian-Americans who were victim of public violent attacks during the first year of the pandemic, were more likely to be attacked by people who were unfamiliar or little known to them. Varying our definition of public space or the start date of the pandemic matters little for the results. Dropping Hispanic victims from our large cities models increases the size of coefficients, although the standard errors are very large because this nearly halves our observations in large city models. Notably, acquaintances effects are slightly yet consistently larger than stranger effects. All models that yield statistically significant effects use the NIBRS data, while none of the models using the pooled city-level data return significant effects.

5 Discussion

Did anti-Asian violence rise in 2020 after the onset of the COVID-19 pandemic? Efforts to answer this question are compromised by three key measurement challenges. First, hate crimes are incompletely reported and operate under a narrow definition which excludes a potentially large subset of racially-motivated crimes. Second, national victimization surveys do not sample a sufficient number of Asian-American crime victims to draw meaningful conclusions about shifts in racially-motivated attacks. Finally, behavioral shifts during the pandemic – especially the amount of time that people spent in public and potential changes in their willingness to report hate crimes to law enforcement – hamper efforts to understand changes in the true incidence of racially-motivated crimes. Illustrating the extent of the challenge, official data on overall hate crimes point in two different directions: data from the FBI's Uniform Crime Reports indicate that hate crimes increased sharply in 2020, whereas data from the National Crime Victimization Survey suggest that hate crimes fell, in line with a more general fall in violent public victimizations after the onset of the pandemic.

In this paper, we pursued an alternative approach to studying whether anti-Asian violence rose after the onset of the COVID-19 pandemic which, under reasonable assumptions, addresses all three of these concerns. We used data from the FBI's National Incident-Based Reporting System, alongside microdata from several tactically-selected cities to study inter-race violence occurring in public spaces. Our empirical strategy is motivated by the premise that if the COVID-19 pandemic compromised the safety of Asian-Americans, we would expect to observe race-specific changes in victimization for the types of crimes in which racial animus is especially likely to play a role: stranger attacks. The most straightforward way to study stranger attacks would be to observe whether more Asian-Americans suffered stranger victimization in public after March 2020 relative to other Americans. However, the presence of race-specific changes in the amount of time spent in public during the COVID-19 pandemic precluded such analysis. As it turns out, Asian-Americans responded to the pandemic by increasing the amount of time spent inside their homes to a greater extent than other Americans. Failing to account for race-specific changes in opportunities for victimization, then, would mechanically lead to an underestimate of the change in Asian victimization. In order to address this issue, we focused explicitly on violent crimes that occurred in public spaces, studying whether the *share of attacks* committed by strangers or acquaintances changed more for Asian-Americans than for other Americans after March 2020.

In our models that rely on NIBRS data, we find evidence that the share of attacks by strangers and acquaintances in public spaces rose by 2.5 percentage points for Asian-Americans relative to other groups after the onset of the pandemic, from 84.7% to 87.2%. Given that approximately 40% of Asian-Americans living in NIBRS-reporting jurisdictions are East Asian, our estimates are conservative under the assumption that people of East Asian origin (Chinese-Americans as well as individuals of other national origins who may be more likely than South Asians to be mistaken for being Chinese-American) suffered greater stigma than people of South Asian origin. Under the potentially restrictive assumption that the stigma of COVID-19 affected only Americans of East Asian origin, our estimates would be $\frac{1}{0.4} = 2.5$ times too small. As such, there are reasons to believe that our estimates are, if anything, conservative.

Importantly, the police agencies from which these data are drawn and upon which these analyses rely cover approximately half of the population of the United States. We observe much smaller coefficients in our large city sample that are not statistically significant. This might be the result of insufficient power to identify changes this small, and/or point to a qualitatively different pattern in larger cities with a sizable Asian-American population. Notably, the increase appears to be more pronounced for acquaintance-offenders than for strangers in both NIBRS and city data. This might suggest that the pandemic-related moral panic disproportionately affected attacks on victims to which offenders had "weak ties," the people who they are not close to but nevertheless have cause to interact with. It is not difficult to speculate on the types of acquaintance relationships which might be driving this result. For example, we might consider disputes between neighbors of different races which might have always been acrimonious but which become more racially charged in the shadow of the COVID-19 pandemic. The same could be true of relationships between co-workers or individuals situated within overlapping friend networks – people who are not friends but know of one another and who might run into one another at a social gathering. Our results suggest that assaults of this nature increased among Asian-Americans after March 2020 to a significantly greater extent than among Americans of other backgrounds.

Our results contribute to a growing body of studies that have shown that "threatening events" and political rhetoric can lead to race-specific increases in hate crimes (Albornoz et al., 2020; Devine, 2021; Disha et al., 2011; Dugan & Chenoweth, 2020; Frey, 2020; Hanes & Machin, 2014; Ivandic et al., 2019; Jäckle & König, 2018; Rushin & Edwards, 2018). Beyond the specific results we report in this paper, however, this research offers an approach to studying racially-motivated crimes that allows researchers to rely less urgently on hate crimes data which have a tendency to be poorly collected and are subject to a vast array of overlapping biases that are difficult to even correctly sign – particularly when it comes to a small population group. We see no reason why our approach could not be used to study changes in victimization for other groups in any country – all that is needed are victimization data which document the protected characteristic of interest, data on victim-offender relationships, and, ideally, a credibly exogenous event.

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Core Tables and Figures

Table 1: Descriptive Statistics of Public Violent Crimes - NIBRS Data.

			Subset by victim/offender race combination			
Variable	Overall	Analytic dataset	Asian/non-Asian	White/non-White	Black/non-Black	Indian/non-Indian
Victim-offender relationship						
Family	0.273	0.137	0.114	0.132	0.146	0.291
Friend	0.032	0.022	0.018	0.021	0.026	0.026
Acquaintance	0.423	0.390	0.288	0.386	0.437	0.325
Stranger	0.271	0.451	0.579	0.462	0.392	0.358
Victim characteristics						
Victim age	31.639	32.958	35.154	33.341	31.086	32.574
Victim is female	0.532	0.489	0.417	0.509	0.428	0.547
Victim's race						
Asian victim	0.013	0.050	1.000	0.000	0.000	0.000
White victim	0.682	0.725	0.000	1.000	0.000	0.000
Black victim	0.294	0.203	0.000	0.000	1.000	0.000
American Indian victim	0.011	0.022	0.000	0.000	0.000	1.000
Unique offender's race						
Asian offender	0.009	0.030	0.000	0.033	0.027	0.031
White offender	0.572	0.234	0.516	0.000	0.957	0.627
Black offender	0.405	0.703	0.467	0.927	0.000	0.343
American Indian offender	0.014	0.033	0.017	0.040	0.016	0.000
Location of offense						
Public space and outdoors	0.490	0.447	0.379	0.448	0.456	0.478
Semi-public space indoors	0.346	0.391	0.505	0.388	0.371	0.401
Schools	0.125	0.127	0.089	0.127	0.143	0.081
Other places	0.038	0.035	0.027	0.037	0.031	0.040
Type of offense						
Assault	0.726	0.660	0.589	0.644	0.731	0.689
Intimidation	0.160	0.154	0.131	0.153	0.168	0.130
Robbery	0.067	0.136	0.234	0.152	0.055	0.121
Sexual offense	0.045	0.048	0.043	0.049	0.043	0.056
Murder and manslaughter	0.002	0.002	0.002	0.002	0.003	0.003
% of offenses after March 1, 2020	0.184	0.188	0.181	0.187	0.190	0.214
Mean # of offenders	1.193	1.165	1.193	1.186	1.086	1.121
# of police departments	5,487	1,453	1,453	1,419	1,302	705
# of states	40	40	40	40	40	38
Obs.	1,271,602	252,805	12,678	183,240	51,216	5,671

Notes: Column (2) (*Analytic dataset*) represents the NIBRS dataset used in the analysis as described in Section 3.2 of the paper. The last four columns show this dataset split out by the race of the victim. For example, column (3) provides summary statistics for all Asian victims in our sample. Public violent crimes in which the victim is of a different race than the offender are a minority of all public violent crime incidents. Therefore, column (1) (*Overall*) represents an augmented version of the dataset had we not dropped offenders that were of a different race than the victim. This column is provided for the reader's reference only - it is not used in analyses in this paper.

Table 2: Descriptive Statistics of Public Violent Crimes - Pooled-City Data.

Variable	Overall	Analytic dataset	Subset by victim/offender race-ethnicity combination: Asian/non-Asian	White/non-White	Black/non-Black	Indian/non-Indian	Hisp/non-Hisp
Victim-offender relationship							
Family	0.239	0.084	0.065	0.087	0.104	0.043	0.079
Friend	0.018	0.009	0.008	0.011	0.011	0.000	0.008
Acquaintance	0.235	0.178	0.114	0.174	0.249	0.109	0.169
Stranger	0.508	0.729	0.813	0.728	0.636	0.848	0.744
Victim characteristics							
Victim age	35.090	36.629	38.350	38.782	36.951	37.282	34.371
Victim is female	0.527	0.423	0.360	0.424	0.443	0.232	0.429
Victim race-ethnicity							
Asian victim (NH)	0.030	0.079	1.000	0.000	0.000	0.000	0.000
White victim (NH)	0.164	0.353	0.000	1.000	0.000	0.000	0.000
Black victim (NH)	0.471	0.143	0.000	0.000	1.000	0.000	0.000
American Indian victim (NH)	0.002	0.007	0.000	0.000	0.000	1.000	0.000
Hispanic victim	0.333	0.419	0.000	0.000	0.000	0.000	1.000
Unique offender race-ethnicity							
Asian offender (NH)	0.013	0.026	0.000	0.026	0.055	0.036	0.021
White offender (NH)	0.098	0.145	0.172	0.000	0.348	0.143	0.192
Black offender (NH)	0.620	0.614	0.602	0.661	0.000	0.707	0.785
American Indian offender (NH)	0.001	0.002	0.004	0.003	0.003	0.000	0.002
Hispanic offender	0.268	0.213	0.222	0.311	0.593	0.114	0.000
Location of offense							
Public space and outdoors	0.686	0.673	0.608	0.683	0.650	0.605	0.687
Semi-public space indoors	0.172	0.223	0.303	0.214	0.224	0.339	0.213
Schools	0.039	0.032	0.017	0.027	0.041	0.005	0.036
Other places	0.103	0.072	0.072	0.076	0.085	0.052	0.065
Type of offense							
Assault	0.800	0.708	0.640	0.711	0.858	0.711	0.667
Intimidation	0.006	0.006	0.012	0.007	0.006	0.002	0.005
Robbery	0.160	0.244	0.319	0.231	0.087	0.261	0.294
Sexual offense	0.031	0.041	0.028	0.050	0.047	0.025	0.033
Murder and manslaughter	0.003	0.002	0.001	0.002	0.002	0.000	0.001
% of offenses after March 1, 2020	0.196	0.211	0.187	0.191	0.212	0.152	0.232
Mean # of offenders	1.247	1.279	1.269	1.264	1.161	1.273	1.334
# of police departments	4	4	4	4	4	4	4
# of states	2	2	2	2	2	2	2
Obs.	197,425	62,414	4,905	22,029	8,901	440	26,139

Notes: Column (2) (*Analytic dataset*) represents the pooled-city dataset used in the analysis as described in Section 3.2 of the paper. The last four columns show this dataset split out by the race of the victim. For example, column (3) provides summary statistics for all Asian victims in our sample. Public violent crimes in which the victim is of a different race than the offender are a minority of all public violent crime incidents. Therefore, column (1) (*Overall*) represents an augmented version of the dataset had we not dropped offenders that were of a different race than the victim. This column is provided for the reader's reference only - it is not used in analyses in this paper.

Table 3: Difference-in-Difference Regression Estimates of the Effect of the COVID-19 Pandemic on Stranger and Acquaintance Attacks.

	Strangers + Acquaintances			Strangers			Acquaintances		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: NIBRS data									
Covid x Asian victim	0.025**	0.021	0.019	0.028*	0.029	0.020	0.036*	0.021	0.040
	(0.008)	(0.014)	(0.011)	(0.011)	(0.018)	(0.014)	(0.018)	(0.027)	(0.025)
N. of observations	252,805	59,117	177,824	154,244	34,371	110,434	138,743	35,567	93,688
N. of parameters	2,984	2,700	2,773	2,847	2,435	2,584	2,889	2,529	2,628
Pre-period mean	0.847	0.822	0.858	0.742	0.684	0.766	0.726	0.710	0.736
R sq. (adj.)	0.121	0.092	0.149	0.237	0.181	0.279	0.164	0.132	0.199
RMSE	0.341	0.360	0.325	0.380	0.405	0.357	0.410	0.413	0.397
Panel B: City-level data									
Covid x Asian victim	0.004	-0.029	0.011	0.004	-0.037	0.010	0.015	-0.008	0.080
	(0.018)	(0.037)	(0.013)	(0.019)	(0.043)	(0.014)	(0.027)	(0.050)	(0.053)
N. of observations	62,414	9,026	38,334	51,318	6,862	32,995	16,920	3,311	7,855
N. of parameters	234	233	233	234	233	233	234	232	233
Pre-period mean	0.898	0.857	0.929	0.876	0.812	0.917	0.637	0.627	0.664
R sq. (adj.)	0.075	0.077	0.069	0.099	0.108	0.085	0.165	0.152	0.180
RMSE	0.279	0.316	0.238	0.300	0.346	0.253	0.431	0.423	0.416
Police dept-COVID FE	X	X	X	X	X	X	X	X	X
Weekday-hour FE	X	X	X	X	X	X	X	X	X
Month-year FE	X	X	X	X	X	X	X	X	X
Race of victim FE	X	X	X	X	X	X	X	X	X
Subset of offenders	All	White	Black	All	White	Black	All	White	Black

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions based on Equation 1. Columns (1), (4) and (7) use our full dataset, columns (2), (5) and (8) restrict our sample to non-White victims with a White offender, and columns (3), (6) and (9) restrict our sample to non-Black victims with a Black offender. Panel A uses our NIBRS data, and Panel B uses our pooled-city data for Chicago, Los Angeles, San Francisco and San Jose. The race of victim fixed effect is a race-ethnicity fixed effect in Panel B. Standard errors are clustered at the police department/city level.

Table 4: Triple Interaction Regression Estimates of the Effect of Individual Characteristics on the Share of Time Spent in Public Post-Pandemic. Data: ATUS.

Age 15-24 * COVID * Asian	−0.134
	(0.089)
Age 35-49 * COVID * Asian	−0.043
	(0.057)
Age 50-64 * COVID * Asian	−0.013
	(0.072)
Age 65+ COVID * Asian	0.094
	(0.186)
Male * COVID * Asian	0.080
	(0.046)
Edu: some college+ * COVID * Asian	0.036
	(0.075)
Income <30K * COVID * Asian	−0.023
	(0.068)
Income 75-100K * COVID * Asian	−0.114
	(0.072)
Income 100K+ * COVID * Asian	−0.080
	(0.061)
R^2	0.096
Adj. R^2	0.092
Obs.	7337
RMSE	577.898

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions using data from The American Time Use Survey (ATUS) (Bureau of Justice Statistics, 2021) for January 1 to March 17 and for May 10 to December 31 of 2019 and 2020. This is due to the pandemic-related suspension of data collection from March 18, 2020, to May 9, 2020. Data are for 2019 and 2020 only because ATUS only provides the relevant weights for these two years. Regressions are a linear model of the share of time spent in public on respondent characteristics, interacted with variables for COVID (time use after March 1, 2020) and whether the respondent was Asian. Only triple interaction terms are shown. Standard errors are robust.

Table 5: Difference-in-Difference Estimates of the Effect of the COVID-19 Pandemic on Clearance Rates. Data: NIBRS.

	Strangers + Acquaintances			Strangers			Acquaintances		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Covid x Asian victim	-0.003	-0.003	0.005	-0.004	-0.020	0.011	-0.003	0.021	-0.006
	(0.007)	(0.014)	(0.010)	(0.007)	(0.016)	(0.011)	(0.010)	(0.017)	(0.015)
N. of observations	1,897,109	932,734	721,224	1,277,861	582,450	452,890	1,497,815	713,521	545,621
DoF (residual)	5,481	5,403	3,656	5,375	5,222	3,134	5,455	5,362	3,493
R sq. (adj.)	0.115	0.144	0.110	0.110	0.137	0.109	0.118	0.150	0.114
RMSE	0.447	0.458	0.448	0.449	0.464	0.452	0.441	0.455	0.447
Police dept-COVID FE	X	X	X	X	X	X	X	X	X
Weekday-hour FE	X	X	X	X	X	X	X	X	X
Month-year FE	X	X	X	X	X	X	X	X	X
Race of victim FE	X	X	X	X	X	X	X	X	X
Subset of offenders	All	White	Black	All	White	Black	All	White	Black

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions test whether the police became differentially less likely to solve crimes with an Asian victim in 2020. Results are based on Equation 1 on a larger dataset than our base sample. This dataset includes all crimes, including those where no offender information is known. The dependent variable in this specification is a binary variable that takes on the value of 1 if crime incident i on day t in city j with a victim of race g resulted in at least one arrest, and zero if otherwise. Standard errors are clustered at the police agency (ORI) level.

Table 6: Heterogeneity analysis - Strangers.

	(1)	(2)	(3)	(4)	(5)
Panel A: NIBRS data					
Covid x Asian victim	0.028*	0.075*	0.033	0.003	0.022
	(0.011)	(0.030)	(0.037)	(0.013)	(0.016)
N. of observations	154,244	33,113	41,547	40,757	38,827
Pre-period mean	0.742	0.653	0.540	0.912	0.858
N. of parameters	2,847	2,254	2,426	2,253	2,285
R sq. (adj.)	0.237	0.194	0.157	0.146	0.206
RMSE	0.380	0.415	0.445	0.257	0.300
Panel B: City-level data					
Covid x Asian victim	0.004	-0.040	0.024	-0.014*	0.041
	(0.019)	(0.037)	(0.075)	(0.004)	(0.025)
N. of observations	51,318	10,111	10,798	17,327	13,082
N. of parameters	234	232	232	232	232
Pre-period mean	0.876	0.812	0.749	0.949	0.939
R sq. (adj.)	0.099	0.092	0.062	0.026	0.035
RMSE	0.300	0.356	0.408	0.202	0.225
Police dept-COVID FE	X	X	X	X	X
Weekday-hour FE	X	X	X	X	X
Month-year FE	X	X	X	X	X
Race of victim FE	X	X	X	X	X
Subset of victims	All cases	Female 33+ y.o.	Female <33 y.o.	Male 33+ y.o.	Male <33 y.o.

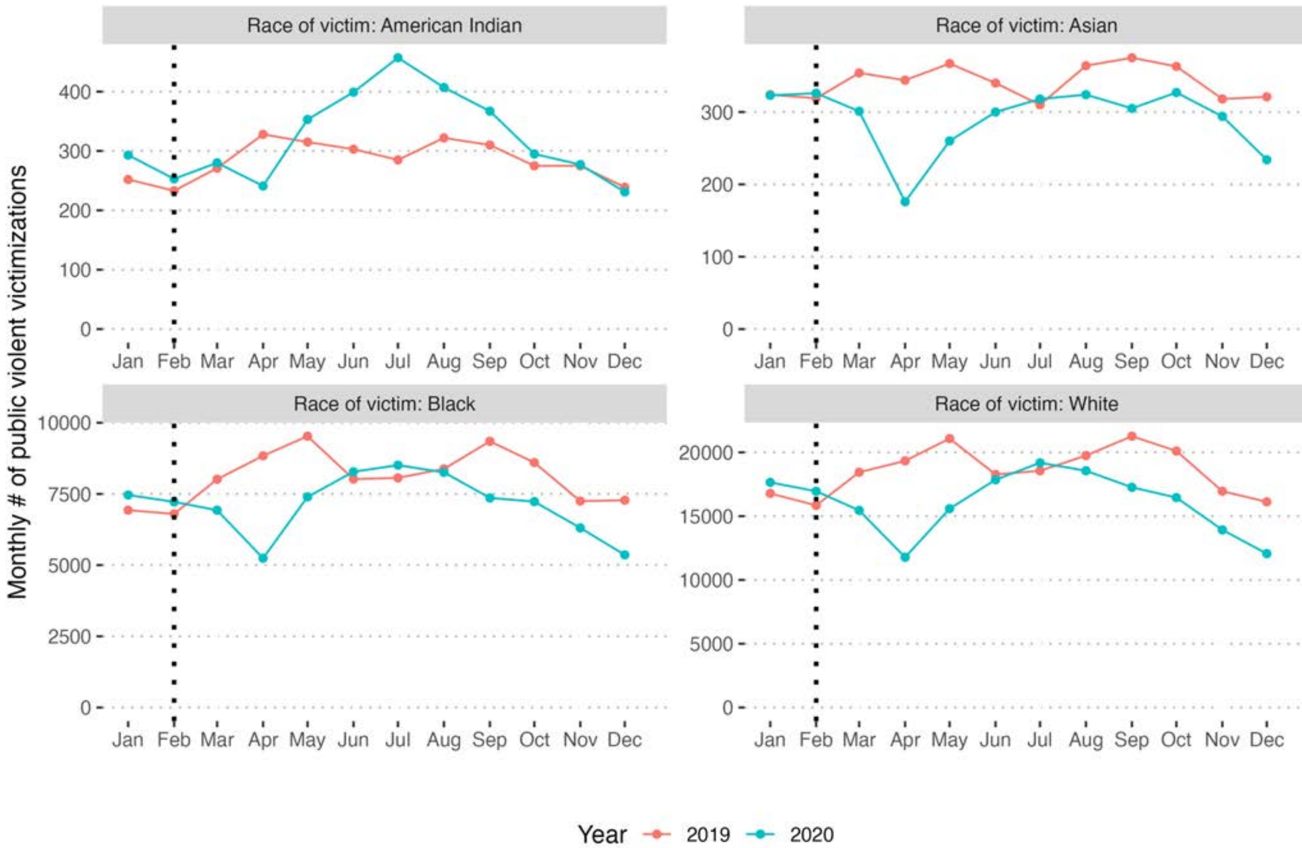
Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions based on Equation 1. Column (1) reproduces our baseline result as shown in Column (4) of Table 3. Columns (2) to (5) subset our data to male and female victims of 33 years and older, and of 32 years and younger. Panel A uses our NIBRS data, and Panel B uses our pooled-city data for Chicago, Los Angeles, San Francisco and San Jose. The race of victim fixed effect is a race-ethnicity fixed effect in Panel B. Standard errors are clustered at the police department/city level.

Table 7: Heterogeneity analysis - Acquaintances.

	(1)	(2)	(3)	(4)	(5)
Panel A: NIBRS data					
Covid x Asian victim	0.036*	0.042	0.018	0.013	0.057
	(0.018)	(0.044)	(0.044)	(0.026)	(0.035)
N. of observations	138,743	31,437	48,577	25,465	33,264
Pre-period mean	0.726	0.645	0.624	0.863	0.845
N. of parameters	2,889	2,278	2,543	2,209	2,356
R sq. (adj.)	0.164	0.187	0.142	0.120	0.112
RMSE	0.410	0.420	0.441	0.315	0.336
Panel B: City-level data					
Covid x Asian victim	0.015	-0.015	0.099	-0.082	0.148
	(0.027)	(0.078)	(0.110)	(0.041)	(0.068)
N. of observations	16,920	4,580	5,206	4,252	2,882
N. of parameters	234	231	232	232	231
Pre-period mean	0.637	0.599	0.483	0.802	0.736
R sq. (adj.)	0.165	0.148	0.190	0.063	0.118
RMSE	0.431	0.437	0.440	0.363	0.393
Police dept-COVID FE	X	X	X	X	X
Weekday-hour FE	X	X	X	X	X
Month-year FE	X	X	X	X	X
Race of victim FE	X	X	X	X	X
Subset of victims	All cases	Female 33+ y.o.	Female <33 y.o.	Male 33+ y.o.	Male <33 y.o.

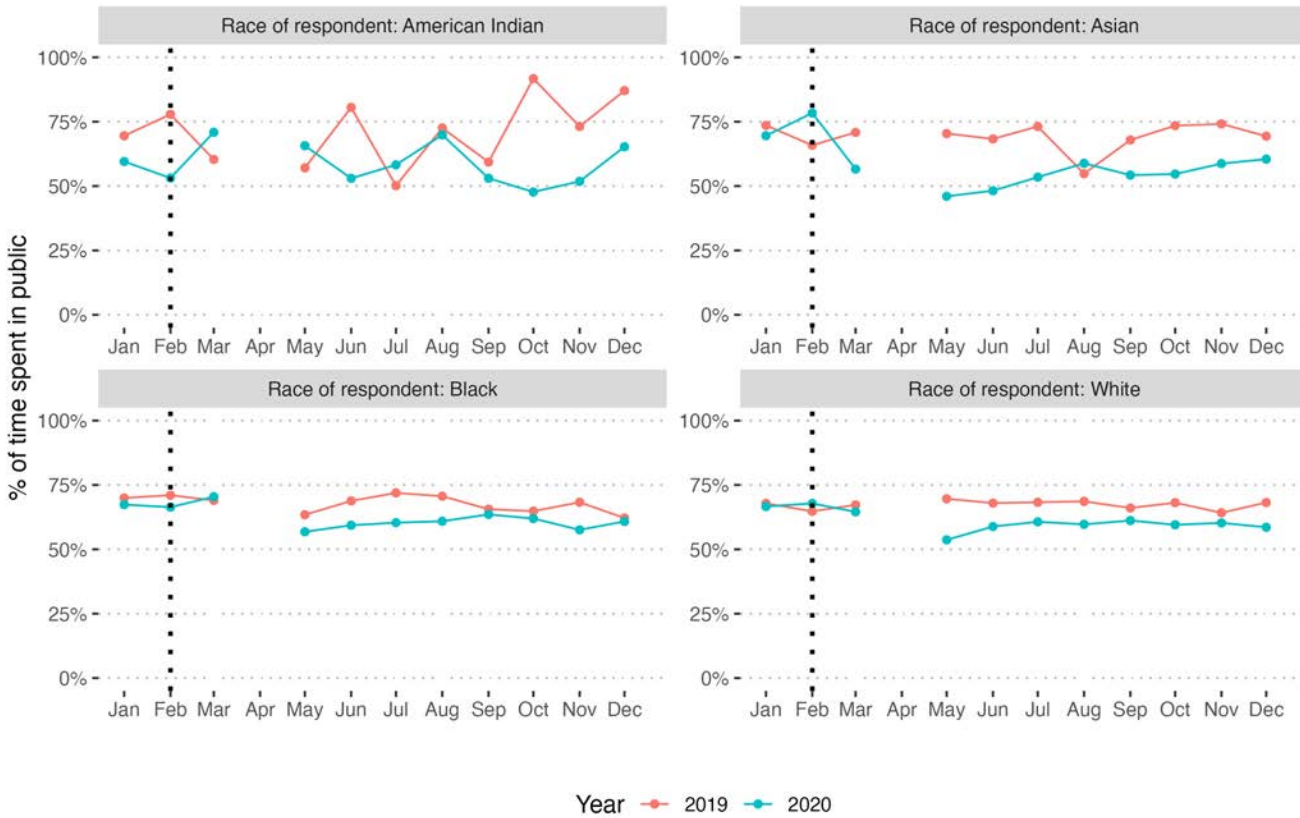
Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions based on Equation 1. Column (1) reproduces our baseline result as shown in Column (7) of Table 3. Columns (2) to (5) subset our data to male and female victims of 33 years and older, and of 32 years and younger. Panel A uses our NIBRS data, and Panel B uses our pooled-city data for Chicago, Los Angeles, San Francisco and San Jose. The race of victim fixed effect is a race-ethnicity fixed effect in Panel B. Standard errors are clustered at the police department/city level.

Figure 1: Public Violent Victimizations, by Race



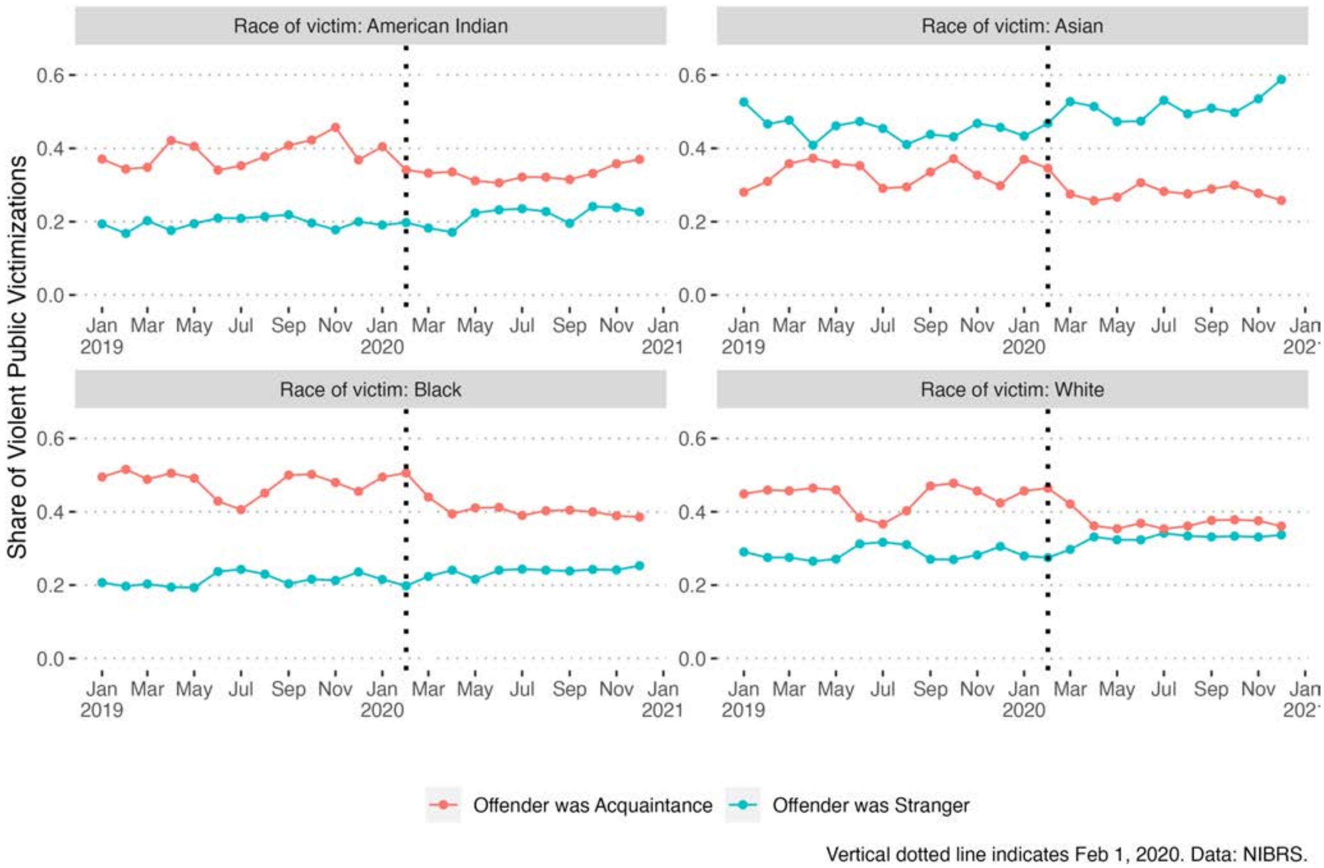
Notes: Figure shows a monthly count of all public violent victimizations in the United States in 2019-2020, by race of the victim. Data: NIBRS.

Figure 2: Time Spent in Public, by Race.



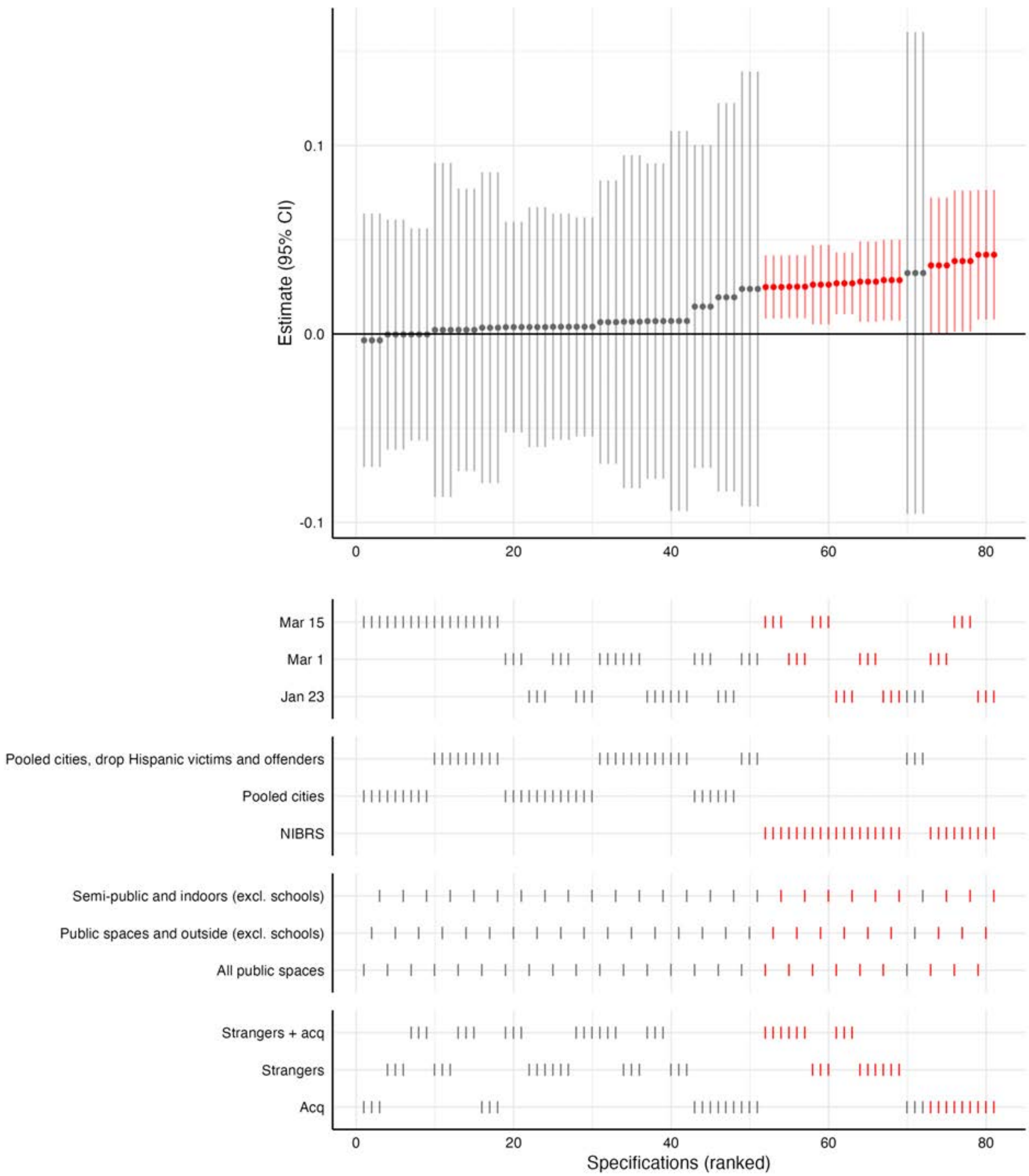
Notes: Figure shows the population-weighted share of time spent in public in 2019-2020 by race using data from the the American Time Use Survey (ATUS) (Bureau of Justice Statistics, 2021). Data are for January 1 to March 17 and for May 10 to December 31 of 2019 and 2020. This is due to the pandemic-related suspension of data collection from March 18, 2020, to May 9, 2020. Data are for 2019 and 2020 only because ATUS only provides the relevant weights for these two years.

Figure 3: Share of public violent victimizations in which offender was acquaintance or stranger by race.



Notes: Figure is based on all White, Black, Asian and American Indian victimizations reported to NIBRS by agencies that reported in 2017, 2018, 2019 and 2020.

Figure 4: Specification curve.



Notes: Figure shows the specification curve analysis for the main regression model. The top panel plots 81 regression coefficients for our quantity of interest (the pandemic change in the share of stranger or acquaintance offenders in public violent attacks by offenders of a different race) and the associated 95% confidence intervals. The bottom panel shows the specification choices corresponding to the estimands at the top panel. The models that result in a statistically significant estimand are printed in red. The coefficients are ranked in ascending order.

ONLINE APPENDIX

A Appendix - Additional Tables and Figures

Table A.1: Sample Restrictions - NIBRS data.

Restrictions	# of police departments	# of victimizations (observations)	% of the starting dataset	% of obs. from previous row
Universe: All public violent victimizations 2017-2020*	5,570	2,002,314	1.000	
Incidents with some offender information	5,570	2,002,314	1.000	1.000
Victim race is Black, White, Asian or American Indian	5,563	1,918,283	0.958	0.958
Victim age and sex are known	5,561	1,897,592	0.948	0.989
Offender-victim relationship is Known + all offenders related to the victim in the same way	5,494	1,351,006	0.675	0.712
Offender race is known + all offenders are of the same race	5,487	1,271,602	0.635	0.941
Offenders are of a different race than the victim	4,377	285,654	0.143	0.225
Agencies that reported at least one Asian victim	1,453	252,805	0.126	0.885

Notes: This table documents the sample restrictions described in Section 3.2. Line 1 in the table represents all public violent victimizations in NIBRS reported by agencies who reported in all four years 2017-2020. Public refers to crimes that did not occur uniquely in a 'residence/home'. Crimes that occur partially at home (e.g. have multiple location code) count as public. The subsequent lines of the table document the number of observations, the share of total observations and the number of agencies that remain in the sample after each exclusion.

Table A.2: Sample Restrictions - Chicago data.

Restrictions	# of victimizations (observations)	% of the starting dataset	% of obs. from previous row
All public violent victimizations in 2017-2020	240,486	1.000	
Incidents with at least one victim and one offender	234,824	0.976	0.976
Victim is Black, White, Asian, Am.Indian, or Hispanic	211,438	0.879	0.900
Victim's age and sex are known	210,763	0.876	0.997
Offender-victim relationship is Known + all offenders related to the victim in the same way	146,906	0.611	0.697
Offender race-ethnicity is known + all offenders are of the same race-ethnicity	124,812	0.519	0.850
Offenders are of a different race-ethnicity than the victim	35,438	0.147	0.284

Notes: This table documents the sample restrictions described in Section 3.2. Line 1 in the table represents all public violent victimizations in 2017-2020. Public refers to crimes that did not occur uniquely in a 'residence/home'. Crimes that occur partially at home (e.g. have multiple location code) count as public. The subsequent lines of the table document the number of observations, the share of total observations and the number of agencies that remain in the sample after each exclusion.

Table A.3: Sample Restrictions - Los Angeles Data.

Restrictions	# of victimizations (observations)	% of the starting dataset	% of obs. from previous row
All public violent victimizations in 2017-2020	158,892	1.000	
Incidents with at least one victim and one offender	152,432	0.959	0.959
Victim is Black, White, Asian, Am.Indian, or Hispanic	135,499	0.853	0.889
Victim's age and sex are known	132,967	0.837	0.981
Offender-victim relationship is Known + all offenders related to the victim in the same way	70,158	0.442	0.528
Offender race-ethnicity is known + all offenders are of the same race-ethnicity	63,688	0.401	0.908
Offenders are of a different race-ethnicity than the victim	22,763	0.143	0.357

Notes: This table documents the sample restrictions described in Section 3.2. Line 1 in the table represents all public violent victimizations in 2017-2020. Public refers to crimes that did not occur uniquely in a 'residence/home'. Crimes that occur partially at home (e.g. have multiple location code) count as public. The subsequent lines of the table document the number of observations, the share of total observations and the number of agencies that remain in the sample after each exclusion.

Table A.4: Sample Restrictions - San Jose data.

Restrictions	# of victimizations (observations)	% of the starting dataset	% of obs. from previous row
All public violent victimizations in 2017-2020	23,794	1.000	
Incidents with at least one victim and one offender	7,705	0.324	0.324
Victim is Black, White, Asian, Am.Indian, or Hispanic	6,627	0.279	0.860
Victim's age and sex are known	6,229	0.262	0.940
Offender-victim relationship is Known + all offenders related to the victim in the same way	4,320	0.182	0.694
Offender race-ethnicity is known + all offenders are of the same race-ethnicity	4,219	0.177	0.977
Offenders are of a different race-ethnicity than the victim	1,864	0.078	0.442

Notes: This table documents the sample restrictions described in Section 3.2. Line 1 in the table represents all public violent victimizations in 2017-2020. Public refers to crimes that did not occur uniquely in a 'residence/home'. Crimes that occur partially at home (e.g. have multiple location code) count as public. The subsequent lines of the table document the number of observations, the share of total observations and the number of agencies that remain in the sample after each exclusion.

Table A.5: Sample Restrictions - San Francisco Data.

Restrictions	# of victimizations (observations)	% of the starting dataset	% of obs. from previous row
All public violent victimizations in 2017-2020	39,253	1.000	
Incidents with at least one victim and one offender	6,092	0.155	0.155
Victim is Black, White, Asian, Am.Indian, or Hispanic	5,731	0.146	0.941
Victim's age and sex are known	5,718	0.146	0.998
Offender-victim relationship is Known + all offenders related to the victim in the same way	4,905	0.125	0.858
Offender race-ethnicity is known + all offenders are of the same race-ethnicity	4,706	0.120	0.959
Offenders are of a different race-ethnicity than the victim	2,349	0.060	0.499

Notes: This table documents the sample restrictions described in Section 3.2. Line 1 in the table represents all public violent victimizations in 2017-2020. Public refers to crimes that did not occur uniquely in a 'residence/home'. Crimes that occur partially at home (e.g. have multiple location code) count as public. The subsequent lines of the table document the number of observations, the share of total observations and the number of agencies that remain in the sample after each exclusion.

Table A.6: Descriptive Statistics of Public Violent Crimes - Chicago Data.

			Subset by victim/offender race-ethnicity combination				
Variable	Overall	Analytic dataset	Asian/non-Asian	White/non-White	Black/non-Black	Indian/non-Indian	Hisp/non-Hisp
Victim-offender relationship							
Family	0.254	0.073	0.049	0.064	0.094	0.036	0.082
Friend	0.023	0.011	0.009	0.011	0.011	0.000	0.011
Acquaintance	0.184	0.135	0.076	0.125	0.205	0.096	0.134
Stranger	0.539	0.781	0.867	0.800	0.689	0.868	0.773
Victim characteristics							
Victim age	34.650	36.128	36.812	37.931	36.732	37.384	33.649
Victim is female	0.542	0.414	0.313	0.409	0.463	0.195	0.429
Victim race-ethnicity							
Asian victim (NH)	0.027	0.083	1.000	0.000	0.000	0.000	0.000
White victim (NH)	0.164	0.408	0.000	1.000	0.000	0.000	0.000
Black victim (NH)	0.584	0.139	0.000	0.000	1.000	0.000	0.000
American Indian victim (NH)	0.003	0.010	0.000	0.000	0.000	1.000	0.000
Hispanic victim	0.222	0.359	0.000	0.000	0.000	0.000	1.000
Unique offender race-ethnicity							
Asian offender (NH)	0.011	0.025	0.000	0.022	0.072	0.016	0.017
White offender (NH)	0.086	0.134	0.133	0.000	0.402	0.110	0.184
Black offender (NH)	0.730	0.654	0.719	0.735	0.000	0.775	0.798
American Indian offender (NH)	0.001	0.003	0.003	0.003	0.005	0.000	0.002
Hispanic offender	0.172	0.184	0.145	0.240	0.521	0.099	0.000
Location of offense							
Public space and outdoors	0.648	0.635	0.614	0.657	0.584	0.627	0.634
Semi-public space indoors	0.157	0.217	0.264	0.211	0.232	0.307	0.206
Schools	0.048	0.038	0.017	0.032	0.050	0.005	0.047
Other places	0.147	0.109	0.105	0.100	0.134	0.060	0.113
Type of offense							
Assault	0.821	0.725	0.661	0.709	0.898	0.742	0.691
Intimidation	0.003	0.002	0.002	0.003	0.002	0.000	0.003
Robbery	0.150	0.241	0.320	0.251	0.062	0.247	0.282
Sexual offense	0.024	0.030	0.017	0.037	0.037	0.011	0.024
Murder and manslaughter	0.002	0.001	0.001	0.001	0.001	0.000	0.001
% of offenses after March 1, 2020	0.152	0.146	0.133	0.134	0.151	0.148	0.160
Mean # of offenders	1.247	1.289	1.346	1.302	1.132	1.279	1.323
Obs.	124,812	35,438	2,938	14,475	4,930	365	12,730

Notes: Column (2) (*Analytic dataset*) represents the Chicago dataset used in the analysis as described in Section 3.2 of the paper. The last four columns show this dataset split out by the race of the victim. For example, column (3) provides summary statistics for all Asian victims in our sample. Public violent crimes in which the victim is of a different race than the offender are a minority of all public violent crime incidents. Therefore, column (1) (*Overall*) represents an augmented version of the dataset had we not dropped offenders that were of a different race than the victim. This column is provided for the reader's reference only - it is not used in analyses in this paper.

Table A.7: Descriptive Statistics of Public Violent Crimes - Los Angeles Data.

Variable	Overall	Analytic dataset	Subset by victim/offender race-ethnicity combination: Asian/non-Asian	White/non-White	Black/non-Black	Indian/non-Indian	Hisp/non-Hisp
Victim-offender relationship							
Family	0.196	0.083	0.079	0.114	0.102	0.000	0.062
Friend	0.009	0.006	0.007	0.007	0.011	0.000	0.004
Acquaintance	0.345	0.248	0.219	0.292	0.322	0.259	0.208
Stranger	0.450	0.663	0.696	0.587	0.565	0.741	0.726
Victim characteristics							
Victim age	35.659	37.066	42.318	40.361	37.049	29.926	34.973
Victim is female	0.502	0.436	0.449	0.458	0.422	0.519	0.428
Victim race-ethnicity							
Asian victim (NH)	0.021	0.047	1.000	0.000	0.000	0.000	0.000
White victim (NH)	0.147	0.268	0.000	1.000	0.000	0.000	0.000
Black victim (NH)	0.289	0.150	0.000	0.000	1.000	0.000	0.000
American Indian victim (NH)	0.000	0.001	0.000	0.000	0.000	1.000	0.000
Hispanic victim	0.543	0.534	0.000	0.000	0.000	0.000	1.000
Unique offender race-ethnicity							
Asian offender (NH)	0.010	0.018	0.000	0.019	0.024	0.037	0.017
White offender (NH)	0.101	0.139	0.173	0.000	0.243	0.296	0.177
Black offender (NH)	0.448	0.594	0.485	0.523	0.000	0.481	0.806
American Indian offender (NH)	0.000	0.001	0.000	0.001	0.000	0.000	0.000
Hispanic offender	0.441	0.249	0.342	0.457	0.733	0.185	0.000
Location of offense							
Public space and outdoors	0.767	0.746	0.668	0.752	0.742	0.667	0.750
Semi-public space indoors	0.183	0.209	0.290	0.203	0.202	0.333	0.205
Schools	0.024	0.024	0.017	0.017	0.033	0.000	0.026
Other places	0.026	0.022	0.025	0.028	0.023	0.000	0.018
Type of offense							
Assault	0.765	0.682	0.659	0.706	0.806	0.407	0.637
Intimidation	0.002	0.001	0.002	0.002	0.001	0.000	0.001
Robbery	0.183	0.258	0.284	0.205	0.123	0.333	0.319
Sexual offense	0.046	0.058	0.055	0.084	0.066	0.259	0.042
Murder and manslaughter	0.005	0.002	0.000	0.003	0.004	0.000	0.001
% of offenses after March 1, 2020	0.286	0.318	0.356	0.330	0.307	0.222	0.311
Mean # of offenders	1.279	1.313	1.273	1.233	1.228	1.667	1.380
Obs.	63,688	22,763	1,066	6,100	3,409	27	12,161

Notes: Column (2) (*Analytic dataset*) represents the Los Angeles dataset used in the analysis as described in Section 3.2 of the paper. The last four columns show this dataset split out by the race of the victim. For example, column (3) provides summary statistics for all Asian victims in our sample. Public violent crimes in which the victim is of a different race than the offender are a minority of all public violent crime incidents. Therefore, column (1) (*Overall*) represents an augmented version of the dataset had we not dropped offenders that were of a different race than the victim. This column is provided for the reader's reference only - it is not used in analyses in this paper.

Table A.8: Descriptive Statistics of Public Violent Crimes - San Jose Data.

Variable	Overall	Analytic dataset	Subset by victim/offender race-ethnicity combination: Asian/non-Asian	White/non-White	Black/non-Black	Indian/non-Indian	Hisp/non-Hisp
Victim-offender relationship							
Family	0.373	0.224	0.127	0.278	0.200	0.217	0.248
Friend	0.019	0.016	0.002	0.028	0.005	0.000	0.018
Acquaintance	0.164	0.141	0.101	0.154	0.210	0.087	0.137
Stranger	0.445	0.619	0.769	0.539	0.585	0.696	0.597
Victim characteristics							
Victim age	34.436	36.383	38.320	38.332	35.641	38.652	33.597
Victim is female	0.507	0.452	0.372	0.491	0.349	0.304	0.507
Victim race-ethnicity							
Asian victim (NH)	0.136	0.228	1.000	0.000	0.000	0.000	0.000
White victim (NH)	0.224	0.303	0.000	1.000	0.000	0.000	0.000
Black victim (NH)	0.085	0.105	0.000	0.000	1.000	0.000	0.000
American Indian victim (NH)	0.006	0.012	0.000	0.000	0.000	1.000	0.000
Hispanic victim	0.550	0.352	0.000	0.000	0.000	0.000	1.000
Unique offender race-ethnicity							
Asian offender (NH)	0.074	0.089	0.000	0.096	0.077	0.174	0.140
White offender (NH)	0.207	0.266	0.264	0.000	0.344	0.261	0.472
Black offender (NH)	0.151	0.253	0.195	0.241	0.000	0.217	0.377
American Indian offender (NH)	0.005	0.010	0.012	0.009	0.005	0.000	0.011
Hispanic offender	0.563	0.383	0.529	0.654	0.574	0.348	0.000
Location of offense							
Public space and outdoors	0.659	0.595	0.487	0.637	0.723	0.435	0.598
Semi-public space indoors	0.290	0.359	0.473	0.307	0.246	0.565	0.358
Schools	0.050	0.044	0.035	0.057	0.031	0.000	0.044
Other places	0.000	0.001	0.005	0.000	0.000	0.000	0.000
Type of offense							
Assault	0.706	0.617	0.409	0.668	0.723	0.522	0.680
Intimidation	0.049	0.049	0.049	0.057	0.046	0.000	0.046
Robbery	0.205	0.285	0.504	0.223	0.195	0.478	0.216
Sexual offense	0.037	0.045	0.035	0.048	0.031	0.000	0.055
Murder and manslaughter	0.003	0.003	0.002	0.004	0.005	0.000	0.003
% of offenses after March 1, 2020	0.191	0.206	0.191	0.218	0.221	0.130	0.204
Mean # of offenders	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Obs.	4,219	1,864	425	564	195	23	657

Notes: Column (2) (*Analytic dataset*) represents the San Jose dataset used in the analysis as described in Section 3.2 of the paper. The last four columns show this dataset split out by the race of the victim. For example, column (3) provides summary statistics for all Asian victims in our sample. Public violent crimes in which the victim is of a different race than the offender are a minority of all public violent crime incidents. Therefore, column (1) (*Overall*) represents an augmented version of the dataset had we not dropped offenders that were of a different race than the victim. This column is provided for the reader's reference only - it is not used in analyses in this paper.

Table A.9: Descriptive Statistics of Public Violent Crimes - San Francisco Data.

Variable	Overall	Analytic dataset	Subset by victim/offender race-ethnicity combination: Asian/non-Asian	White/non-White	Black/non-Black	Indian/non-Indian	Hisp/non-Hisp
Victim-offender relationship							
Family	0.289	0.158	0.082	0.166	0.202	0.04	0.184
Friend	0.020	0.010	0.008	0.009	0.011	0.00	0.012
Acquaintance	0.181	0.166	0.124	0.181	0.188	0.16	0.162
Stranger	0.510	0.667	0.786	0.644	0.599	0.80	0.641
Victim characteristics							
Victim age	39.630	40.165	38.979	42.091	39.684	42.48	38.421
Victim is female	0.469	0.402	0.437	0.399	0.420	0.40	0.369
Victim race-ethnicity							
Asian victim (NH)	0.126	0.203	1.000	0.000	0.000	0.00	0.000
White victim (NH)	0.351	0.379	0.000	1.000	0.000	0.00	0.000
Black victim (NH)	0.276	0.156	0.000	0.000	1.000	0.00	0.000
American Indian victim (NH)	0.006	0.011	0.000	0.000	0.000	1.00	0.000
Hispanic victim	0.240	0.252	0.000	0.000	0.000	0.00	1.000
Unique offender race-ethnicity							
Asian offender (NH)	0.062	0.073	0.000	0.085	0.109	0.20	0.086
White offender (NH)	0.291	0.257	0.336	0.000	0.599	0.36	0.364
Black offender (NH)	0.443	0.490	0.502	0.657	0.000	0.40	0.538
American Indian offender (NH)	0.006	0.012	0.015	0.011	0.011	0.00	0.012
Hispanic offender	0.198	0.167	0.147	0.246	0.281	0.04	0.000
Location of offense							
Public space and outdoors	0.634	0.613	0.538	0.656	0.638	0.36	0.604
Semi-public space indoors	0.312	0.335	0.422	0.287	0.311	0.60	0.342
Schools	0.002	0.001	0.002	0.001	0.003	0.00	0.000
Other places	0.053	0.051	0.038	0.056	0.049	0.04	0.054
Type of offense							
Assault	0.816	0.778	0.674	0.803	0.869	0.76	0.766
Intimidation	0.072	0.073	0.061	0.076	0.068	0.04	0.081
Robbery	0.084	0.117	0.227	0.074	0.046	0.20	0.132
Sexual offense	0.024	0.031	0.032	0.044	0.016	0.00	0.020
Murder and manslaughter	0.003	0.002	0.006	0.002	0.000	0.00	0.000
% of offenses after March 1, 2020	0.143	0.149	0.134	0.153	0.142	0.16	0.159
Mean # of offenders	1.024	1.021	1.021	1.018	1.025	1.00	1.024
Obs.	4,706	2,349	476	890	367	25	591

Notes: Column (2) (*Analytic dataset*) represents the San Francisco dataset used in the analysis as described in Section 3.2 of the paper. The last four columns show this dataset split out by the race of the victim. For example, column (3) provides summary statistics for all Asian victims in our sample. Public violent crimes in which the victim is of a different race than the offender are a minority of all public violent crime incidents. Therefore, column (1) (*Overall*) represents an augmented version of the dataset had we not dropped offenders that were of a different race than the victim. This column is provided for the reader's reference only - it is not used in analyses in this paper.

Table A.10: Regressions of Stranger Attacks on Victim Characteristics, by Race. Data: NCVS.

	Victim race subset				
	Overall	White	Black	Asian	American Indian
Intercept	0.112***	0.101***	0.148	0.296*	0.392
	(0.026)	(0.028)	(0.077)	(0.148)	
Male	0.041*	0.030	0.149**	0.085	−0.277
	(0.016)	(0.017)	(0.046)	(0.076)	
Age 12-24 (ref is 25-34)	0.021	0.030	−0.083	0.180	−0.191
	(0.030)	(0.034)	(0.070)	(0.113)	
Age 35-49	0.016	0.014	0.016	0.033	0.080
	(0.020)	(0.020)	(0.080)	(0.094)	
Age 50-64	0.053*	0.052*	0.115	0.166	−0.119
	(0.024)	(0.025)	(0.085)	(0.128)	
Age 65+	0.035	0.045	−0.007	0.024	−0.160
	(0.033)	(0.034)	(0.144)	(0.216)	
Age unknown	0.052	0.068	−0.228**	0.144	
	(0.052)	(0.055)	(0.072)	(0.366)	
Income <30K (ref is 30-75K)	0.050	0.059	−0.044	−0.103	0.249
	(0.030)	(0.035)	(0.066)	(0.140)	
Income 75-100K	−0.027	−0.010	−0.105	−0.212	−0.038
	(0.020)	(0.021)	(0.070)	(0.116)	
Income 100K+	−0.048*	−0.036	−0.143	−0.125	−0.217
	(0.022)	(0.023)	(0.093)	(0.126)	
Income unknown	−0.025	−0.027	−0.009	−0.136	0.287
	(0.021)	(0.021)	(0.075)	(0.141)	
Edu: some college+ (ref is no college)	−0.025	−0.022	−0.024	−0.123	−0.255
	(0.024)	(0.026)	(0.056)	(0.114)	
Population weighted	Yes	Yes	Yes	Yes	Yes
R^2	0.017	0.016	0.076	0.108	0.339
Adj. R^2	0.014	0.013	0.051	0.048	0.227
Obs.	4286	3617	423	176	70
RMSE	18.160	17.598	20.367	22.170	14.733

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions show linear probability models of stranger victimization (with victimization by family and friends as zeros in the dependent variable) across all violent victimizations that occurred outside of the home using the National Crime Victimization Survey (NCVS) pooled over 2015-2019 (Bureau Of Justice Statistics, 2021). The column "Overall" shows the estimation results from pooled dataset, and the next columns present estimates on the subsets by victim's race. The estimated model is $Y_i = \beta_0 + \beta_1 Sex_i + \gamma Age_i + \delta Income_i + \beta_2 Education_i + \epsilon_i$. Standard errors are robust. Observations are series weighted.

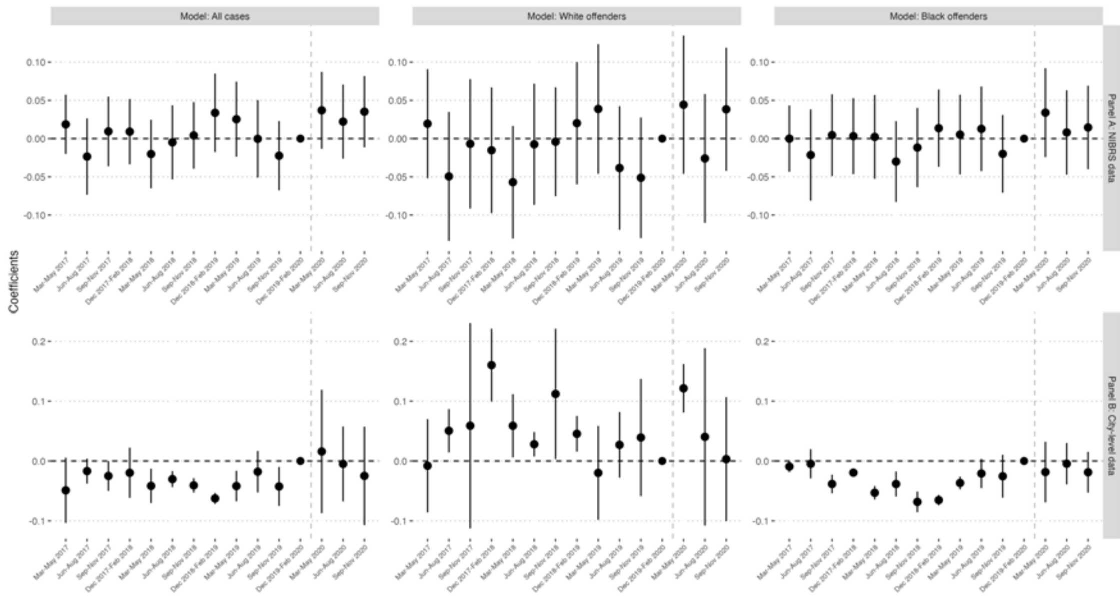
Table A.11: Regressions of Acquaintance Attacks on Victim Characteristics, by Race. Data: NCVS.

	Victim race subset				
	Overall	White	Black	Asian	American Indian
Intercept	0.302^{***}	0.314^{***}	0.163	0.465	-0.009
	(0.038)	(0.042)	(0.096)	(0.238)	(0.157)
Male	-0.059^{**}	-0.072^{**}	0.029	-0.021	-0.062
	(0.022)	(0.024)	(0.066)	(0.105)	(0.135)
Age 12-24 (ref is 25-34)	0.088^{**}	0.074^{*}	0.175^{*}	0.100	0.393^{**}
	(0.033)	(0.036)	(0.078)	(0.116)	(0.138)
Age 35-49	-0.052	-0.069^{*}	0.038	0.045	0.324^{*}
	(0.029)	(0.031)	(0.075)	(0.131)	(0.157)
Age 50-64	0.013	0.007	0.141	-0.322^{**}	0.334
	(0.035)	(0.039)	(0.085)	(0.105)	(0.172)
Age 65+	-0.071^{*}	-0.096^{**}	0.066	-0.157	0.518
	(0.034)	(0.036)	(0.145)	(0.099)	(0.273)
Age unknown	0.031	0.040	-0.060	0.266	
	(0.129)	(0.160)	(0.077)	(0.341)	
Income <30K (ref is 30-75K)	-0.027	-0.060	0.128	-0.384	0.253
	(0.031)	(0.033)	(0.087)	(0.211)	(0.153)
Income 75-100K	0.078^{*}	0.050	0.268	0.010	0.470^{**}
	(0.034)	(0.034)	(0.138)	(0.173)	(0.153)
Income 100K+	-0.026	-0.049	0.109	-0.055	-0.061
	(0.036)	(0.035)	(0.111)	(0.244)	(0.126)
Income unknown	0.003	0.012	0.019	-0.378^{*}	-0.083
	(0.034)	(0.038)	(0.089)	(0.151)	(0.149)
Edu: some college+ (ref is no college)	-0.121^{***}	-0.109^{***}	-0.188^{**}	-0.113	-0.254
	(0.023)	(0.025)	(0.068)	(0.113)	(0.139)
Population weighted	Yes	Yes	Yes	Yes	Yes
R^2	0.060	0.057	0.139	0.195	0.362
Adj. R^2	0.057	0.055	0.117	0.135	0.265
Obs.	4605	3917	450	161	77
RMSE	21.921	21.176	25.761	23.649	18.731

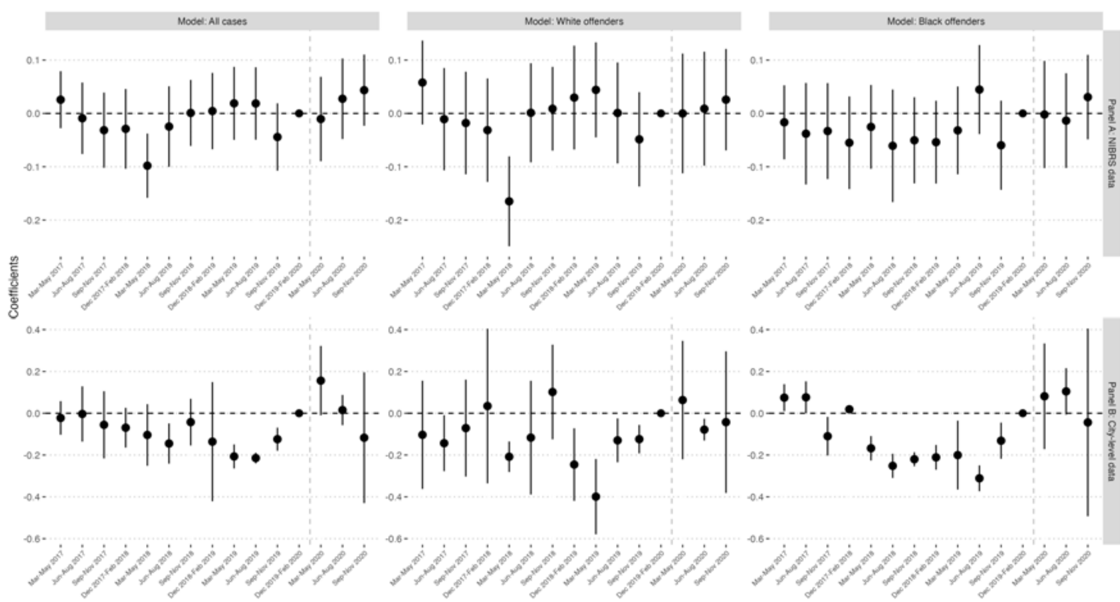
Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions show linear probability models of acquaintance victimization (with victimization by family and friends as zeros in the dependent variable) across all violent victimizations that occurred outside of the home using National Crime Victimization Survey (NCVS) pooled over 2015-2019 (Bureau Of Justice Statistics, 2021). The column "Overall" shows the estimation results from pooled dataset, and the next columns present estimates on the subsets by victim's race. The estimated model is $Y_i = \beta_0 + \beta_1 Sex_i + \gamma Age_i + \delta Income_i + \beta_2 Education_i + \epsilon_i$. Standard errors are robust. Observations are series weighted.

Figure A.1: Event Study Results of the Effect of the COVID-19 Pandemic on Stranger and Acquaintance Attacks.

(a) Victimizations by stranger vs family and friends

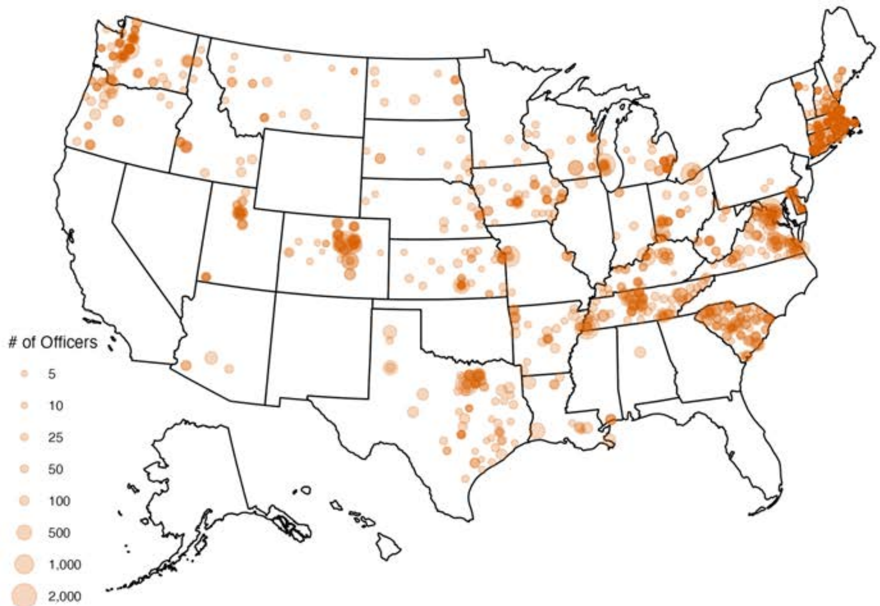


(b) Victimizations by acquaintances vs family and friends



Notes: Figure presents event study regressions by race of the offender (columns) and source of the data (rows). Panels (a) and (b) model the probability of being attacked by a stranger or by an acquaintance respectively. The event studies are based on Equation 1 where the main difference-in-differences term (COVID*ASIAN) is replaced by dummies that interact 3-month time periods with the dummy for Asian-American victims. Coefficients are estimated relative to the period December 2019 to February 2020. Vertical lines on estimates indicate the 95% confidence interval.

Figure A.2: Agencies present in the NIBRS data.



Notes: Figure shows the geographic location of the law enforcement agencies that submitted data to NIBRS in 2020. The legend shows the number of law enforcement officers working in the corresponding agencies.