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Investment in Preventive Care for Children of Middle Eastern Ancestry During the Trump Administration
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ABSTRACT

Individuals of Middle Eastern and North African (MENA) ancestry in the US have been targeted by anti-immigrant and counterterrorism policies and have been the focus of vitriolic political rhetoric. Despite this, lack of data identifying MENA individuals has prevented systematic evaluation of the impact of these policies and rhetoric on MENA communities' wellbeing, including investment in health capital. This paper begins to address this gap in knowledge using a large, longitudinal medical records database with expanded race and ethnicity measures to describe disparities and evaluate the impact of immigration policies and anti-MENA rhetoric on preventive care use among MENA children in the US. Specifically, we evaluate the election of Donald Trump, and find that the election decreased MENA children's utilization of vaccinations and well visits. Documenting MENA health and outcomes following official US policy and rhetoric is paramount for understanding the full consequences of policies that target underrepresented groups.

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Introduction

Parental investment in children is multifaceted, including monetary investments in food and clothing, healthcare investments in terms of preventive and acute/chronic care receipt, and human capital investment in education and time with children. While these investments may vary within families, environmental and contextual factors are also important, especially among groups subject to harsh anti-immigration and counterterrorism policies and accompanying rhetoric. In this paper, we study one such population: individuals of Middle Eastern or North African (MENA) descent in the United States. Since 9/11, MENA communities have been disproportionately affected by anti-immigrant and anti-terrorism public policies and inflammatory official rhetoric. However, as MENA individuals are forced to self-identify as either White or Asian in the Census and other administrative records and surveys, they are rarely identified in administrative or survey datasets. This lack of data has limited the evaluation of the burden of anti-MENA policies and rhetoric on the wellbeing of members of these communities.

In the past decade, there has been a notable increase in studies focusing on the mental and physical burden of anti-Islamic, anti-Arabic, and, more broadly, anti-MENA sentiment on individuals of MENA ancestry in the US (Abuelezam et al., 2018, Abdulrahim et al., 2012; El-Sayed and Galea, 2009; Müller and Schwarz, 2023). Yet, a clear gap in the literature exists in identifying and quantifying the magnitudes of disparities in health and healthcare access for these communities. This paper is among the first to fill this gap, quantifying existing differences in preventive healthcare utilization by MENA children relative to White, Asian, and Hispanic children. Furthermore, we evaluate the impact of anti-MENA rhetoric leading up to and during the administration of President Donald Trump as well as the intersection of that administration with variation in enforcement of immigration policies on use of preventive health care among children.

Our focus on children's healthcare receipt allows us to assess how parental investments respond to anti-MENA sentiment. While these investments are generally endogenous (e.g. Attanasio et al., 2020; Cunha and Heckman, 2007, 2009), we argue that changes in enforcement of immigration policies and changing official rhetoric about MENA individuals leading up to and during the Trump administration cause an exogenous shift in parental investment in children. By focusing on these events, we estimate a plausibly causal effect of anti-MENA sentiment on children's health capital investment. These effects on health investment may be due to changes in parental preferences as well as the non-pecuniary costs of investing in children's health (Hobbs and Lajevardi, 2019). In particular, we argue that during the Trump Administration, the costs of receiving health care may have increased for MENA individuals. This is supported by evidence of increases in anti-Muslim hate crimes following President Trump's anti-Muslim tweets during his presidency (Müller and Schwarz, 2023) and additional evidence that Trump era policies led Arab and Muslim Americans to reduce both their online and in person public presence (Hobbs and Lajevardi, 2019).

We begin by documenting the baseline differences in preventive and primary care utilization between MENA and White individuals in the US using a large, longitudinal health records database linked to demographic characteristics, including an indicator for MENA ancestry. Focusing on procedures performed and medical records, we identify primary well-visits, vaccinations, and lead testing for children. Then, we examine the changes to these relative differences in healthcare utilization associated with two events: changing enforcement of the

Secure Communities (SC) program and the beginning of the Trump administration, which included policies and inflammatory rhetoric aimed at individuals of MENA ancestry.

Our results suggest that while MENA children experienced a gap in the likelihood of compliance with the American Academy of Pediatrics (AAP) recommended vaccines or well visits at the start of the study period, the gap was quickly closing before the start of the Trump administration. However, using a difference-in-differences approach, we find that MENA children decreased their receipt of health care following the 2016 election. Overall, we find robust evidence of a decrease in total vaccinations of approximately 12.5% for MENA children compared to White children. We also find a decrease in well visits in a given month of nearly 20% and an overall decrease in cumulative well visits of nearly 6%. These estimates do not vary consistently with the intensity of SC enforcement pre- and post-election, suggesting that increased immigration enforcement does not explain the bulk of these changes.

We make several contributions to the literature on MENA healthcare utilization, health disparities, and parental investments in children, following anti-immigration policy and anti-immigrant rhetoric. First, given the dearth of data and studies on health and socioeconomic wellbeing of MENA communities, we contribute by providing the first systematic evaluation of healthcare utilization by MENA children using a large, national sample.

Second, using this sample, we also make a methodological contribution. When working with healthcare data, data providers may choose to censor age and birth year information beyond what is required by the Health Insurance Portability and Accountability Act (HIPAA) of 1996. This abundance of caution on data provider's part, however, often presents substantial challenges to evaluation of health care utilization, particularly during childhood, as AAP-recommended care changes rapidly through early and late childhood. We develop a novel technique of recovering a limited amount of age information from age-specific procedure codes in medical records. This technique may expand the types and sources of data used by researchers.

Third, we contribute to the growing literature on the impact of immigration policies on the health and health care of immigrants. The immigration status of an individual may impact the medical care they receive through multiple avenues: socioeconomic factors such as income, insurance status, and access to providers; cultural and language barriers which impede individual willingness to seek care and understand the treatment; and trust of authorities, and medical authorities specifically, in light of federal deportation policies (Derose and Baker, 2000; Calvo, 2016; El Reda et al., 2007; Lee et al., 2017; Diamond et al., 2019; Jang and Kim, 2019). By quantifying the health outcomes resulting from immigration enforcement policies and anti-immigrant rhetoric on MENA communities across the US, we provide initial estimates of the burden imposed by these policies – essential for identifying and reducing health disparities for this population. Our work provides evidence of exacerbated health disparities for MENA communities throughout the Trump administration, laying groundwork for more extensive evaluation of intergenerational, socioeconomic, and health outcomes for these communities in response to these and other federal policies that target MENA populations.

Background

Middle Eastern and North African (MENA) Ancestry

MENA individuals represent a population of more than 3.5 million individuals in the US (Marks et al., 2023), with the largest communities in California, Michigan, and New York. Until recently, in the absence of a federal designation as minority group, administrative records and surveys – federal, state, and local – did not include a MENA ethnic category. This prompted MENA individuals to self-identify as either White, Asian, Black, or Hispanic. This makes it difficult to establish baseline health estimates of the MENA population and it is thus nearly impossible to estimate differences in health between MENA and other minority and non-minority groups in the US.

Anti-MENA Rhetoric and Federal Policies

Despite the difficulty in identifying MENA individuals, they are commonly targeted by anti-immigration policies and political rhetoric. Anti-Muslim, and more generally anti-MENA, sentiment increased drastically following the attacks in New York, Pennsylvania, and Washington, DC on September 11, 2001. Though the events precipitated the wars in Iraq and Afghanistan, President Bush was careful to emphasize his support for Muslims in the US, visiting the Islamic Center in Washington DC, issuing presidential messages on Eid al-Fitr, and explicitly stating support for the peaceful practice of Islam.[1]

Nonetheless, during the Bush administration, and the following Obama administration, increased surveillance of Muslim and MENA communities, combined with treatment of Americans of MENA origin with suspicion, has resulted at times in political mobilization (Bakalian and Bozorgmehr, 2005), but also in increased mistrust of authority in these communities (Howell and Shryock, 2003; Mishra and Lokaneeta, 2021). Figure 1 shows that while hate incidents against Muslims peaked in 2001, incidents have since remained elevated, and again spiked in the mid- to late-2010s, leading up to and during the administration of President Donald Trump.

The Trump administration differed in substance from previous administrations rhetoric and policy. During his election campaign and subsequent to election, Donald Trump singled out

[1] Backgrounder: The President's Quotes on Islam https://georgewbush-whitehouse.archives.gov/infocus/ramadan/islam.html

Muslims, and MENA individuals more widely, as a source of threat and danger to Americans.[2] During the election and his first year of presidency, Donald Trump posted nearly 300 anti-Muslim messages on Twitter, including: "Refugees from Syria are now pouring into our great country. Who knows who they are -- some could be ISIS. Is our president insane?" (Posted November 18, 2015, while still a Republican presidential candidate). Subsequent to his election, President Trump signed an Executive Order banning travel from seven predominantly Muslim countries to the US on January 27, 2017.[3] Though this Executive Order was challenged by the American Civil Liberties Union, President Trump proceeded to reissue the order on March 6, 2017 and on September 24, 2017, reinforcing what was termed the Muslim ban.[4]

More broadly, the Trump administration focused greater policy attention on immigration, in terms of introduction of new restrictions and enforcement of existing policies. In 2019, the Trump administration revised the Public Charge rule. Historically, the Public Charge rule restricted immigrant access to public programs, though it excluded the Supplemental Nutritional Assistance Program (SNAP) and Medicaid. The Trump administration revision extended the rule to include these two programs, which undermined immigrant willingness to seek care, especially during the COVID-19 pandemic (Page et al., 2020).

The rhetoric and enforcement of immigration laws have been shown to negatively impact immigrant health (Abuelezam, 2020; Amuedo-Dorantes et al., 2020, 2018; Vargas and Ybarra, 2017; Vu, 2024; Wang and Kaushal, 2019), and safety net program participation (Alsan and Yang, 2022; Vargas and Pirog, 2016; Watson, 2014). However, few studies document the effect

[2] "Trump Calls for 'Complete Shutdown' of Muslims Entering the US" December 7, 2015. https://www.nbcnews.com/politics/2016-election/trump-calls-complete-shutdown-muslims-entering-u-s-n475821
[3] To be clear, we recognize the distinction between individuals of MENA ancestry and Muslim Americans. There are both MENA individuals who are not Muslim and Muslim countries that are not included in the MENA designation. However, public perception may differ from reality and makes these policies and statements pertinent to the larger MENA populations.
[4] "Timeline of the Muslim Ban" https://www.aclu-wa.org/pages/timeline-muslim-ban

of these policies on the MENA population. Lauderdale (2006) showed that women with Arabic-sounding names were 34% more likely to have low birthweight infants after September 11, 2001. Cunningham, Ruben, and Narayan (2008), summarizing survey responses, show that though Middle Eastern respondents do not differ in self-reported general health, they are more likely to have worse mental health and diabetes rates than native respondents.

Secure Communities

Secure Communities (SC) was an immigration enforcement program active between 2008-2021 aimed at allowing the US Immigration and Customs Enforcement (ICE) agency to identify and deport undocumented immigrants who were charged with or convicted of serious criminal offenses (Alsan and Yang, 2022; Cox and Miles, 2013). The program achieved this by establishing interagency cooperation between ICE, the Federal Bureau of Investigation (FBI), and the Department of Homeland Security (DHS). SC mandated that the fingerprints for all individuals arrested for any crime be shared with DHS, in addition to the previous practice of sharing them with the FBI. If the fingerprints matched, ICE would determine if the individual was plausibly removable under immigration law; if so, ICE would issue a “detainer” on the person and assume physical custody of the individual within 48 hours for initiation of removal proceedings. The “detainer” meant that individuals whose criminal case may have been dismissed or who may be released pre-trial, would now be apprehended by ICE and subject to removal proceedings. The program was rolled out between 2008 and 2013 county by county due to implementation challenges (see Figure A1).

While the initial rollout of SC varied by state and county, we focus only on the variable enforcement of the SC program at the state level during the Trump administration.[5] Though the

[5] We provide additional details on the initial rollout of the program in Appendix A.

focus of SC was immigrants from Latin American countries, the policy also affected immigrants of MENA origin. Figure A2, panel (a) shows total detainers under SC between 2013 and 2019 on a monthly basis, while panel (b) provides details specific to MENA individuals.

Data

COVID-19 Research Database project

We combine two databases provided by the COVID-19 Research Database: electronic health record (EHR) data provided by HealthJump, and individual consumer demographic data provided by AnalyticIQ.[6]

HealthJump is an EHR data management service providing hospitals, private practices, and insurance providers with EHR services. HealthJump data contains both encounters and health records, which includes limited demographic information and detailed health utilization information. Health utilization data includes healthcare appointment information, diagnoses, procedures, lab orders and results, and medications and immunizations from a given encounter. We focus on children in this project and thus limit our sample to those under age 18.

AnalyticIQ data comes from the PeopleCore database, which conducts periodic market surveys of potential consumers that includes 242.5 million US adults. As part of these surveys, AnalyticIQ collects demographic information such as race and ethnicity, including a classification for Middle Eastern.[7] We also identify Hispanic, White, and Asian individuals. In all analyses MENA, Hispanic, and Asian children are compared to non-Hispanic White children.

Data from the HealthJump and AnalyticIQ datasets were linked using tokens based on several combinations of individuals' private information including first name, last name, date of

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[6] The COVID-19 Research Database project, which began in 2020 in response to the spread of COVID-19, consists of voluntary contributions of exclusive de-identified medical data.
[7] Because of the proprietary nature of the data, we are not certain whether the Middle Eastern indicator is generated by a respondent self-report or using an algorithm.

birth, and gender[8]. The resulting dataset allows us to track between 23,000 and 51,000 children annually between 2013 and 2019 (see Appendix Figure B1). We focus on 2013-2019 because the EHR data is particularly stable over this time period, allowing us to estimate effects that are identified off of policy, rather than sample composition changes.[9]

We focus on the procedure and immunization files of the EHR data, which provide a detailed picture of each medical interaction. The procedure file provides the date and identifying code (Current Procedural Terminology (CPT)) of procedures such as lead testing, well-visits, and the administration of vaccinations. However, we use the immunization file to identify the date and type of vaccine, as it additionally includes self-reports and past medical records, reflecting a more complete record. The data also contain partial demographic data, including categories for age, income, race/ethnicity, and state of residence. Though some fields are redacted to ensure individual privacy, judicious analyses allow us to identify healthcare utilization by type.[10]

The analyses conducted in this study focus on children (ages 0-18). This focus is motivated by existing consensus around well-care for this age group: the American Academy of Pediatrics (AAP) has a detailed preventive care schedule for children by age in months, specifying well-visits, vaccinations, and lead testing. These milestones are also recommended

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[8] Because of the proprietary nature of the data, we are not certain how the data provider obtains or defines the gender indicator.

[9] Appendix Figure B2 provides evidence of these state composition changes over time. While the data go back to 1998, the earlier years have a limited sample of MENA individuals; furthermore, the composition of states in the sample stabilizes in 2013, giving us more confidence in the data quality; and, data from 2020 and after include changes in healthcare utilization associated with the pandemic period, which is not the focus of this study. While the change in composition presents a challenge to the nationally representative nature of our results, we mitigate the impact of these compositional changes in all analyses by including state by year fixed effects.

[10] These datasets have certain documented limitations. First, these EHR were not extracted with the intent of conforming with any particular study design. The data tracks a sample of patients from states and insurers whose EHR are managed by HealthJump. The sample size is substantially larger in the later period in the data. Therefore, though the longitudinal nature allows us to track patients across time, it is not a balanced panel. Second, the data captures EHR from hospital systems and insurers which are clients of HealthJump. If a patient changes insurance, their healthcare utilization may no longer be included in the data. Therefore, we cannot be certain that the data contain every record of healthcare encounters for the patients tracked therein. Finally, the data include a sample of patients which may not be representative of the population of the state.

by the Centers for Disease Control and Prevention (CDC), Medicaid, and state and federal policies around lead screening and testing.

Outcomes of Interest

The outcomes of interest are point in time and aggregate measures of well-visits, vaccinations, and lead testing at the month level for each child. We identify well-visits using procedure codes for new or established patients (CPT 99381-99384 and 99391-99394) and focus on incidence in a given month and the cumulative number of well-visits.

To conduct analysis on vaccines, we use the AAP recommended vaccination schedule by age in months and designate a child as on schedule in a given month if within our data, they have the number of injections indicated for that age. Figure 2 depicts the total number of AAP-recommended vaccinations by age in months, with vertical lines delineating pediatric age groups. While late childhood and adolescence have many vaccination requirements, these are few compared to infancy and early childhood. In addition to this "on schedule" measure, we also track the cumulative number of vaccinations. As separate outcomes, we focus on specific vaccines including diphtheria/tetanus/pertussis (DTaP), hepatitis A, hepatitis B, influenza, measles/mumps/rubella (MMR), meningococcal, pneumonia, polio, rotavirus, and varicella. Finally, we also examine the administration of blood lead screening, measured as whether the child ever had a blood lead test.[11]

[11] Procedure codes are used to identify these vaccines and screenings: DTaP: 90702,90700,90606,90723,90698, 90714,90715; Hep A: 90633; Hep B: 90740,90743,90744,90746,9074; Flu: 90672,90674,90685,90686,90687,90688,90756; MMR: 90707,90710; Meningococcal: 90620,90621,90734; Pneumonia: 90670,90732; Polio: 90713; Rotavirus: 90680,90681; Varicella: 90716; lead screening: 83655

Identifying Age from Procedures

One major shortcoming of the data is that, in an effort to protect individual privacy, the data grantor omits children's year of birth. [12] The only information provided is that the individual was born in or after 1996, preventing us from identifying children's ages. Yet, we are interested in compliance with vaccines recommended by the AAP, which requires matching of number of vaccines received to the child's age.

We mitigate this data limitation using the fact that well-visits for children, whether for new or existing patients, are pediatric age group specific. In particular, well-visits that occur in infancy (younger than 1 year), early childhood (age 1-4 years), late childhood (5-11 years), and adolescence (12-17 years) each have different CPT coding.[13] This allows us to use the associated procedure codes and the date of the visit to construct lower and upper bounds for a child's birth year. For example, an infant-coded visit in 2015 implies the child's date of birth is between 2014 (if the child made the visit as a one-year-old) and 2015 (if the child made the visit as a newborn). For children with more than one well-visit in our data, we can narrow the range of birth years by repeating this exercise, and by observing the year when a child changes category of care. As a child ages but the procedure code remains the same, this raises the lower bound for year of birth without affecting the upper bound.[14]

[12] We note that many Data Use Agreements, including the one in effect for this study stipulate: "You will not obtain access to any information that could be used to link, on an individual basis, to the Data, or use "mash-up" or similar technology with, combine other data with, or reengineer or modify the Data in any way, with the intent of re-identification of any Data in contravention of any privacy laws." While the re-identification of age does constitute a "reengineering" of data, the data provider confirmed that they allow it under the terms of the DUA as it does not aim to identify the precise age of the patient.

[13] CPT codes infant (99381, 99391), early childhood (99382, 99392), late childhood (99383, 99393), adolescence (99384, 99394).

[14] One complication of this method is that the child may have a visit before or after their birth month, extending the bounds implied by the procedure code. For example, a child may have a well visit upon turning 5, and when they are 11 years and 11 months, thus allowing for 7 years between these visits.

We note that the distribution of the computed age ranges is similar among White, Asian, Hispanic, and MENA individuals (see Appendix Figure B3). For our main analysis, we use the average from within the computed range of year of birth. Using this age specific feature of CPT coding to bolster the measures available in our data and to counter a specific limitation of the data as provided is an additional contribution of our study. [15]

The use of CPT code to identify the age of the child means that we exclude children in our data without well-visits. This is because an individual born in 1996 or later may receive medical care for non-preventive care, but not have had a well-visit in the EHR data. Such a person may appear in the data because of a single episode of care or a short period of medical care and thus only have had a very limited interaction in our care settings. For example, individuals with at least one well-visit have an average panel length of 57 months, while individuals without these visits born after 1996 have an average panel length of a few months. Given their limited sample time, the exclusion of these individuals should not bias our results.

Secure Communities Enforcement Data

We obtain SC enforcement data from the publicly available Transactional Records Access Clearinghouse (TRAC) at Syracuse University. Specifically, we extract monthly counts of Immigration and Customs Enforcement Detainers issued in each state during the time period of analysis. During our sample period, at its highest, close to 18,000 detainers were issued each month (April 2013 and August 2018); the lowest months occurred during the transition between administrations, at around 6,000 detainers in November 2015 (see Appendix Figure A2). We

[15] Appendix Figure B3 summarizes the distribution of length of ranges for birth year by race and ethnicity of the individuals in our data. The horizontal axis represents the length of the range, against the frequency of persons in the data. Late childhood and adolescence have 6 to 7 years in range in the procedure code for visits, and these age groups also have the fewest recommended well-visits and vaccinations. Thus, while the well-visit code and date allows us to narrow the date of birth for most of our sample, the data shows between 40 and 50% of individuals have a birth year range of 5 years.

normalize the counts of detainers issued by the population in the state in that year, generating a treatment variable of the number of detainers per 100,000 population.

Method

This analysis is both descriptive and causal in nature. First, we characterize the prevalence of preventive care among MENA relative to non-Hispanic White children. Then, we aim to establish a causal link between anti-MENA rhetoric from government officials and its intersection with immigration policy enforcement on the preventive care for this demographic group. In an ideal identification, we would randomly assign individuals differentially to experience rhetoric and follow up on the uptake of preventive care following these shocks. Though we have noted the multiple instances of anti-MENA rhetoric by President Trump, none of these statements were exogenous to other events which may have affected utilization. Thus, our next best alternative is to evaluate the impact of the change of administration in 2017 on MENA children relative to non-Hispanic White, Asian, and Hispanic children. To conduct this analysis, we evaluate a two-way fixed-effects (TWFE) estimation method with a single treatment date. We discuss this methodology below.

Two-way Fixed-effects of the Trump Administration

First, we focus on the administration of Donald Trump, using his inauguration in January 2017 as the policy implementation. Our outcomes of interest in these analyses are preventive healthcare utilization by MENA children. We compare MENA, Asian, and Hispanic individuals to Whites. To do so, we estimate the following model:

$$Y_{ist} = a + \sum_{j=1}^{3} \beta_1^j Race_i^j + \sum_{j=1}^{3} \beta_2^j Post_t * Race_i^j + T_i + \gamma_t + \delta_s + \zeta_{st} + bx_i + \varepsilon_{ist} \tag{1}$$

where Y_{ist} represents preventive healthcare utilization outcomes for individual i, state s, and time t, measured using both incidence in a given month and cumulative total count. The summation over $Race_i^j$ constitutes an indicator variable for $Asian_i$, $Hispanic_i$, $MENA_i$, with White the omitted reference group. The difference by time is represented by $Post_t$, an indicator for the period after the start of the Trump administration, which, on its own, is suppressed by time fixed-effects. The interaction term $\sum_{j=1}^{3} \beta_2{}^j Post_t * Race_i{}^j$ represents the difference in healthcare utilization outcomes by race and ethnicity after the change in administration. T_i is the number of years of panel data for person i. We impose time and state fixed effects; specifically, γ_t are year-month, δ_s are state, and ζ_{st} are state by year. Finally, bx_i are birth year fixed effects. These fixed effects account for nationwide trends in health care, state-wide policy, economic, and political cultures that do not vary over our sample period, and cohort-specific changes in vaccination recommendations. State by year fixed effects also account for changing panel composition over time. To account for cohort specific serial autocorrelation, standard errors are clustered at the birth year level.

The coefficients of interest are $\beta_1{}^{MENA}$ and $\beta_2{}^{MENA}$ which measure baseline difference in outcomes of interest between MENA and non-Hispanic White patients, and the incremental change in the differences in outcomes after the change in administration. We also separate these differences by year in an event study format to examine time dynamics in these differences.

For our difference-in-differences identification to be valid, the treatment and control groups should have similar trends in the pre-period. Figure 3 provides annual incidence and counts of vaccines, well-visits, and lead tests adjusted for birth year, panel length, state and time fixed effects for MENA and non-Hispanic White children. Appendix Figure C1 shows the same annual trends, additionally, for Asian and Hispanic children. Figure 3 shows that MENA patients experienced increasing utilization throughout the 2013-2016 period. To measure a change in this pre-period trend and to ensure that our estimates are valid, we detrend the data using pre-period trends as recommended by Goodman-Bacon (2018).

To implement the Goodman-Bacon (2018) method, we first estimate race/ethnicity-specific trends for the pre-period. Including all fixed effects in this trend regression provides an ethnicity specific intercept. To get this we estimate the following:

$$Y_{ist} = a + \sum_{j=1}^{3} \alpha_1^j Race_i^j + \sum_{j=1}^{3} \alpha_2^j gamma_t^j * Race_i^j + \gamma_t + \delta_s + \zeta_{st} + bx_i + \varepsilon_{ist} \qquad (2)$$

where the sample is restricted to 2013-2016, and the outcome is regressed on race indicators interacted with race-specific linear time trends ($gamma_t{}^j$). We then calculate the residual, $\tilde{Y}_{ist}$ for the entire time period (through 2019). This method essentially subtracts the pre-period trend from the post-period observed values in the outcome of interest. We perform all analyses using the resulting residual as the outcome when estimating equation (1). After this detrending, our analysis rests on the assumption that MENA children do not deviate from the MENA-specific linear trend in a different way than non-Hispanic White children from their trend.

Mechanism

To disentangle the impact of the changing immigration enforcement after the Trump administration from other policies and rhetoric by the administration which affected MENA, Asian, and Hispanic children, we estimate an expanded version of equation (1). Specifically, we add terms which indicate the intensity of SC enforcement in the following manner:

$$Y_{ist} = \alpha + \sum_{j=1}^{3} \beta_1{}^j Race_j + \sum_{j=1}^{3} \beta_2{}^j Race_j * Post_t + \sum_{j=1}^{3} \beta_3{}^j Race_j * Post_t * Detainers_{st} +$$

$$+\sum_{j=1}^{3} \beta_4{}^j Race_j * Detainers_{st} + \beta_5\, Detainers_{st} * Post_t + \beta_6\, Detainers_{st} + T_i + \gamma_t$$

$$+\delta_s + \zeta_{st} + bx_i + \varepsilon_{ist} \qquad (3)$$

We introduce an interaction term $Detainers_{st}$ which is the rate of SC detainers issued in state *s* in month *t*. This term reflects the intensity of enforcement of SC in state *s* throughout the 2013-2019 period. In this equation, we interpret ${\beta_3}^j$ as the incremental effect of one additional detainer issued per 100,000 population on MENA children relative to non-Hispanic White children.

Results

Descriptive Results

Prior to presenting results of estimates of equation (1), we present unadjusted trends in healthcare utilization. Table 1 shows unadjusted averages in outcomes and demographics for MENA and non-Hispanic White children. Appendix Table D1 additionally includes averages for Hispanic and Asian children. The averages are separated by before (column (1)) and after (column (2)) the start of the Trump administration. Our sample includes approximately 2.05 million person-months in the before and 950,000 person-months in the after period, corresponding to 65,180 and 43,390 children tracked, respectively. MENA children in our sample are slightly less likely to be female and more likely to be enrolled in Medicaid than non-Hispanic White children. In terms of preventive care use, MENA children compare favorably to non-Hispanic White children, particularly in the pre-period. In any given month, 20% of MENA children are on schedule with their vaccines, compared to 22% of non-Hispanic White, though cumulatively, MENA children have 1.1 more vaccines than their counterparts. MENA children also have more frequent and higher total count of well-visits than non-Hispanic White children, though they lag in blood lead testing.

When evaluating these indicators over time, however, we notice substantial dynamics among MENA children's use. In Figure 3, we present estimates for vaccines, well-visits, and lead testing, adjusted for birth year, state and time fixed effects. In all three measures, we see a general flat trend for non-Hispanic White children during this period. However, MENA children have generally rising counts of all measures of utilization. Our main analysis tests whether these trends slowdown or reverse in the period during the Trump administration.

Main Analysis

Table 2 presents estimates of equation (1), where each column of the table is a separate outcome. As we show substantial trends in children's healthcare utilization prior to the Trump administration, the Goodman-Bacon (2018) detrending method is applied so that our TWFE approach isolates the incremental change occurring during the 2013-2019 period. We report the coefficient for baseline MENA and the incremental change for MENA after the start of the Trump administration. Appendix Table D2 reports coefficients for Hispanic and Asian children as well. All estimates are adjusted for birth year, panel length, and state, month, year, and state-by-year fixed effects.

Keeping in mind that detrending removes pre-period differences, we find that in the period during the Trump administration, MENA children experience significant declines in vaccines and well-visits relative to non-Hispanic White children. In particular, the likelihood of vaccine compliance fell by 2.8 pp in the post period, constituting a 10% effect on the mean.[16] While this estimate is not statistically significant at conventional levels, cumulatively, MENA

[16] We report non-detrended pre-period dependent variable mean for MENA children in all tables, and calculate effect magnitudes relative to this non-detrended mean.

children received 1.7 vaccines fewer vaccines in the after period, constituting a statistically significant 11.5% decline relative to the mean. We observe a 0.8 pp decrease in the probability of a well-visit in any month, a 20% effect on the mean. We find no statistically significant change in lead testing in the after period, though the coefficient is negative and of a meaningful magnitude.

We next examine the dynamic relative differences in vaccines, well-visits, and lead testing using an annual event study format. The results reported above in Table 2 show significant declines in vaccines and in well-visits, but no statistically significant change in lead testing. To evaluate the validity of these estimates, we need to ascertain whether there are differential deviations from the linear trend (Goodman-Bacon, 2018). Figure 4 presents results for MENA, and Appendix Figure C2 for Asian and Hispanic, additionally. For all outcomes, we find no evidence that MENA and White children differentially deviate from the linear trend, supporting the validity of our identification strategy.

Though the results in Table 2 show statistically significant declines only in the total number of vaccines, Figure 4 shows evidence of up to a 0.04 pp decline in the monthly probability of being on schedule in 2018 and 2019. There is a similar trend in well-visits – both monthly and cumulative number of well-visits decline in 2018 and 2019. Finally, though lead tests showed no statistically significant change in the post-period, we find a clear downward trend.

The data is at monthly frequency; therefore, an annual event study may obfuscate dynamics. Appendix Figure E1 repeats the event study analysis for well-visits, only, at quarterly and monthly frequency. While the monthly incidence of well visits is dominated by noise, the cumulative count of visits shows a clear and consistent decrease starting in the months after the Trump administration.

Vaccines

Our estimates show that MENA children have fewer vaccines on record after the start of the Trump administration. To better understand which vaccinations are driving these results, we separately analyze vaccines by type in Figure 5, which reports the difference in the cumulative number of vaccines before and after the administration of MENA relative to non-Hispanic White children. First, we note that 5 of the 10 vaccines listed here decline in the post-period. The 5 remaining vaccines experience indistinguishable differences to modest increases.

Of the vaccines with wider disparities, two stand out: varicella and Hepatitis A. MENA children are 4.5 pp less likely to have received a varicella vaccine relative to non-Hispanic White children at baseline. In the post period, this gap increased to 6.3 pp, an almost 40% widening of the disparity. MENA children had higher Hepatitis A vaccination rates compared to non-Hispanic White children in the pre-period, leading by 6 pp. The increased prevalence may be due to the fact that the vaccine is recommended to all individuals traveling internationally to areas where HepA is common. In the post period, the difference declined to 3.5 pp, a 41% decrease. The declines in these vaccines constitute a divestment in health of MENA infant and toddler preventive care.

Mechanisms: Secure Communities

Prior to presenting the results of our immigration enforcement analysis, we focus on the source of identifying variation in the data. Heightened enforcement of the SC program consisted of increased use of detainers, as defined in the Background section (see Appendix A for more detail), as well as removals resulting from these. Though few detainers result in actual removals, they generate substantial fear and mistrust of authorities (Howell and Shryock, 2003; Mishra and Lokaneeta, 2021), making the detainers an appropriate measure of SC enforcement. Appendix Figure A2 provides monthly detainer counts during this period. Though the SC program was introduced by the Bush administration, it was implemented during the Obama administration, then greatly rolled back in Obama's second term. Issuance of detainers increased substantially at the start of the Trump administration, reaching levels seen at the height of the program in the first Obama administration. We make use of the asymmetric increase in detainers by state to disentangle the impact of fears of immigration enforcement from anti-MENA rhetoric in the administration.

To do this, we interact the TWFE model with the rate of detainers per 100,000 population as specified in equation (3) and present these results in Table 3. The interaction term *MENA*DETAINERS* represents the effect of detainers on MENA healthcare receipt pre-Trump administration, while the interaction of those terms with *POST* represents the relationship of detainers with MENA healthcare receipt post administration. The results in this analysis are mixed. We find no negative incremental impact of SC enforcement on vaccines and well-visits. However, we find that detainers affect lead testing significantly, with a 0.26 pp reduction in any lead testing for each one unit increase in detainers per 100,000, constituting close to a 50% effect on the mean. The full output of this analysis, including Asian and Hispanic children, is presented in Appendix Table D3.

Heterogeneity and Robustness

Gender Differences

Parental investment in health may differ by the gender of the child, especially in the presence of increased personal or family costs. In Table 4, we stratify our estimates from Table 2 by gender of the child. We find that MENA girls in the after period experience a larger and statistically significant decline (-2.29, 16.4%) in vaccines than MENA boys (-1.18, 7%). On the other hand, MENA boys experience a 27% decline in monthly likelihood of a well-visit, while girls experience a non-statistically significant 14% decline. We find no significant difference in lead testing between boys and girls. These results suggest that both MENA boys and girls experience a negative effect on preventive care, though the channels of impact differ.

Payer Differences

MENA households may respond differently to the anti-MENA rhetoric depending on their socioeconomic status. For example, financially secure MENA households may be less affected, while households relying on public programs may feel more threatened by administrative rhetoric. While the data includes insurance status, approximately 40% of children have missing payer information. In a given month, if a child has Medicaid identified as a payer, we continue to categorize that child as Medicaid eligible until they have an encounter where the payer is private, at which point they are categorized as privately insured. Then, we continue to classify the child as privately insured until an encounter indicates otherwise. Children with no insurance information at any point during the panel are classified as missing. We test the heterogeneous impact by insurance by separating our sample into three groups: Medicaid-insured, privately-insured, and those with missing insurance information. The results are presented in Table 5.

We find that Medicaid eligible MENA children experience a greater decline in vaccines, well-visits, and lead tests than privately insured children. Medicaid children have a 11.8 pp (32%) decline in compliance and 7.3 (45%) fewer vaccines in the post-period while privately insured children experience no statistically significant decrease in compliance and 3.1 (23%) fewer vaccines total in the post-period. We find that both Medicaid and privately insured have similar declines (between 0.6 and 0.9pp) in monthly likelihood of a well visit.

Children with missing insurance information appear to differ from the Medicaid and privately insured children. In particular, they are between one-third and one-half as likely to be on schedule on vaccines as the other groups and have much fewer vaccines on average. Surprisingly, these children are just as likely as the Medicaid or privately insured to have well-visits. In terms of the impact of the Trump administration on their receipt of preventive care, they experience a 7.3 pp decline in vaccination schedule compliance. However, they do not experience significant declines in number of vaccines or well-visits. It is unclear whether these children are self-paying, whether these are publicly or privately insured children missing insurance information, or whether these are short-term or occasional users of the healthcare system resulting in incomplete payer information. Thus, this lack of context does not allow us to further interpret the differential impact the Trump administration has on this group of children.

Sample Composition Robustness

The opportunistic nature of the dataset means that the composition of MENA population may determine the extent to which these effects are geographically concentrated. For example, since the state composition in the data is not nationally representative, our estimates may give undue weight to populations in over-represented states. To assess whether certain states drive our findings, we perform leave-one-out testing of our main TWFE equation (2), sequentially dropping one state at a time and visually reporting the resulting estimate in Appendix Figure F1. Each panel represents one outcome from our main specification in Table 2. In each panel, the first point (filled in black) represents the main estimate for that outcome along with a 95% confidence interval. The subsequent hollow points represent the estimate after leaving out the corresponding state on the horizontal axis. In each panel, we find that exclusion of most states does not materially affect our point estimate and its confidence interval. However, the exclusion of New York or Ohio does affect the estimates substantially. We discuss these states in detail below.

Exclusion of Ohio makes the estimates for the vaccine gap larger, but has little effect on the estimates for well-visits and lead testing. However, in all cases, excluding Ohio increases the confidence interval of estimates. As discussed previously, Ohio represents between 20% and 25% of the sample. Thus, its exclusion reduces statistical power, resulting in noisier estimates. Furthermore, the change in vaccine estimate suggests that MENA children in the states have a smaller gap in care in this dimension.

Exclusion of New York changes the coefficient estimates substantially. Contrary to Ohio, New York is not over-represented in our sample. Thus, the change in estimate upon its exclusion suggests that MENA children in New York have substantially worse outcomes compared to non-Hispanic White children. This difference could stem from differences in the MENA populations in New York compared to other states. According to the 2020 census, New York has the third largest MENA population in the United States, and it has a relatively wide mix of ethnicities, including Egyptian, Lebanese, and Israeli (Marks et al., 2023). In fact, New York may be home to more recent immigrants compared to other states, as it is a prominent port of entry for travelers from the region. Therefore, the gap in effect for the New York MENA population could be due to recency of immigration.

Age Range Robustness

In Appendix Table G1, we evaluate the robustness of our estimates to the choice of mean of age range. In Panel A, we choose the highest possible birth year from the range, effectively defining the youngest possible cohort of children in our sample. In Panel B, we define the age based on lowest possible birth year, and thus defining the oldest possible cohort of children. Our estimates remain similar in magnitude and sign for all outcomes. However, some estimates lose statistical significance. As expected, when defining the youngest possible cohort, the gaps in vaccines and well-visits are less significant. In Panel C, we include all individuals born after 1996, irrespective of presence of well-visit on record which would allow us to narrow birth year. This wider sample shows very similar gaps in vaccines and well visits for MENA children.

Discussion

Our Results in the Context of Literature

Our first result shows that at the start of our analysis window, MENA children lag in many preventive care measures compared to non-Hispanic White children. Figure 3 shows that, adjusting for age, state and time attributes, MENA children are 13 pp less likely to be on-schedule with their vaccines, have 0.20 fewer well- visits, and are 2 pp less likely to have had a blood lead test. This gap is consistent with experience of other immigrant communities in the US, documented by other studies (see e.g. Mahmoudi and Jensen, 2012; Vega et al., 2009), but as Appendix Figure D1 shows, MENA children lag other minorities along most dimensions of preventive care.

Second, we show that between 2013 and 2016, MENA children experienced improvement in all of these outcomes. By the end of this period, while MENA children still lagged behind in vaccine schedule compliance and lead testing, they had caught up in the cumulative number of vaccines and well visits relative to non-Hispanic White children. In fact, we find that in 2016, MENA children had the largest number of well-visits compared to all groups analyzed here. This closing of disparities is consistent with overall trends in US. This period coincides with the implementation of the Affordable Care Act (ACA) insurance exchanges, which have been shown to decrease disparities in access for Black and Hispanic individuals (Angier et al., 2017; Ukert and Giannouchos, 2023) as well as for low income individuals (Buettgens et al., 2021).

Third, we find that after the start of the Trump administration, existing differences between MENA and non-Hispanic White children were exacerbated. Therefore, the pace of progress in this community slowed, and in some cases reversed, after the start of the Trump administration. While we cannot isolate the exact policy or policies that led to this increased disparity, we do not find a consistent relationship between immigration enforcement, as measured by Secure Communities detainers, and healthcare utilization after the change in administration.

This leaves the tone set by rhetoric as one prominent mechanism through which the change in administration may have affected preventive care for MENA children. The Trump administration's rhetoric may have reduced public engagement among MENA individuals, which is consistent with literature on this topic in sociology (Hobbs and Lajevardi, 2019). The rhetoric mechanism has also been explored by Muller and Schwarz (2023), who found evidence supporting a causal link between anti-MENA Twitter messages by President Trump and anti-

Muslim hate crimes in the days that follow. We do not find a consistent relationship between anti-MENA Trump messages and healthcare utilization, either in a direct endogenous relationship or using the instrumental variable approach proposed by Muller and Schwarz (2023). However, since preventive health care is generally scheduled well in advance, it is unlikely that negative sentiment will affect appointments in the immediate week that follows. Furthermore, the instrument requires use of a very small sample for analysis, which may make estimates underpowered to detect an effect.[17]

Our findings are consistent with other literature on Trump era policies and immigrant health. Mesa et al. (2020) and Fleming et al. (2019) provide qualitative evidence of increased stress, mental health burden, fear of deportation, and fear of family separation among providers serving Latino immigrants as well as their patients in Southeast Michigan after the 2016 Presidential election. In turn, Benavides et al. (2021) show qualitative evidence that immigrant families would pursue alternative, whether formal and informal, ways of accessing health care. In a small sample qualitative interview study of immigrant children, Lieberman et al. (2023) explicitly show the negative impact of threat of parental deportation on psychological and emotional well-being. Giuntella et al. (2021) show that while the Deferred Action for Childhood Approvals (DACA) improved sleep patterns among immigrants when it was enacted in 2012, these gains were reversed when President Trump terminated the program in 2017.

The Trump administration also coincided with the reversal and repeal of some ACA features. Courtemanche et al. (2021) show that insurance coverage gains resulting from a combination of Medicaid expansion, subsidies, and insurance mandate increased in 2017, but declined to pre-election levels by 2019. As the ACA reduced disparities in access to care among

[17] The results of this IV analysis are available upon request.

Black and Hispanic individuals, the effects we estimate here may in part reflect changing implementation of ACA benefits. However, our stratified analysis of Medicaid and privately insured children does not support this conclusion.

Policy Implications

On March 29, 2024, the Office of Management and Budget issued a revision to the Standards for Maintaining, Collecting, and Presenting Federal Data on Race and Ethnicity (SPD15) which required adding "MENA as a minimum reporting category, separate and distinct from the White category" (Federal Register 89 FR22182 p 22182).[18] For the first time, this shift in identification of MENA respondents in surveys and administrative records allows for acknowledgement of their experience as distinct from that of non-Hispanic White individuals in United States. This change in collection and presenting of data opens a range of policy imperatives which stem from our findings.

Our study highlights the existing disparities in preventive healthcare utilization among MENA children. Abuelezam, El-Sayed, and Galea (2018) point out that recent increases in Islamophobia both around the world and in the US have resulted in an extensive psychological burden on Arab-American individuals – a healthcare need which will remain unaddressed because little data exists to assess disparities in healthcare access for these groups. Overcoming such data limitations, this study is the first to effectively evaluate MENA healthcare utilization at the national scale. As we find disparities in preventive care among children, our study motivates funding and policy actions towards creation of data sources for such evaluations.

This study also provides additional evidence of declining disparities by race and ethnicity which are consistent with the literature for other racial and ethnic groups (Angier et al., 2017;

[18] Available at https://www.federalregister.gov/documents/2024/03/29/2024-06469/revisions-to-ombs-statistical-policy-directive-no-15-standards-for-maintaining-collecting-and

Ukert and Giannouchos, 2023). However, though policies such as the ACA increased access to care for many minority groups, immigrants have benefited much less from these expansions, complicated by lack of insurance, language barriers, fear of deportation, and cultural barriers. To address these concerns, the Centers for Medicare and Medicaid Services (CMS) released an updated framework to advance health equity for people covered by their programs.[19] While such programs can be readily implemented towards closing gaps in health for other minority groups, identifying and reaching out to MENA individuals will be more challenging.

Finally, we provide evidence of the real effect of anti-MENA policy and rhetoric on health care use of MENA individuals. Muller and Schwarz (2023) caution against the use of their results on the impact of anti-Muslim sentiment on social media to restrict this medium of communication. Though our results do not point directly towards social media or presidential language as the driver of our findings, they nonetheless motivate greater care in policy formulation when singling out a race or ethnic group. They also motivate closer evaluation and understanding of the burden imposed by policies which specifically single out MENA individuals.

[19] CMS Framework for Health Equity 2022-2023. https://www.cms.gov/files/document/cms-framework-health-equity-2022.pdf Accessed May 23, 2024.

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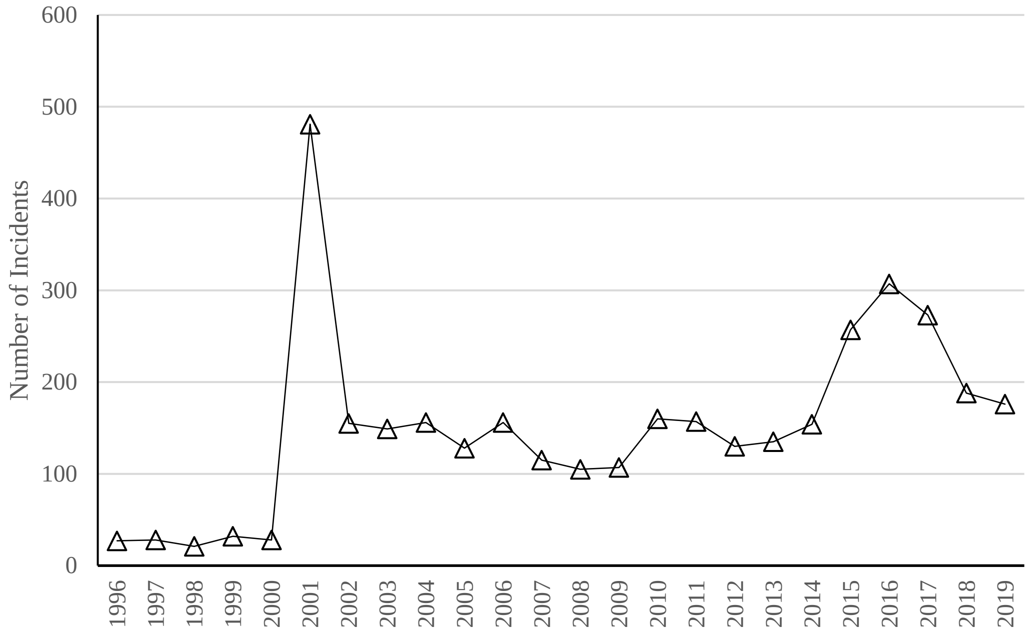
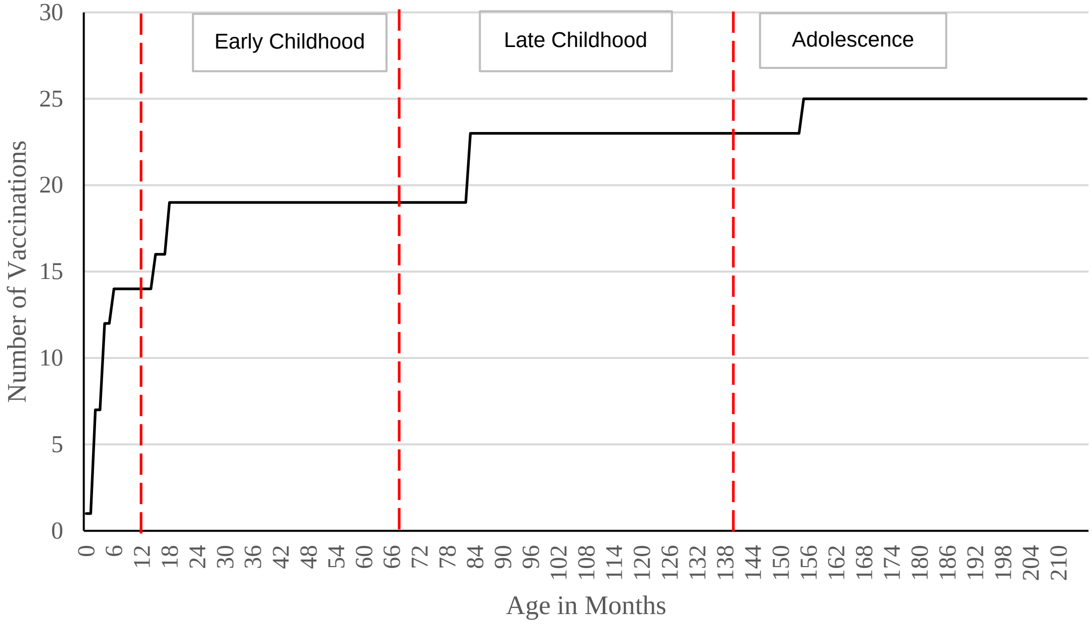
Figure 1: Number of hate-crime incidents against Muslims by year



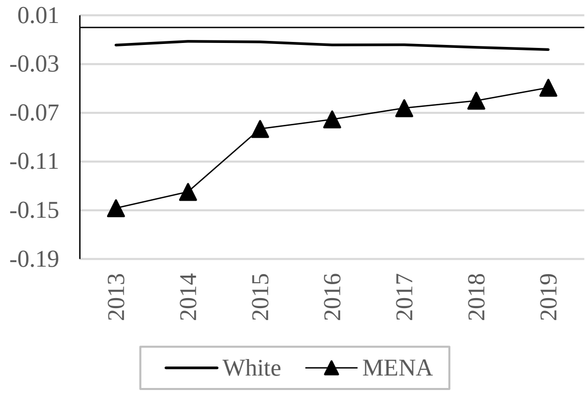
Source: FBI Hate Crime Report

Figure 2: Vaccination schedule matched against well-visit categories

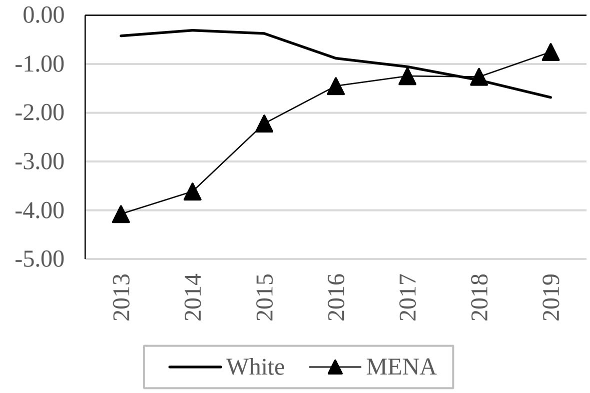


Source: American Academy of Pediatrics.

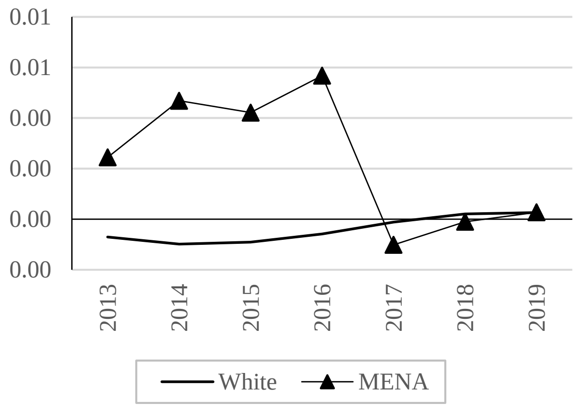
Figure 3: Time trends by race and ethnicity, children



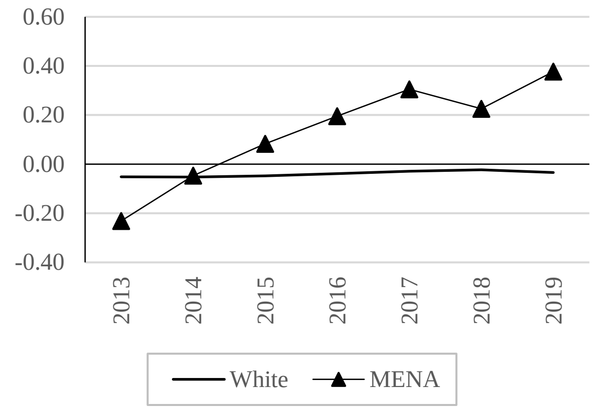
(a) On schedule on vaccines



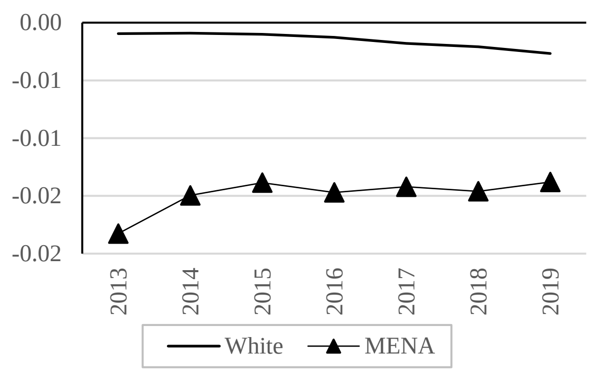
(b) Total count of vaccines



(c) Any well-visits in month



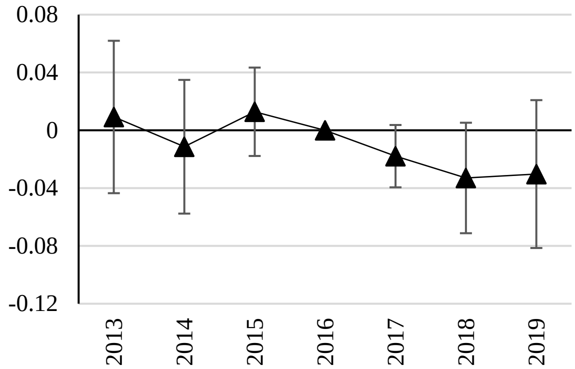
(d) Total count of well-visits



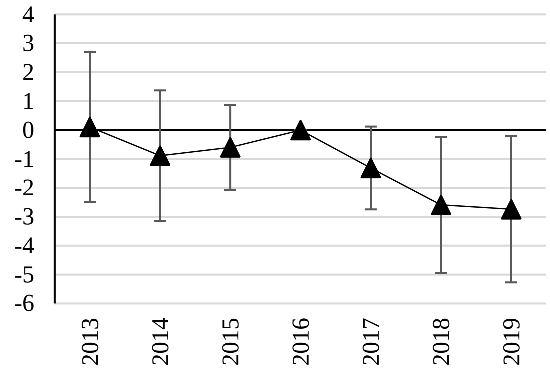
(e) Total count of lead tests

Source: COVID-19 Research Database, 2013-2019
Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year.

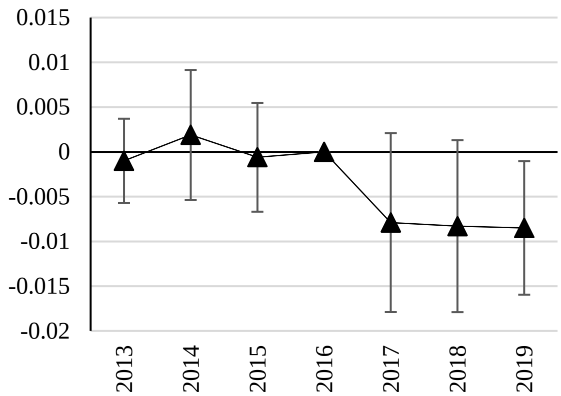
Figure 4: Event study of health outcomes for MENA relative to non-Hispanic White children



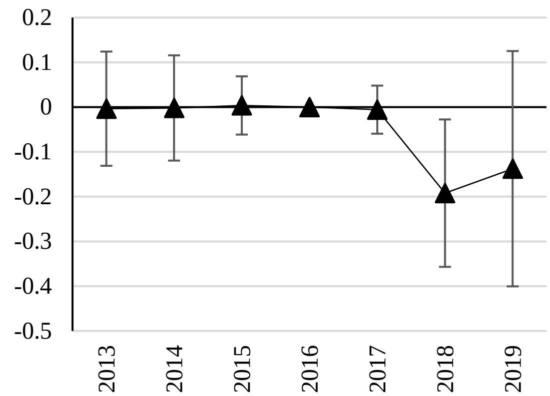
(a) On schedule on vaccines



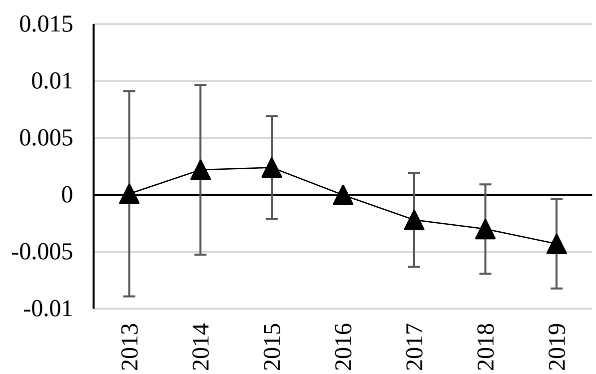
(b) Total count of vaccines



(c) Any well-visits in month



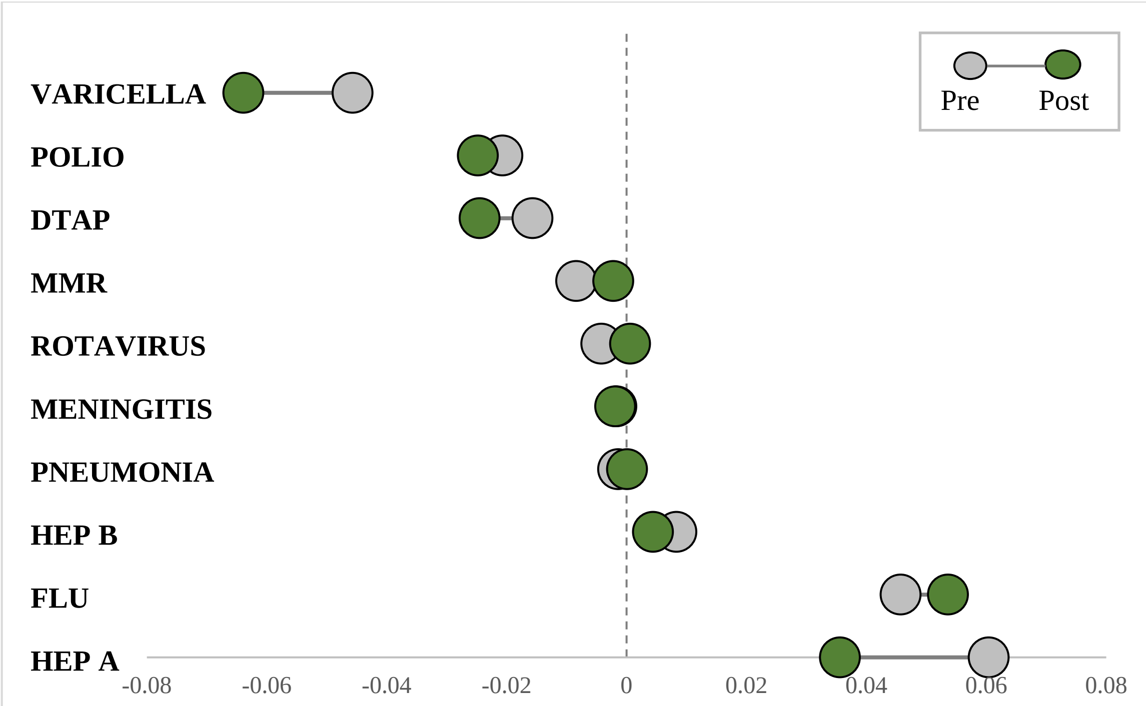
(d) Total count of well-visits



(e) Total count of lead tests

Source: COVID-19 Research Database, 2013-2019
Notes: Each point is estimate of difference between MENA and non-Hispanic White child relative to 2016. Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. 95% confidence intervals around estimate.

Figure 5: Pre- to Post-period comparison of specific vaccines for MENA relative to non-Hispanic children.



Source: COVID-19 Research Database, 2013-2019

Notes: Each point is estimate of difference between MENA and non-Hispanic White in the pre-period (grey) and the post-period (green). Outcomes are the cumulative count of vaccines by type. Estimated adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year.

Table 1: Summary Statistics

	(1) Before	(2) After
Panel A: Vaccines		
% on schedule		
MENA	0.2080	0.2952
Non-Hispanic White	0.2215	0.2893
Total count		
MENA	8.2965	3.6053
Non-Hispanic White	7.1877	3.8358
Panel B: Well visits		
% with any in month		
MENA	0.0891	0.0582
Non-Hispanic White	0.0804	0.0536
Total count		
MENA	1.5991	0.8636
Non-Hispanic White	1.3764	0.8007
Panel C: Blood lead testing		
Total count		
MENA	0.0000	0.0000
Non-Hispanic White	0.0004	0.0005
Panel D: Demographics		
Female		
MENA	0.4493	0.4904
Non-Hispanic White	0.5120	0.5347
Medicaid		
MENA	0.2368	0.2036
Non-Hispanic White	0.1726	0.1405
n	65182	43493
N	**2050337**	**948907**

Source: COVID-19 Research Database, 2013-2019
Notes: For vaccines, the monthly indicator is whether child is compliant with AAP recommended schedule.

Table 2: Two-way fixed effects for MENA relative to non-Hispanic White children.

	(1) Vaccines		(2) Well-Visits		(3) Lead Test
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
MENA	-0.0006	-0.0361	0.0002	-0.0036	0.0001
	(0.0154)	(0.3675)	(0.0013)	(0.0533)	(0.0046)
MENA * POST	-0.0283	-1.6976**	-0.0083***	-0.0964	-0.0041
	(0.0204)	(0.7276)	(0.0028)	(0.0661)	(0.0039)
Dep. Var. Mean	0.2808	14.6871	0.041	2.025	0.0055
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES
N	2999244	2999244	2999244	2999244	2999244

Source: COVID-19 Research Database, 2013-2019

Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.

Table 3: Two-way fixed-effects estimates, differentiating impact of Secure Communities

	(1) Vaccines		(2) Well-Visits		(3) Lead Test
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
MENA	-0.0281	-0.7433**	-0.0004	-0.1067	-0.0002
	(0.0218)	(0.3002)	(0.0016)	(0.0628)	(0.0039)
DETAINERS	0.0044***	0.1748***	-0.0002	0.0050**	0.0004***
	(0.0005)	(0.0352)	(0.0004)	(0.0024)	(0.00004)
MENA * DETAINERS	0.0134*	0.3523***	0.0003	0.0480*	0.0003
	(0.0071)	(0.1180)	(0.0004)	(0.0263)	(0.0006)
MENA * POST	-0.007	-2.5378***	-0.0069	-0.0702	0.0024
	(0.0193)	(0.7852)	(0.0053)	(0.1414)	(0.0035)
DETAINERS * POST	0.0001	0.0487	-0.0001	-0.0029	-0.000001
	(0.0012)	(0.0687)	(0.0006)	(0.0064)	(0.0001)
MENA * DETAINERS * POST	-0.0107	0.2554	-0.0005	-0.0184	-0.0026***
	(0.0091)	(0.1746)	(0.0015)	(0.0596)	(0.0007)
Dep. Var. Mean	0.2808	14.6871	0.041	2.025	0.0055
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES
N	2999244	2999244	2999244	2999244	2999244

Source: COVID-19 Research Database, TRAC Immigration Data 2013-2019.

Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.

Table 4: Two-way fixed effects estimates stratified by gender

	(1) **Vaccines**		(2) **Well-Visits**		(3) **Lead Test**
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
Panel A: Female					
MENA	0.0082	-0.2927	-0.0007	0.0373	-0.0025
	(0.0234)	(0.6020)	(0.0011)	(0.0609)	(0.0047)
MENA * POST	-0.0489	-2.2960**	-0.0059	-0.0809	-0.0047
	(0.0307)	(1.0832)	(0.0040)	(0.0669)	(0.0049)
Dep. Var. Mean	0.2653	13.9532	0.0425	2.061	0.0051
N	1402068	1402068	1402068	1402068	1402068
Panel B: Male					
MENA	-0.0099	0.2177	0.0012	-0.056	0.0038
	(0.0262)	(0.6543)	(0.0018)	(0.0855)	(0.0073)
MENA * POST	-0.0097	-1.1858	-0.0110***	-0.116	-0.0041
	(0.0236)	(1.9627)	(0.0027)	(0.1063)	(0.0067)
Dep. Var. Mean	0.2943	15.3312	0.0398	1.9935	0.0059
N	1597176	1597176	1597176	1597176	1597176
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES

Source: COVID-19 Research Database, 2013-2019.
Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.

Table 5: Two-way fixed effects estimates stratified by insurance type

	(1) Vaccines		(2) Well-Visits		(3) Lead Test
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
Panel A: Medicaid					
MENA	0.1315**	4.6248***	-0.0045*	0.2549*	-0.0039
	(0.0527)	(1.4627)	(0.0025)	(0.1301)	(0.0050)
MENA * POST	-0.1189**	-7.3359***	-0.0060**	-0.3893	-0.0039
	(0.0491)	(1.3371)	(0.0024)	(0.2329)	(0.0057)
Dep. Var. Mean	0.3714	16.1327	0.0394	2.4087	0.0203
N	400736	400736	400736	400736	400736
Panel B: Private					
MENA	0.1274**	3.0582**	0.0019	0.0761	0.0213*
	(0.0459)	(1.1806)	(0.0032)	(0.1264)	(0.0123)
MENA * POST	-0.0407	-3.1721**	-0.0093**	-0.0684	-0.0014
	(0.0462)	(1.3425)	(0.0042)	(0.1042)	(0.0083)
Dep. Var. Mean	0.2555	13.1012	0.0401	2.2515	0.0039
N	1276263	1276263	1276263	1276263	1276263
Panel C: Missing					
MENA	0.0413**	1.2346***	0.0008	0.1293*	0.0101**
	(0.0167)	(0.3268)	(0.0008)	(0.0685)	(0.0048)
MENA * POST	-0.0731**	0.7661	-0.0075	0.1109	-0.0068
	(0.0298)	(1.6391)	(0.0045)	(0.1648)	(0.0045)
Dep. Var. Mean	0.1245	8.9864	0.054	2.3128	0.0048
N	1322245	1322245	1322245	1322245	1322245
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES

Source: COVID-19 Research Database, 2013-2019.

Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.

Appendix A: Secure Communities

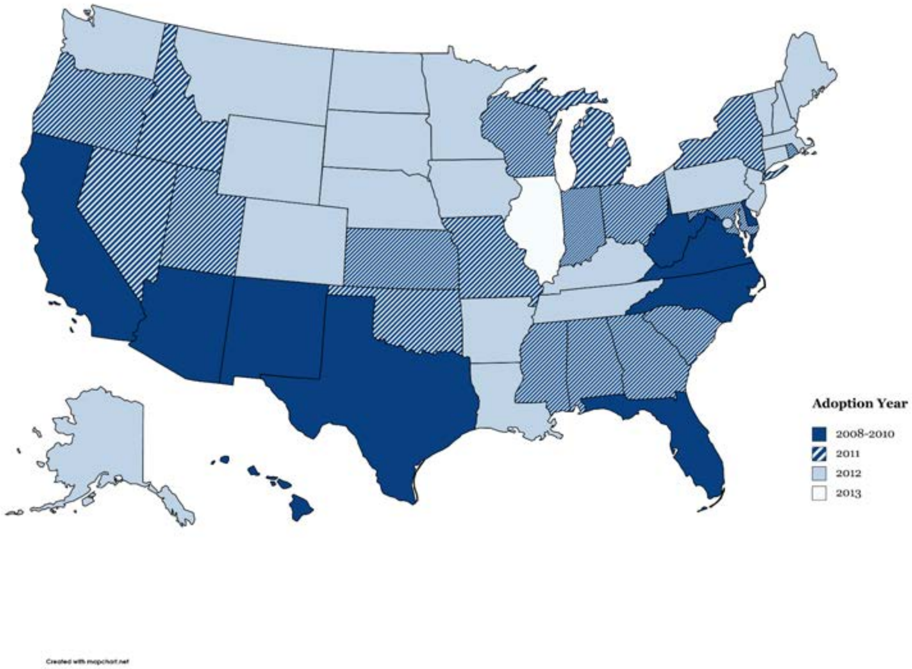
Secure Communities (SC) was an immigration enforcement program active between 2008-2021 aimed at helping the US Immigration and Customs Enforcement (ICE) agency identify and deport undocumented immigrants who were charged with or convicted of serious criminal offenses (Cox & Miles 2013, Aslan & Yang 2018). The program achieved this by establishing interagency cooperation between ICE, the Federal Bureau of Investigation (FBI), and the Department of Homeland Security (DHS). Before SC, an individual arrested for a crime by a state or local law enforcement agency would be fingerprinted, and these would be checked and submitted to FBI databases to identify criminal background which is then conveyed back to the local agency. The individual's immigration status, and violation of federal immigration law, was determined through a lengthy interview at the time of jail or prison intake, which occurred at fewer than 15% of jails and prisons in only about 2% of US counties (Cox & Miles 2013).

SC circumvented this inefficient process by mandating that all fingerprints received by the FBI be shared with DHS. If the fingerprints matched, ICE would determine if the individual lacked documentation or was plausibly removable under immigration law; if a probable cause for removability existed, ICE would issue a "detainer" on the person and assume physical custody of the individual within 48 hours for ICE for initiation of removal proceedings. The "detainer" meant that individuals whose criminal case may have been dismissed or who may be released pre-trial, would now be apprehended by ICE and subject to removal proceedings.

Though the program was approved in October 2008, its implementation was mired in administrative difficulties, as states were tasked with initiating an agreement with DHS for data sharing. Even within a state, technical difficulties prevented all counties from implementing the data sharing at the same time: many jurisdictions did not have fingerprint scanners. Thus, the program was slowly adopted over several years, and fully activated across the entire country only in January 2013 (Figure A1). Additionally, while the program was adopted by state, states rolled out the program by county, creating additional within state variation.

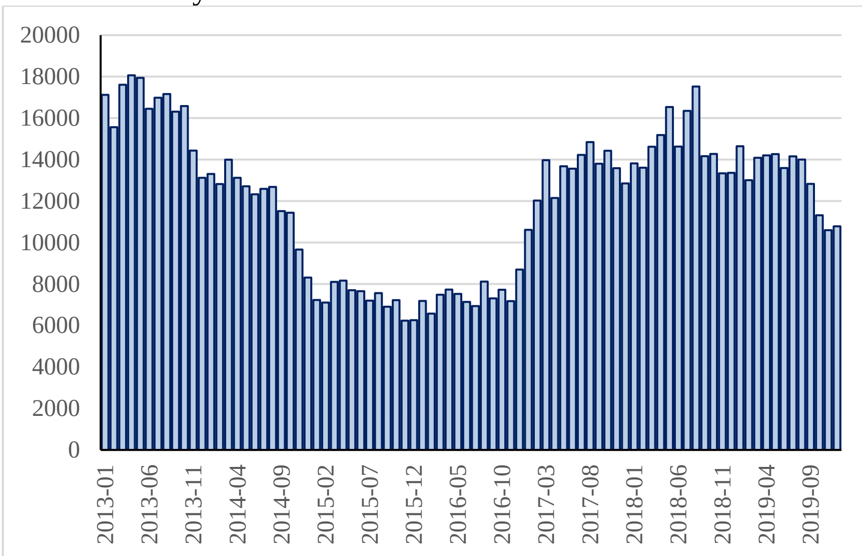
Though the focus of SC was immigrants from Latin American countries, the policy also affected immigrants of MENA origin. Figure A2 shows detainers and removals under SC between 2013 and 2020 on a monthly basis. As the figure shows, SC had multiple phases of implementation: In the initial 2009-2011 period, detainer orders were issued indiscriminately, and few of them resulted in eventual removal of the individual from the country. Enforcement peaked 2012-2014, as more detainers resulted in removals, though the former outnumbered the latter twofold. Towards the end of this period, detainers declined sharply though removals remained steady as ICE refined the detainer order process. At the start of the Trump administration, SC once again gained prominence, with a surge in detainer orders. SC was put on hold at the start of the COVID-19 pandemic and was fully revoked by the Biden administration in 2021. Figure A2, panel (b) contains MENA specific detainers.

Figure A1: Adoption of Secure Communities by states

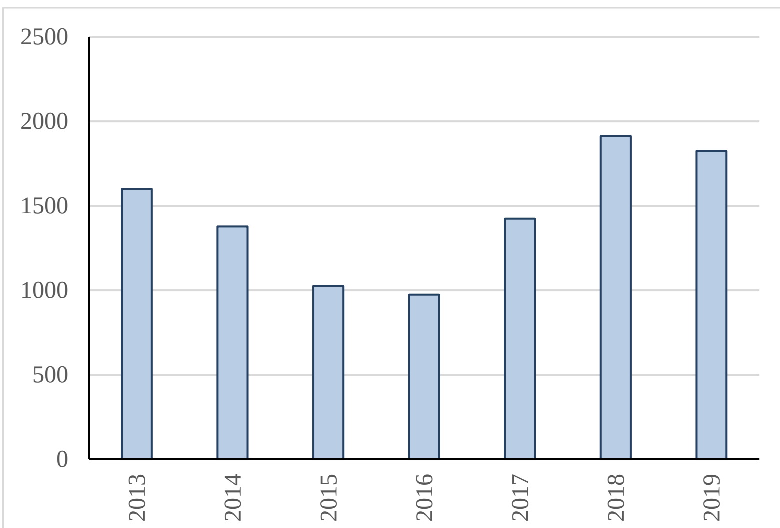


Source: US Immigration and Customs Enforcement Secure Communities Monthly Statistics through August 31, 2014 https://www.ice.gov/doclib/foia/sc-stats/nationwide_interop_stats-fy2014-to-date.pdf

Figure A2: Detainer orders by month



(a) All detainers by month



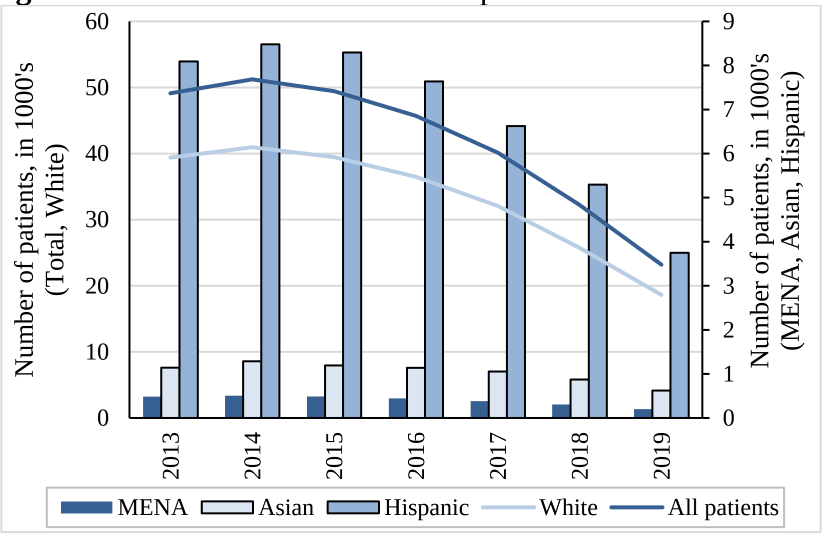
(b) Detainers issued to individuals from MENA countries by year

Source: TRAC Immigration https://trac.syr.edu/immigration/ Accessed January 25, 2023.

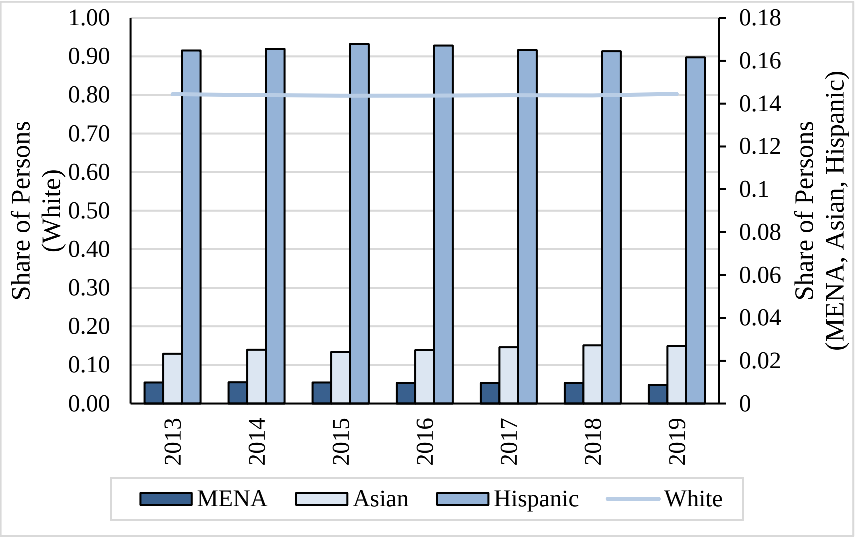
Appendix B: Data

Racial and Ethnic composition of patients

Figure B1: Individual counts and composition over time.



(a) Count



(b) Share

Source: COVID-19 Research Database, 2013-2019
Notes: Each bar/point represents the number or share of unique patients with an encounter within each year by race and ethnicity. Asian, Hispanic, and MENA individual patient counts are based on the secondary y-axis, while all patient and White patient counts are based on the primary y-axis.

State composition

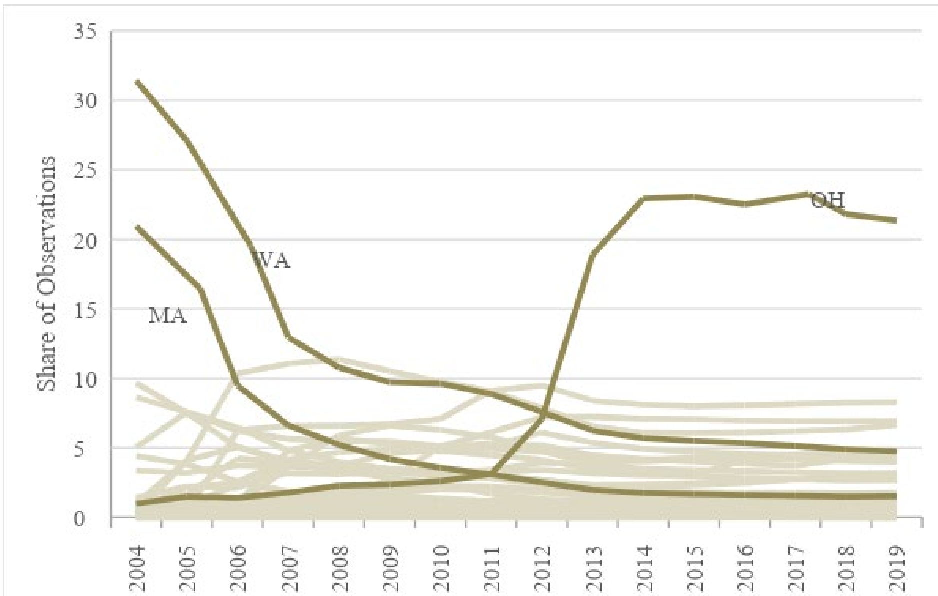
Since the data was not extracted with a study design in mind, it does not represent a balanced panel of either persons or states. This raises the concern that as states enter and exit the panel, the composition of individuals tracked over time changes, creating omitted variable bias. In this appendix, we explore the impact of the changing composition of states.

Figure A1 shows the share of sample by state over the years of panel for children and women. In the children's sample, we see that the early years of the panel (2004-2008) are dominated by Washington and Massachusetts. By 2009, these states have a smaller share, though they continue to have an outsize share. In 2013-2014 observations from Ohio begin to dominate the sample, remaining a steady 20%-23% of the sample through the end of the panel period. The women sample has a similar dominance by Florida and North Carolina in the early period of the panel – a dominance which wanes by 2009. As in the children's sample, Ohio becomes overrepresented in the panel in 2013-2014.

To address these compositional changes, all analyses include state by year fixed effects which allows for interpretation of coefficients on race and ethnicity as deviations from state specific annual means in outcome variables. As the analysis spans an 11 year period, these interactions remove up to 550 degrees of freedom. Table A1 shows estimates of equation (1) without these state by year fixed effects for children. Compared to Table 1, the coefficients are mostly unchanged. MENA children are 5.2 pp less likely to be on schedule with their vaccines. Though they are 0.16 pp more likely to have well-visits, the significance and magnitude of this effect disappears. Similarly, the number of vaccines, though 0.78 fewer than White children, is not statistically significant at conventional levels.

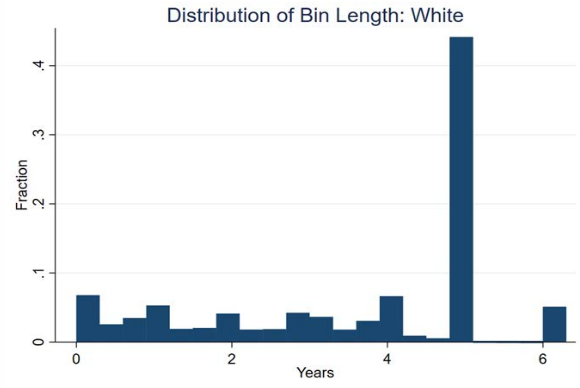
Therefore, though we recognize significant compositional changes attributable to states drifting in and out of the sample, adjusting for these in our analyses increases the magnitude and precision of effects for MENA children.

Figure B2: State shares in samples across years.

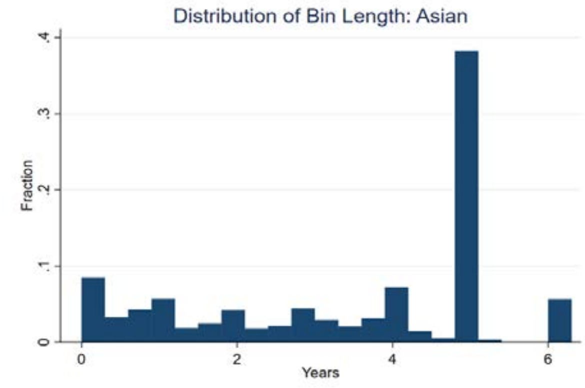


Source: COVID-19 Research Database, HealthJump and AnalyticIQ 2004-2019.

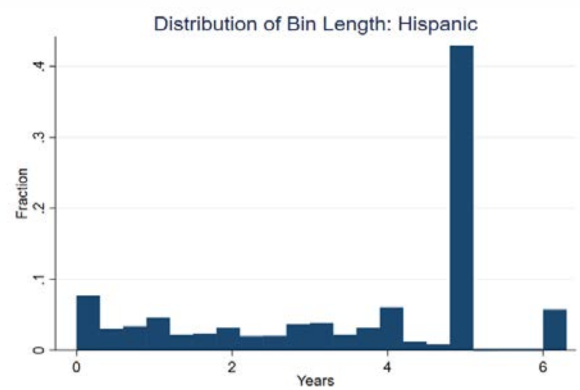
Figure B3: Length in range of birth year by race and ethnicity of patient.



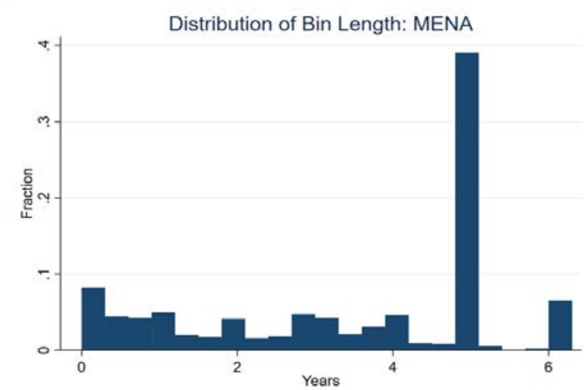
(a) White



(b) Asian



(c) Hispanic

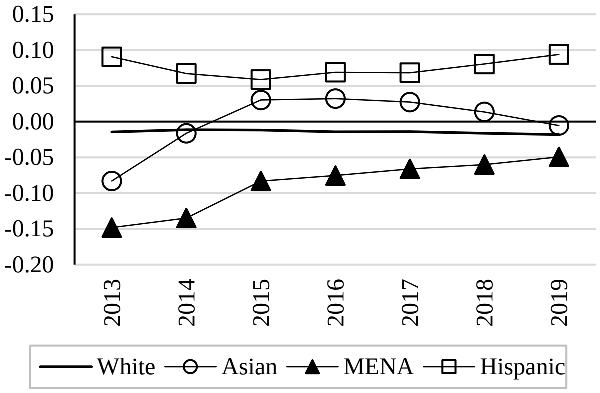


(d) MENA

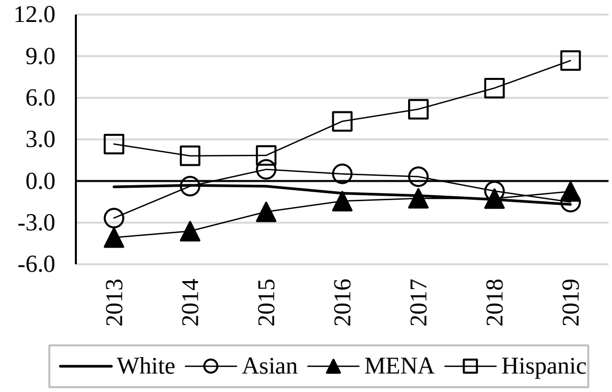
Source: COVID-19 Research Database, 2013-2019
Notes: Each bar/point represents the share of unique patients whose age range has the length specified on the horizontal axis.

Appendix C: Adjusted time trends, all groups

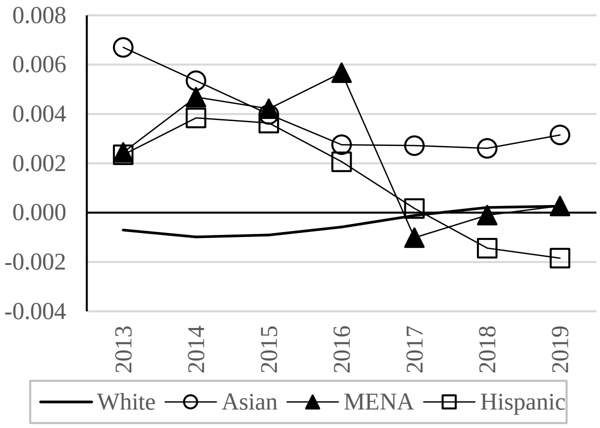
Figure C1: Adjusted time trend by race/ethnicity



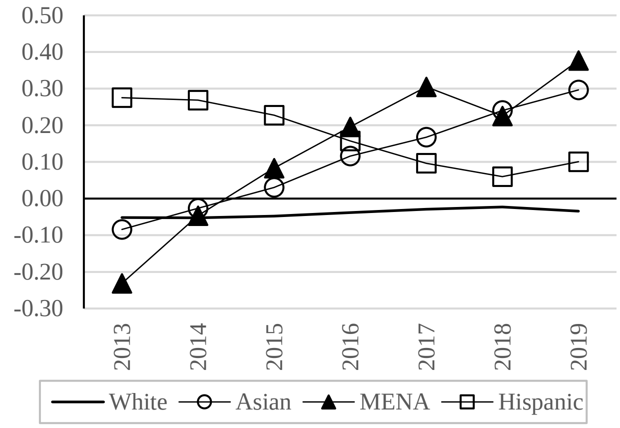
(a) On schedule on vaccines



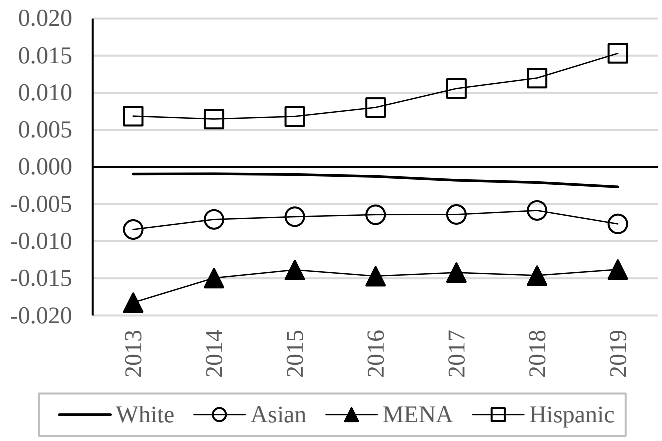
(b) Total count of vaccines



(c) Any well-visits in month



(d) Total count of well-visits

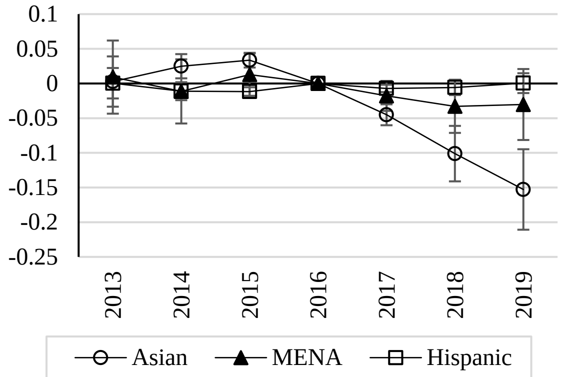


(e) Total count of lead tests

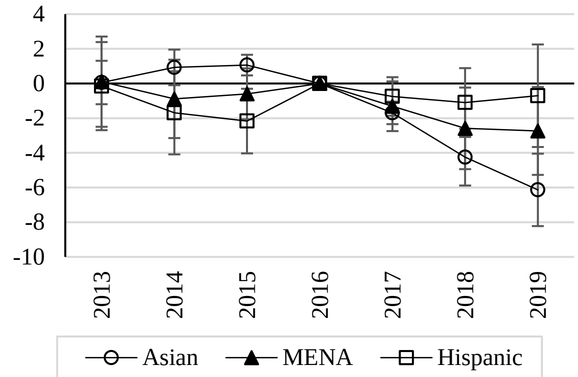
Source: COVID-19 Research Database, 2013-2019

Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year.

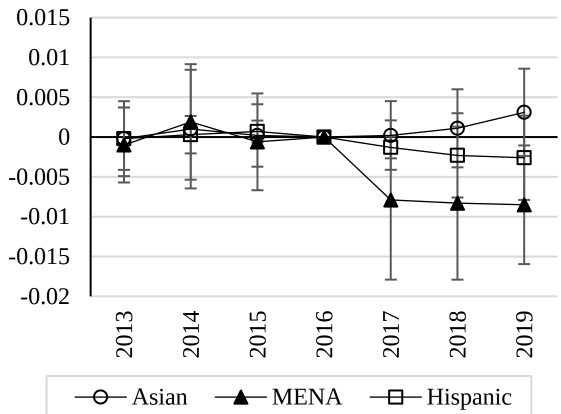
Figure C2: Event study of health outcomes for MENA relative to non-Hispanic White children



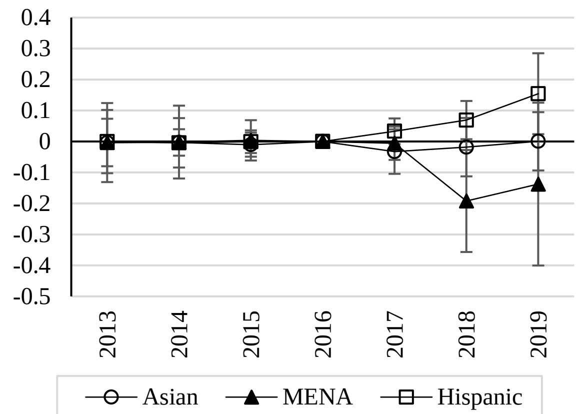
(a) On schedule on vaccines



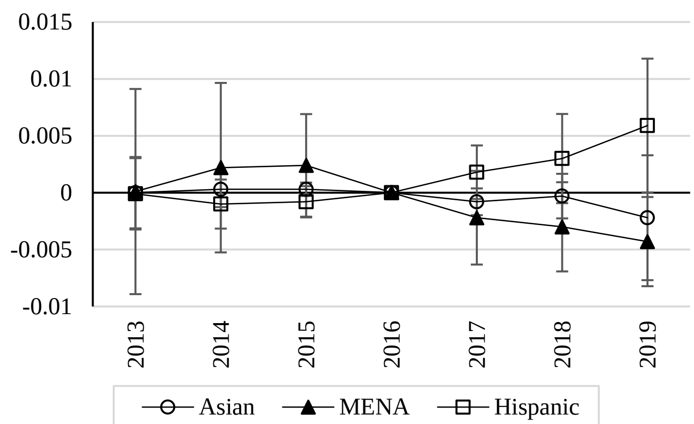
(b) Total count of vaccines



(c) Any well-visits in month



(d) Total count of well-visits



(e) Total count of lead tests

Source: COVID-19 Research Database, 2013-2019

Notes: Each point is estimate of difference between MENA and non-Hispanic White child relative to 2016. Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. 95% confidence intervals around estimate.

Appendix D: Additional regression results, all groups

Table D1: Summary Statistics

	(1) Before	(2) After
Panel A: Vaccines		
% on schedule		
MENA	0.2080	0.2952
Hispanic	0.3625	0.4390
Asian	0.2553	0.3289
Non-Hispanic White	0.2215	0.2893
Total count		
MENA	8.2965	3.6053
Hispanic	10.4024	4.7683
Asian	9.9870	3.7879
Non-Hispanic White	7.1877	3.8358
Panel B: Well visits		
% with any in month		
MENA	0.0891	0.0582
Hispanic	0.0943	0.0525
Asian	0.1041	0.0726
Non-Hispanic White	0.0804	0.0536
Total count		
MENA	1.5991	0.8636
Hispanic	1.2654	0.7206
Asian	1.6447	0.9676
Non-Hispanic White	1.3764	0.8007
Panel C: Blood lead testing		
Total count		
MENA	0.0000	0.0000
Hispanic	0.0034	0.0028
Asian	0.0000	0.0009
Non-Hispanic White	0.0004	0.0005
Panel D: Demographics		
Female		
MENA	0.4493	0.4904
Hispanic	0.5448	0.5646
Asian	0.5102	0.5329
Non-Hispanic White	0.5120	0.5347
0-2 years of age		
MENA	0.0030	0.00001
Hispanic	0.0068	0.0059
Asian	0.0025	0.0018
Non-Hispanic White	0.0035	0.0034
Medicaid		
MENA	0.2368	0.2036

Hispanic	0.5834	0.5451
Asian	0.1832	0.1395
Non-Hispanic White	0.1726	0.1405
n	65182	43493
N	**2050337**	**948907**

Source: COVID-19 Research Database, 2013-2019.
Notes: For vaccines, the monthly indicator is whether child is compliant with AAP recommended schedule.

Table D2: Two-way fixed-effects, all groups

	(1) Vaccines		(2) Well-Visits		(3) Lead Test
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
ASIAN	-0.0004	-0.0225	-0.00001	0.0002	0.0001
	(0.0126)	(0.4320)	(0.0013)	(0.0373)	(0.0021)
MENA	-0.0006	-0.0361	0.0002	-0.0036	0.0001
	(0.0154)	(0.3675)	(0.0013)	(0.0533)	(0.0046)
HISPANIC	0.0005	0.0303	0.0001	-0.0184	-0.0001
	(0.0060)	(0.4288)	(0.0007)	(0.0232)	(0.0023)
ASIAN * POST	-0.1054***	-4.1374***	0.0009	-0.0159	-0.0011
	(0.0192)	(0.7825)	(0.0014)	(0.0390)	(0.0013)
MENA * POST	-0.0283	-1.6976**	-0.0083***	-0.0964	-0.0041
	(0.0204)	(0.7276)	(0.0028)	(0.0661)	(0.0039)
HISPANIC * POST	0.001	0.171	-0.0021	0.0754***	0.0037
	(0.0056)	(1.2153)	(0.0013)	(0.0267)	(0.0022)
Dep. Var. Mean	0.2808	14.6871	0.041	2.025	0.0055
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES
N	2999244	2999244	2999244	2999245	2999246

Source: COVID-19 Research Database, 2013-2019.
Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.

Table D3: Two-way fixed-effects with differentiating impact of SC, all groups

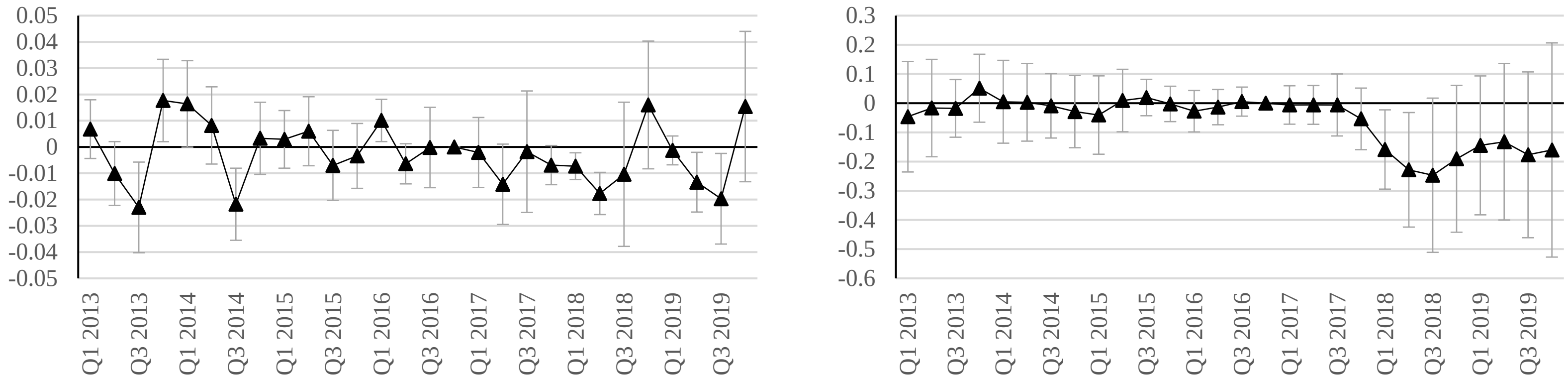
	(1)		(2)		(3)
	Vaccines		**Well-Visits**		**Lead Test**
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
ASIAN	0.0263	0.978	0.0004	-0.0263	-0.0001
	(0.0166)	(0.5851)	(0.0015)	(0.0622)	(0.0023)
MENA	-0.0281	-0.7433**	-0.0004	-0.1067	-0.0002
	(0.0218)	(0.3002)	(0.0016)	(0.0628)	(0.0039)
HISPANIC	0.0410***	1.4423*	0.0004	0.039	0.0056**
	(0.0081)	(0.7216)	(0.0009)	(0.0317)	(0.0027)
DETAINERS	0.0044***	0.1748***	-0.0002	0.0050**	0.0004***
	(0.0005)	(0.0352)	(0.0004)	(0.0024)	(0.00004)
ASIAN * DETAINERS	-0.0104**	-0.3895**	-0.0002	0.0095	0.0000008
	(0.0046)	(0.1485)	(0.0003)	(0.0139)	(0.0002)
MENA * DETAINERS	0.0134*	0.3523***	0.0003	0.0480*	0.0003
	(0.0071)	(0.1180)	(0.0004)	(0.0263)	(0.0006)
HISPANIC * DETAINERS	-0.0121***	-0.4220***	-0.0001	-0.0166***	-0.0017***
	(0.0017)	(0.1104)	(0.0001)	(0.0035)	(0.0002)
ASIAN * POST	0.0061	-0.9272*	0.0002	0.0418	0.0003
	(0.0141)	(0.5129)	(0.0023)	(0.0549)	(0.0016)
MENA * POST	-0.007	-2.5378***	-0.0069	-0.0702	0.0024
	(0.0193)	(0.7852)	(0.0053)	(0.1414)	(0.0035)
HISPANIC * POST	0.0039	1.2905	0.0004	0.0734*	0.0032
	(0.0134)	(1.5939)	(0.0014)	(0.0375)	(0.0028)
DETAINERS * POST	0.0001	0.0487	-0.0001	-0.0029	-0.000001
	(0.0012)	(0.0687)	(0.0006)	(0.0064)	(0.0001)
ASIAN * DETAINERS * POST	-0.0360***	-1.0308***	0.0002	-0.0202	-0.0005*
	(0.0050)	(0.1742)	(0.0005)	(0.0121)	(0.0003)
MENA * DETAINERS * POST	-0.0107	0.2554	-0.0005	-0.0184	-0.0026***
	(0.0091)	(0.1746)	(0.0015)	(0.0596)	(0.0007)
HISPANIC * DETAINERS * POST	0.0008	-0.209	-0.0006**	0.0033	0.0004
	(0.0035)	(0.1609)	(0.0002)	(0.0064)	(0.0004)
Dep. Var. Mean	0.2808	14.6871	0.041	2.025	0.0055
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES
N	2999244	2999244	2999244	2999245	2999246

Source: COVID-19 Research Database, TRAC Immigration data, 2013-2019.
Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.

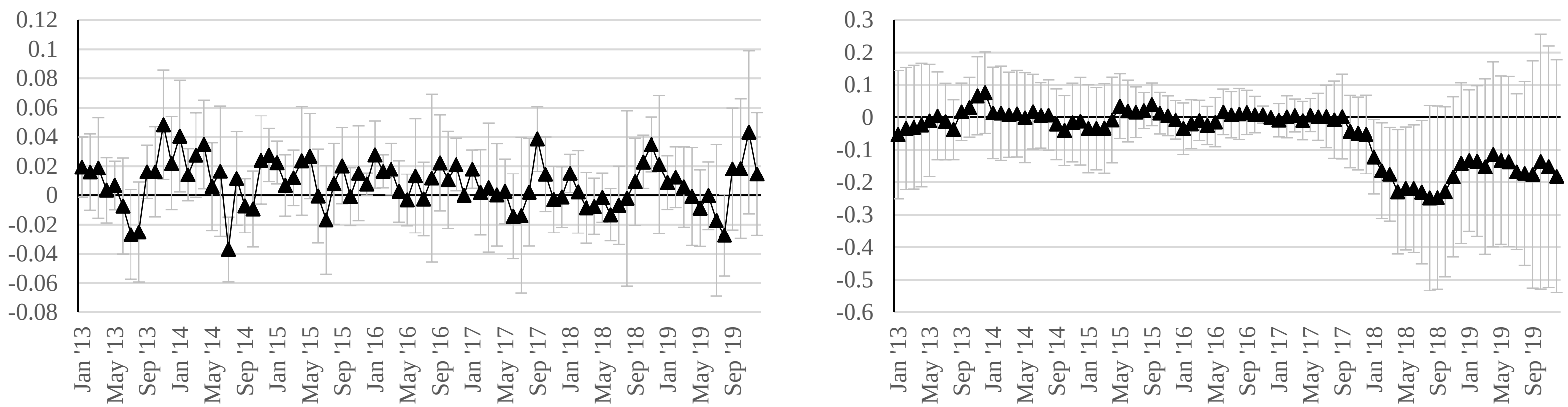
Appendix E: Quarterly and Monthly Event Studies

Figure E1: Quarterly and monthly event studies for well-visits for MENA relative to non-Hispanic White children

On Schedule with Vaccines **Total Count of Vaccines**



(a) Quarterly frequency



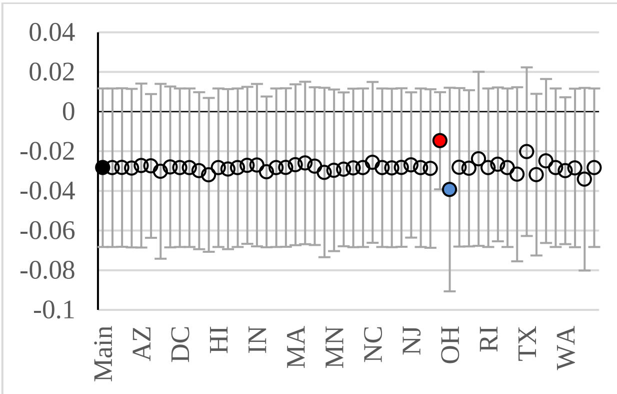
(b) Monthly Frequency

Source: COVID-19 Research Database, 2013-2019

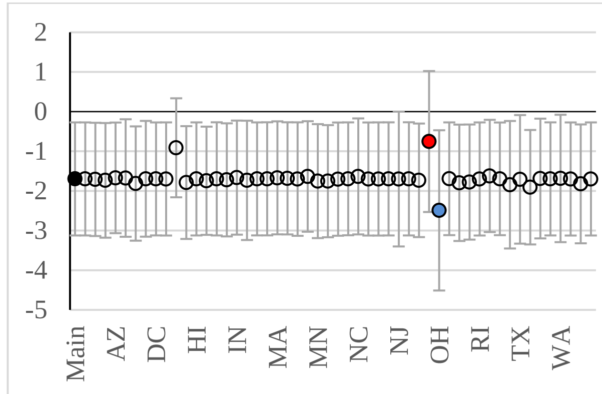
Notes: Each point is estimate of difference between MENA and non-Hispanic White child relative to 2016. Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. 95% confidence intervals around estimate

Appendix F: Sensitivity of main results to state inclusion.

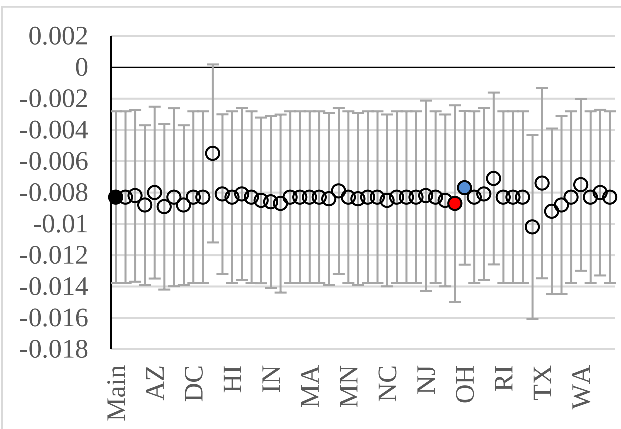
Figure F1: Leave-one-out analysis of states (main estimate in **black**; estimate excluding New York in **red**; estimate excluding Ohio in **blue**)



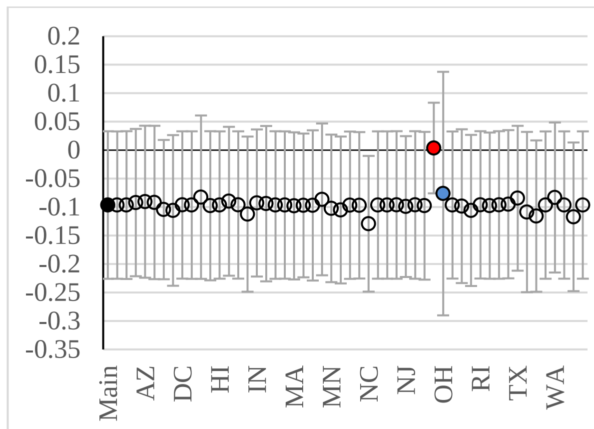
(a) On schedule on vaccines



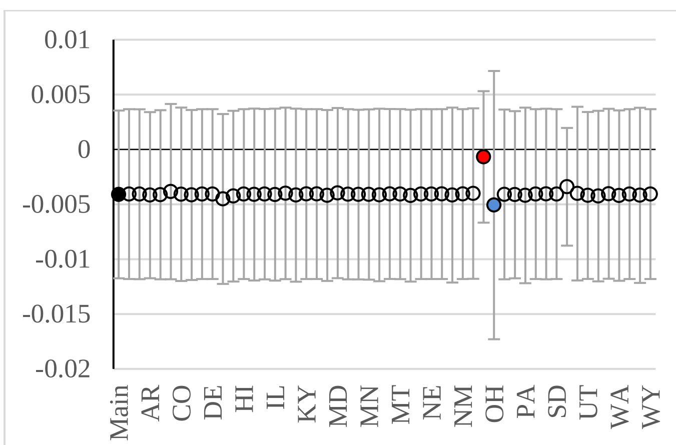
(b) Total count of vaccines



(c) Any well-visits in month



(d) Total count of well-visits



(e) Total count of lead tests

Source: COVID-19 Research Database, 2013-2019

Notes: Each point is estimate of difference between MENA and non-Hispanic White child relative to 2016. Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. The following estimates are highlighted: main estimate in **black**; estimate excluding New York in **red**; estimate excluding Ohio in **blue**. Standard errors clustered at birth year level. 95% confidence intervals around estimate.

Appendix G: Alternative Sample Definitions

Table G1: Alternative assumptions about child age.

	(1) **Vaccines**		(2) **Well-Visits**		(3) **Lead Test**
	On schedule	*Total Count*	*Any in Month*	*Total Count*	*Total Count*
Panel A: Highest Possible Birth Year					
MENA	-0.0009	-0.0825	0.0004	-0.0091	0.0001
	(0.0207)	(1.0052)	(0.0013)	(0.0878)	(0.0045)
MENA * POST	-0.0196	-1.5635	-0.0070***	-0.0125	-0.0018
	(0.0271)	(1.3327)	(0.0018)	(0.0783)	(0.0030)
Dep. Var. Mean	0.198	10.9652	0.0471	2.2854	0.0081
N	3511811	3511811	3511811	3511811	3511811
Panel B: Lowest Possible Birth Year					
MENA	-0.0007	-0.0331	0.0004	0.0061	0.0001
	(0.0188)	(0.5622)	(0.0013)	(0.0469)	(0.0039)
MENA * POST	-0.0395*	-2.3932**	-0.0041*	0.0593	-0.0006
	(0.0228)	(0.9622)	(0.0021)	(0.0775)	(0.0023)
Dep. Var. Mean	0.2161	12.0289	0.0638	2.5022	0.0069
N	2259576	2259576	2259576	2259576	2259576
Panel C: All Births After 1996					
MENA	-0.0011	-0.0683	0.0009	-0.0218	0.00003
	(0.0174)	(0.5610)	(0.0017)	(0.0661)	(0.0031)
MENA * POST	-0.0241	-2.0880***	-0.0053**	-0.2012***	0.0005
	(0.0142)	(0.6544)	(0.0021)	(0.0633)	(0.0027)
Dep. Var. Mean	0.1872	9.953	0.0369	1.6534	0.0056
N	6472755	6472755	6472755	6472755	6472755
State FE	YES	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES	YES
State * Year FE	YES	YES	YES	YES	YES
Demographics	YES	YES	YES	YES	YES

Source: COVID-19 Research Database, 2013-2019.
Notes: Outcomes are vaccines (whether on schedule and total), well-visits (monthly occurrence and total), and lead tests (total) in each month. In Panel A, the birth year is set at the maximum of the range; Panel B, the birth year is set at the minimum of the range; Panel C includes all births, whether or not the age range can be narrowed down further. Annual trends adjusted with fixed effects for years in panel, state, year by month, state by year, and birth year. Standard errors clustered at birth year level. ***p<0.01 **p<0.05 *p<0.1.