Naturalization and Voting Behavior as a Response to Discrimination. Evidence from Immigrants in the U.S.

Ireri Hernandez Carballo[⊥]
and Jorge Soler-Lopez[a]

April 18, 2024

Abstract: This paper explores the effect of discrimination and perceived threat on the naturalization and voting behavior of first-generation U.S. immigrants. Applying a difference-in-differences framework, we use the 2016 presidential candidacy and election of Donald Trump and his explicit targeted attacks towards particular groups of immigrants during his campaign, presidency, and the COVID-19 pandemic, to study the effects on the naturalization and voting patterns of the targeted groups relative to non-targeted groups. Additionally, we use changes in Immigration and Customs Enforcement arrests as a measure of state-varying threat for immigrants with large undocumented populations. We find a positive and significant effects for Mexicans, relative to other non-targeted immigrant groups and relative to other non-Mexican Latinos[1]. Specifically we find an increase of about 13 percent on the naturalizations of Mexicans and about an 8 to 15 percent increase in the reported voting turnout of naturalized Mexicans in the 2016 presidential election.

I. Introduction

How do immigrants respond to political attacks directed against them? Does their political behavior change as a response? Anti-immigrant sentiment, specifically on the basis of race, religion, or ethnicity, has been an element of populist nationalist discourse widely used as a political tool to rally supporters. Of relevance in these settings is how those targeted react politically. Do they increase their civic engagement in an attempt to protect themselves and push back, or do they retreat towards lower political participation in an attempt to minimize their salience? Do attacks affect only explicitly targeted groups, or do they spillover to closely linked immigrant groups?

Immigrants are a rapidly growing segment of the population in many countries. How immigrants cope under hostile settings is of special interest, as discrimination may be a barrier to their successful integration and has been documented to be related to their mental and physical health (Jasinskaja-Lahti, Liebkind, Jaakkola, & Reuter, 2006; Pascoe & Smart Richman, 2009;

[⊥] ireri.hernandez@phd.unibocconi.it
[a] jorge@backpackecon.com

[1] While *Latinx/Latine* is a more inclusive term, we use *Latino* to refer to all persons of Latin American origin or descent. This is done to avoid confusions as only a small percentage of Latinos identify or know the gender-neutral term; and to follow the approach of recent literature, as well as surveys and census questions. https://www.pewresearch.org/short-reads/2023/09/05/who-is-hispanic/

Schmitt, Branscombe, Postmes, & Garcia, 2014; Szaflarski & Bauldry, 2019), housing opportunities (Ahmed & Hammarstedt, 2008; Bosch, Carnero, & Farre, 2010), labor market outcomes, economic performance (Carlsson, 2010; Dancygier & Laitin, 2014; Zschirnt & Ruedin, 2016), and violent encounters with natives and the state (Dancygier & Laitin, 2014). Discrimination is also likely be related to immigrants' political and civic integration and engagement, particularly in settings where they face both societal (interpersonal) and political discrimination, in which the latter "typically refers to discriminatory laws, campaign messages, policies, or practices carried out by state or private institutions and/or their affiliated actors" (Oskooii, 2016, p.616). Empirical work studying the relationship between discrimination and civic engagement of ethnic groups or immigrants has found that both alienation and a rise in political engagement are potential reactions (Chan, Nguy, & Masuoka, 2024; DeSipio, 2002; Oskooii, 2016; Sanchez, 2006; Schildkraut, 2005). While shedding light on the conditions that might increase or decrease political participation, most of these studies focus their attention to the behaviors of broader pan-ethnic groups and include several immigrant generations, with only a few studies that particularly explore the experience of first generation immigrants (Chan et al., 2024; Masuoka, 2006). Furthermore, most report relationships using data from interviews, surveys, and self-reported measures of discrimination and political engagement, with very few estimating causal relationships.

This analysis contributes to the existing literature in several ways. First, while racial, ethnic, and religious discrimination can affect several generations of immigrants and non-immigrants, our focus here is on the behavior of foreign-born naturalized U.S. citizens (first-generation immigrants), whose behavior may differ from second and further removed immigrant generations and has been studied less closely. In the U.S., first-generation immigrants compose a non-trivial part of the population and political electorate. In 2020, first-generation naturalized citizens made up 10% of U.S. eligible voters (Budiman, Noe-Bustamante, & Lopez, 2020). Furthermore, in 2019, there were 9.2 million first-generation lawful permanent residents that were potentially eligible for naturalization (Baker, 2019). Anti-immigrant rhetoric and political agendas that highlight the salience of particular immigrant groups are likely to change the civic and political behavior of targeted immigrant groups. Indeed, Pantoja, Ramirez, and Segura (2001) report that Latino immigrants that naturalized during a politically hostile climate in California had a higher probability of voting. Relative group discrimination in Latino communities has also been associated with a higher propensity to vote democratic in 2016 (Berry, Cepuran, & Garcia-Rios, 2022). Moreover, the rise in COVID-19-linked discrimination towards Asians seems to be consequential to the unprecedented increase in their vote turnover and in the probability of voting democratic during the 2020 elections (Chan, Kim, & Leung, 2022). This analysis further sheds light on this issue by focusing on naturalization and voting turnout separately for more recent threats that were felt at a national level and is related to the recent worldwide rise in anti-immigrant rhetoric in the backdrop of populism and globalization.

Additionally, in comparison to most studies looking at the effect of discrimination on behavior and similarly to Fouka (2019), we use a quasi-experimental design that uses the supply of anti-immigrant rhetoric and policies that focused on particular groups, allowing me to test how the effects of targeted anti-immigrant rhetoric may differ according to nationality of birth. However unlike (Fouka, 2019), who focuses on naturalization of German immigrants that were negatively targeted during the first World War, we focus on more recent groups of immigrants and additionally examine voting turnout and potential spillover effects among immigrant groups. Furthermore, this analysis also contributes to the literature on political cleavages and in-out group formation by drawing a closer look at responses by nationality of origin, which goes beyond the usual treatment of broad pan-ethnic groups as a single political units.

Specifically, we analyze the question of whether individuals that belong to an immigrant group that is politically targeted in anti-immigration rhetoric increase their likelihood of naturalizing and voting. To shed light on this, we use variation in discrimination targeting under the candidacy and presidency of Donald Trump, which was heavily anti-Latino and anti-Mexican during his campaign and first years of presidency. Evolving into a more nuanced but visible anti-Muslim rhetoric. Finally, with the arrival of the global pandemic in 2020, the focus shifted towards anti-Asian and anti-China rethoric. We explore how Mexicans and other targeted groups respond politically, as measured by their yearly naturalization patterns and mid-term and presidential election voting turnout behavior. We employ a several iterations of the difference-in-differences framework by comparing the behaviors of immigrant groups directly targeted and those not explicitly targeted before and after 2016 and 2020. We make use of administrative naturalization counts by country of origin and Current Population Survey voting turnout data to measure the behavioral responses. We further employ Immigration and Customs Enforcement (ICE) arrest data by nationality and state of residence to build a measure of regional nationality-level threat. We find that relative to non-targeted groups, naturalization of Mexican-origin nationals increased during Trump's presidency, and that naturalized Mexicans reacted by increasing their voting turnout behavior in the 2016 presidential election. Furthermore, our results show that that the effects did not spill over to non-Mexican Latinos, a closely linked immigrant group. We find that the effect is also present for Asians after during and after 2020. Finally, we observe no significant changes in behavior for nationals of countries affected by Trump's travel ban.

II. Discrimination, Group Threat, and Political Behavior of Immigrants: Review of the Literature

The study of group identity and behavior under salience and bias has deep roots in social psychology. Social identity and self-categorization theory (Tajfel, Turner, Austin, & Worchel, 1979; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987) state that when social cleavages become salient, individuals categorize themselves into an in- or out-group, and that threat to a group's worth triggers protective reactions from its members, varying in level with the strength of identification.

Taking this a step further, the Rejection-Identification Model (Branscombe, Schmitt, & Harvey, 1999) suggests that under discrimination, members of the out-group maintain psychological well-being by increasing their identity with the out-group and rejecting the negative evaluations of the in-group. Identity can become salient and politically relevant when politicians deliberately supply hate-creating stories against out-groups (Glaeser, 2002). Previous work suggests that anti-immigrant rhetoric and settings increase the salience of ethnic identity within immigrant groups (Armenta & Hunt, 2009; Jiménez, 2010; Rumbaut, 2008).

[From Kim (2023):the current study focuses on pan-ethnic cooperation among Asian Americans, a group that is classified into one racial category in the US. In particular, because of the group's diversity and history of inter-ethnic coalition-building, a question remains regarding the existence of co-ethnic bias among Asian Americans and the extent to which identity-based threats can foster pan-Asian cohesion and political cooperation. This study answers this question by drawing on data from an original survey experiment that assesses novel behavior in the context of a behavioral economic game.]

The literature on discrimination distinguishes between individual discrimination and group discrimination (Oskooii, 2016). In the case of individual discrimination the relationship with political engagement is likely to be mitigated by the strength of identity with the out-group, as social identity theory predicts (Schildkraut, 2005). In contrast, reactions to group level-discrimination are likely to depend on an individual's strength of identification with the group and politicization of the group's identity (Pérez, 2015a, 2015b).

In addition to group politicization, the level of the perceived group threat, which can be triggered by immigration legislation or immigration enforcement actions, is likely to influence the level of the response of individuals. Under highly politicized climate, particularly under the threat of California's 1994 proposition 187[2] which was perceived to be anti-immigrant, Latinos naturalized under this environment voted at substantially higher rates than Latinos naturalized in other times and states, and at higher rates than U.S. born Latinos (Pantoja et al., 2001). Additionally, for immigrant groups with large numbers of undocumented or deportable citizens, threat can also take the form of immigration arrests and deportation, which have been documented to increase voter turnout of eligible group members (White, 2016).

While anti-immigrant legislative threats are likely to affect a wide range of immigrant groups, politicization and salience (or lack thereof) of particular groups (because of their size or composition), has been shown to generate heterogeneity in reactions among groups. The H.R.4437 bill[3] passed by the U.S. House of Representatives in December of 2005 triggered group threat and was a catalyst for the 2006 immigration reform protests that strongly mobilized Latinos and other im-

[2]California's 1994 proposition 187 was a ballot initiative to prohibit non-U.S. citizens from using public services such as health care services and public school education.

[3]This bill called for stricter border enforcement and made it a felony to live undocumented in the U.S. (instead of a misdemeanor), called for the federal government to take custody of undocumented immigrants detained by local authorities, and required stricter verification of workers' legal status by their employer, among other provisions.

migrant groups with large undocumented populations (Barreto, Manzano, Ramírez, & Rim, 2009; Zepeda-Millán, 2014, 2017). However, among non-Latino immigrant groups, mobilization against this bill was mixed. Zepeda-Millán (2014) finds that "several non-Latino immigrant groups failed to mobilize to the same extent because many of them (often mistakenly) did not feel as threatened by the proposed nativist bill", mainly because of how illegal immigration was racialized and framed by the media as a Mexican problem. Barreto et al. (2009) find that while Latinos in general mobilized, Mexican-Americans and those that spoke Spanish at home were more likely to participate in protests in response to the H.R. 4437 bill. This is likely because they identified more with the group being targeted (undocumented immigrants) and due to the politicization of Mexican identity in particular.

Similarly, while Latinos are often portrayed as one cultural and political block, their national origin identity is distinct and there is likely to be heterogeneity in responses to discrimination depending on which particular identities become salient, as different political rhetoric is likely to create different group cleavages. Garcia-Rios, Pedraza, and Wilcox-Archuleta (2019) test this given the specificity of Trump's rhetoric which made national origin identity of Mexicans salient, and find evidence that while other strong-identifying Latinos also viewed Trump unfavorably and were less likely to report voting for him, it was not to the same extent as those of Mexican heritage, suggesting that the recent rhetoric more strongly politicized and made national origin more salient for Mexican-Americans. In order to study the factors that affect the response by non-Mexican origin Latinos Gutierrez, Ocampo, Barreto, and Segura (2019) study how pan-ethnic Latino identity is related to perceptions of Trump. They report that Latinos that share an immigrant-linked fate and those that felt that Latinos are racialized were more likely to feel angry during the 2016 election. Furthermore, they find that those made angry by Trump's remarks were more likely to report being engaged in political activities during and shortly after the 2016 election, including U.S. born Latinos and non-Mexican Latinos who report feeling similarly targeted. However, they still find some heterogeneity in views towards Trump by national origin (e.g. Cubans and Central Americans held a more positive view of Trump relative to Mexicans) and immigrant generation.

Other literature highlights the role of other emotions and factors in the relationship between group discrimination and political action, highlighting that threat can be particularly demobilizing when accompanied with fear and cynicism but mobilizing when in the presence of messages of hope (Valentino, Brader, Groenendyk, Gregorowicz, & Hutchings, 2011), and that anger is likely to increase political participation but fear and anxiety do not necessarily have the same effect (Valentino et al., 2011).

Studies focused on the U.S. Muslim community find that while discrimination increases group identity and the interest to engage politically, it decreases the likelihood of political engagement in the months following 9/11 (Takyar, 2019). The potential explanation for this is that an increase in-group identity might not be sufficient, and what might be needed "is strong ethnic identification in the context of societal encouragement, or at least acceptance, of multiculturalism", and that relative group size and fear could also play a role in how the Muslim community in the U.S. reacted (Takyar, 2019). Studying how feelings mediate the response, Ayers and Hofstetter (2008) found that feelings of anxiety following 9/11 were positively associated with reported political participation. More generally, Oskooii (2016) relates individual societal discrimination with decreased engagement (although the literature suggests this depends on the level identity with the group) and political (group) discrimination with increased political activism (again, contingent on politicization and other factors) and finds that Muslims report being more politically active in response to political discrimination.

While there are reasons to believe and some survey-based studies suggest that strong-identifying Latinos that felt targeted by Trump may report changing their political behaviors due to perceived threats (Garcia-Rios et al., 2019; Gutierrez et al., 2019), there is yet no evidence of this in terms of naturalization behaviors and voter turnout of first-generation immigrants, a group that is particularly likely to feel targeted and whose political integration under discrimination is of particular interest in the study of their political integration. Furthermore, the evidence suggests that while Latino and immigrant identity may be important when triggered, in the case of Trump's rhetoric, there seems to be heterogeneity in responses by generation and nationality, and thus it is not clear ex-ante that the naturalization and voting behaviors of non-Mexican Latino immigrants will change as a response. Finally, while the majority of the literature focuses on Latinos, this study looks at the political behavior or nationals that were targeted by Trump's travel ban, seeking to add to the knowledge other behaviors of migrant groups that may identify as Muslim.

III. Background

Throughout history, immigrant and racial minority groups in the U.S. have been negatively portrayed in the information environment and classified as out groups. Within the current immigration debate, this particularly the case for Arabs and Muslims (Kalkan, Layman, & Uslaner, 2009; Lajevardi & Oskooii, 2018; Oskooii, 2016), Latinos (Abrajano & Hajnal, 2017; Valentino, Brader, & Jardina, 2013), Asians, and other non-white immigrant groups (Abrajano & Hajnal, 2017). While immigration has historically been a highly divisive topic in the political agenda, there was a shift to more explicit openly targeted and prejudiced remarks beginning with the 2016 presidential campaign, which were met with controversy and decried as explicitly racist. Trump infamously began his political campaign by declaring that "When Mexico sends its people, they're not sending their best ....They're bringing drugs. They're bringing crime. They're rapists. And some, we assume, are good people. ... It's coming from more than Mexico. It's coming from all over South and Latin America, and it's coming probably – probably – from the Middle East" (Trump, 2015). In December of 2015, his campaign called for a "total and complete shutdown of Muslims entering the United States"[4]. The rhetoric in place under presidential candidacy and election of Donald Trump

[4]https://www.c-span.org/video/?c4737466/user-clip-trumps-muslim-ban

has been documented to create a sharp worsening of anti-immigrant sentiment and actions at the societal level as well (Bursztyn, Egorov, & Fiorin, 2017; Crandall, Miller, & White, 2018; Newman, Shah, & Collingwood, 2018), triggering both social and political discrimination and threat.

On the week of January 23th, 2017, shortly after his inauguration, Trump signed 3 executive orders related to immigration restriction and enforcement. Executive order 13769 prohibited individuals from predominantly Muslim countries from entering the United States for 90 days, suspended entry into the country from Syrian refugees, and prohibited other refugees from coming into the country for 120 days. While this particular version of the law was blocked by a judge, a new version (Executive order 13780), which was upheld by the Supreme court, replaced it and places limits on travel to the U.S. by nationals of several countries[5].

Two other orders focus on the detention of immigrants and the building of a wall between the U.S. and Mexico. Executive Order 13767 ordered increased border vigilance and included the construction of his key rallying point, a wall across the U.S.-Mexico border, which he had promised Mexico would pay for. Furthermore, Executive Order 13768 ordered a broader application of existing immigration laws for removal of immigrants, allowed local law enforcement to perform functions of immigration officers, and stated that sanctuary jurisdictions that refused to comply with immigration enforcement measures would be denied federal funding. This executive order re-established the Secure Communities program, a federal program administered by Immigration and Customs Enforcement (ICE) started under the Bush administration and suspended 2014.[6]. This program enables ICE to access information on immigrants detained in local jails, in which ICE may issue a detaining order to hold the individual until they can be picked up for immigration detention and deportation.

Immigration enforcement under Trump has created shifts in the types and locations of ICE arrests. Since there has been backlash to the Secure Communities Program and many regions choose not to actively participate, ICE has stated[7] that it then needs to increasingly rely on community arrests, in which they directly encounter individuals they believe are deportable in their communities (e.g. in their homes, workplaces, commutes, or elsewhere). This type of enforcement may lead to spillover encounters with citizens and permanent residents that have not committed any offense or are not deportable. During its operations in 2017, ICE encountered (the process of inter-

[5] The latest revision was in February 2020, and bans travel to the U.S. by nationals of North Korea and Syria; by nationals of Iran except on student or exchange visitor visas; by nationals of Libya and Yemen on immigrant, tourist or business visas; by nationals of Eritrea, Kyrgyzstan, Myanmar, Nigeria and Somalia on immigrant visas; by nationals of Sudan and Tanzania on diversity visas; and by some government officials of Venezuela on tourist or business visas. The order allows case-by-case exceptions under certain circumstances.https://www.whitehouse.gov/presidential-actions/proclamation-improving-enhanced-vetting-capabilities-processes-detecting-attempted-entry/

[6] The last years of immigration enforcement under Obama focused on arresting individuals with serious level criminal convictions and recent immigrants under the Priority Enforcement Program, but under Trump, this hierarchy of priority was removed, widening the type of offenses for which individuals were apprehended. The program has been credited as a very effective way of removing undocumented immigrants, but existing studies suggest that it did not have any effect on reduction of crime (Miles & Cox, 2014; Treyger, Chalfin, & Loeffler, 2014)

[7] https://www.ice.gov/news/releases/dhs-ice-announce-arrests-more-170-large-aliens-sanctuary-jurisdictions

view, screening, and determination of citizenship, which may or may not lead to an arrest) 27,540 U.S. citizens, compared to 5,980 in the last year of the Obama administration (Cantor, Ryo, & Humphrey, 2019). Those that ICE wrongfully encounters are likely to come from communities that have large number of undocumented or deportable permanent residents nationals. According to (Transactional Records Access Clearinghouse (TRAC), 2018) immigration data obtained from ICE about 60% of those arrested in FY2017 and FY2018 were Mexican nationals, with the second largest group (10.5%) from Guatemala, 8.3% from Honduras, and 6.4% from El Salvador. Given the shift of type and nature of arrests under the presidency of Donald Trump, we use variation in arrests by nationality across states and time as a potential variation of group threat.

Taken together, the travel ban and stronger border and immigration enforcement is likely to have triggered fear of travel for non-U.S. citizens, and could have increased the perceived value of becoming a U.S. citizen. This is likely to trigger the most group threat for the nationals which were explicitly targeted and made salient by Trump, particularly those coming from countries targeted by the travel ban and Mexicans, currently the largest group of U.S. immigrants. Additionally, other proposals under Trump included restricting birthright citizenship and threatening the Deferred Action for Childhood Arrivals program (which did not happen); others were enacted and include the cancellation of Temporary Protected Status for nationals of El Salvador, Nicaragua, Haiti, and Sudan (making them deportable) and a ruling that makes the use of public welfare services by non-resident immigrants a reason for future green card denial.[8]

For immigrants, citizenship through naturalization is a pre-requisite to vote. To be naturalized, an immigrant must fulfill certain requirements, such as: being a legal permanent resident; having continuously resided in the U.S. for a certain amount of time; ability to speak, read and write in English; knowledge of U.S. government and history; and being of good moral character. Factors that increase probability of embarking on the naturalization process include length of time living in the U.S., level of education, eligibility for dual citizenship, as well as local institutional contexts (Jones-Correa, 2001). It is also costly, since it involves filling out the application and paying fees[9], learning enough English to pass the written and verbal sections of the test, and passing a civics knowledge exam. While this cost may seem low relative to the benefits, for those that are likely to have lower levels of schooling, less time and monetary resources, this might be a significant investment.

In this analysis, we will be studying the behaviors of 3 groups of foreign-born naturalized immigrants: 1) Mexicans, 2) Latin Americans (excluding Mexicans), and 3) the group of those born in one of the 6 majority Muslim countries affected by Trump's travel ban. We analyze Mexicans and other Latin Americans separately, since Trump has most explicitly targeted Mexicans and Mexico, and other Latin Americans may or may not feel threatened by his remarks and actions. Furthermore,

[8] For a full report of immigration-related policy changes in the first two years of the Trump administration, see Pierce (2019).

[9] In many cases, to reduce the bureaucratic burden and to avoid costly mistakes, this also involves hiring an immigration attorney, whose fees can be significant.

after we establish that there was no effect on Latin Americans, we use this group as a control group for Mexicans.

IV. Data Description and Sources

Naturalizations

We use naturalization data from the U.S. Department of Homeland Security compiled by the Office of Immigration Statistics on the number of persons naturalized by country of origin and state of residence for those 18 years and older who became naturalized in a given fiscal year[10]. Fiscal year of naturalization may be a lag of the year of application for naturalization because of processing times, which may vary from year to year. [11]

Hate Crime

We use hate crime data from the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) program, which complies data on hate crime, particularly crimes that manifest evidence of prejudice based on race, ethnicity, religion, sexual orientation, disability, gender, or gender identity[12]. The types of offenses that are collected as hate crime include: crimes against persons and crimes against property such as robbery, burglary, larceny-theft, motor vehicle theft, arson, and destruction/damage/vandalism. There are several weaknesses of this data, particularly that participation in the FBI UCR Program is mandated for federal law enforcement agencies, but is voluntary for local, state, and tribal law enforcement agencies, thus the number of hate crimes may be undercounting crimes that are not voluntarily reported by non-federal law enforcement agencies. Other critiques of using this data include that in many cases victims never report crimes to the police, many law enforcement agencies do a poor job of consistently collecting and categorizing hate crime data (Loftin & McDowall, 2010; Shanmugasundaram, 2018; Zaykowski, 2010). McVeigh, Welch, and Bjarnason (2003) report that hate crimes are more likely to be reported in counties with a legislative mandate for data collection, in counties with resourceful civil rights organizations, and in counties with more political party competition.[13] Furthermore, another large drawback from this data in this analysis is that there is no indication of whether a victim was an immigrant, and it includes hate crimes committed towards all members of a group, not just those that are foreign-born

[10]Fiscal years run from October 1st of the previous year to September 30th of the current year. Naturalizations data from: https://www.dhs.gov/immigration-statistics/naturalizations for years 2004-2023

[11]While the decision to naturalize may be one taken at the individual level, one's petition might be denied. At the level of observation carried out here we only observe the number of naturalization petitions that were approved successfully. That is, the observed naturalization numbers may be an equilibrium outcome that involves both more petitions but potential increases in denial rates and backlogs that may have slowed down the actual naturalization numbers. If this is the case, then the numbers observed might be attenuated, and the estimates will be a lower bound relative to the number of petitions for naturalization and in a setting with no backlogs and no increase in denial rates; this might not be a problem as long as this affects naturalization from all countries (particularly control and treatment groups) similarly.

[12]Data from https://crime-data-explorer.fr.cloud.gov/downloads-and-docs.

[13]In a next step we can try to compare hate crime data with report from the U.S. Justice Department's Bureau of Justice Statistics, which estimates its numbers from its National Crime Victimization Survey.

immigrants.

Voter Turnout Data

To study voter turnout of naturalized citizens we use the Current Population Survey November Voting and Registration Supplement from IPUMS (Flood, King, Rodgers, Ruggles, & Warren, 2020) pooling data from 1994-2019. Our sample consists of naturalized citizens. After each election, the CPS asks respondents whether they were registered to vote, and if registered, whether they voted. Starting in 1994, the CPS provides country of birth of respondents, and whether they are naturalized citizens. For the voting turnout data, we exclude those individuals that for the voting question responded anything other than yes/no (e.g. We don't know or declines to answer) and missing responses. As other survey data, these responses are subject to vote over-report non-response bias, though CPS results tend to have lower over-report bias compared to other surveys (McDonald, 2019).

ICE Detention Data

We use detention data compiled by the Transnational Records Clearing House, a data gathering, data research and data distribution organization at Syracuse University (TRAC). TRAC compiles arrest-by-arrest records obtained from ICE, which are currently available for arrests that took place during the period October 2014 through October 2017. We use their public data at the nationality by fiscal year and state, giving me 6 years of arrest data: FY2014-FY2019. [14]. The arrests refer to "interior arrests", which includes any community or at-large arrests that are more likely to have spillover effects and increase encounters of ICE with non-deportable immigrants, including permanent residents and naturalized citizens. We use Census Bureau state population data in 2010 to build a measure of a given nationality's arrest per 100,000 capita in each state.

V. Empirical Strategy

We use a combination of Synthetic Differences-in-Differences (SDID) and repeated cross-section difference-in-differences (DID) strategies to estimate the impact of Trump's election on our outcomes of interest. We use the former for the naturalizations analysis as the major treated group (Mexicans and Latin Americans) are significantly larger than any of the other groups. Moreover, compared to traditional DID, SDID is at least as good in terms of consistency and statistical normality Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). For simplicity, we consider the following equation, which describes a traditional DID:

$$Y_{ijk} = \alpha_1 + \boldsymbol{\beta_1} Post_j * T_{ij} + \gamma_{1i} + \delta_{1j} + \lambda_{1k} + \epsilon_{1ij} \quad (1)$$

Y_{ijk} is the variable of interest, be it naturalizations or voter turn out, from birth country i in year j in state k. T_{ij} is a treatment indicator, equal to one for those affected countries or country groups

[14]https://trac.syr.edu/phptools/immigration/arrest/about_data.html

(separately estimated for each group) interacted with $Post_j$ a dummy for the period 2016-2019 . γ_{1i} is a dummy for country of birth or group of treated countries of birth, and δ_{1j} is a post indicator for years 2016 onward (or a full set of year dummies in richer specifications). Furthermore, a region-specific dummy λ_{1k} (where k is state) is added.

For each potentially treated group, a separate regression is estimated omitting the other potentially treated groups. That is, we look at the effects on Mexicans, Latin Americans, and Arabs/Muslims separately, relative to other nationalities. The coefficients of interest are the set of βs.[15]

The *Synthetic Differences-in-Differences* takes the comparison of the treated groups further: it re-weights control units to ensure a parallel trend with the treated pre-treatment trend. By doing so, it allows the parallel trend assumption to be relaxed, as the algorithm implicitly assigns the best 'match' in pre-treatment trends using a mix of the control units. The choice of this method specifically for the naturalization follows the reasoning presented in Figure 1. As noted, Mexicans and Latin-Americans are significantly larger than other groups and the pre-2016 trend is visibly parallel. However, we considered a re-weighting to be a more adequate representation of the situation, even if results using traditional DID are robust to those using SDID (see Annex XXXX)

When using region-specific measures of threat, namely the number of ICE interior arrests by nationality, we go back to DID, but the variation of interest is now at the state-level. The full year availability for this data is for FY 2014-2018, and since Trump took office and was only able to change immigration policy starting in FY 2017, the pre-period is now 2014-2016, and the post period begins in 2017. We compute the pre-period average and assign it to the years 2014-2016, we assign the post measure to the years 2017-2019. As explain in section XXX, COVID-19 restrictions might have severely affected the dynamics of arrest and we thus do not include it in the main analysis.

The equation is now:

$$Y_{ijk} = \alpha_2 + \boldsymbol{\beta_2} Post_j * A_{ijk} + \gamma_{2i} + \delta_{2j} + \lambda_{2k} + \epsilon_{2ijk} \tag{2}$$

Again, Y_{ijk} is naturalizations at year j from birth country i, of those residing in region k. A_{ijk} is now the average pre/post measure of number of arrests of individuals of nationality i per 100,000 capita in state k interacted with a post year dummy or set of dummies P for the fiscal years 2014-2019. We first examine the effects for a given country using state variation. The δ_{2j} is a post dummy (or a set of year fixed effects), and λ_{3k} is a set of state fixed effects.

For the voting turnout analysis, a linear probability model is used, where the outcome is a dummy variable equal to one if naturalized individual h from birth country i reported voting in election year j. PT_{hij} is now the treatment indicator equal to the interaction of an individual being born in a targeted country and it being election year 2016 or 2018 (equations are regressed separately for presidential and midterm elections). A regression is estimated separately using each

[15]The appendix includes the analysis using the post 2020 data. In which case *Asians* are included as a separate group. Please see section XXXXXXX for more information.

potentially targeted group as the treatment group, omitting the other potentially targeted groups. Additionally, state of residence dummies are used as controls in some of the specifications.

$$Y_{hij} = \alpha_3 + \boldsymbol{\beta_3} PT_{hij} + \gamma_{3i} + \delta_{3j} + \lambda_{3k} + \epsilon_{3ij} \tag{3}$$

Using Latinos as a control group for Mexicans is a plausible strategy that might lead to better comparisons. In general, Latinos as a group take longer to naturalize, and naturalization rates among Latinos (except for Cubans) have tended to be the lowest and historically about half the naturalization rate of non-Latino immigrant groups (Pantoja & Gershon, 2006). Furthermore, immigrants from Latin America are more likely to behave more like Mexican immigrants than any other group. Once we establish that there were no significant effects for non-Mexican Latinos, we therefore repeat the analysis for Mexican nationals using other Latinos as a control group.

VI. Sample Description and Summary Figures

For the naturalization outcomes, we use yearly naturalization counts at the country of birth by state level for 2010-2023 as the unit of observation. We restrict the sample to observations that are present for all years studied (balanced panel). This means that we drop the naturalizations from countries that are not present for all the years, where there are non-zero non-reported values (these are mostly countries with few naturalizations and likely grouped into the group "other country" in non-reporting years). Additionally, we drop observations with withheld naturalization values (cells with less than 3 naturalizations are marked as withheld by the Department of Homeland Security).

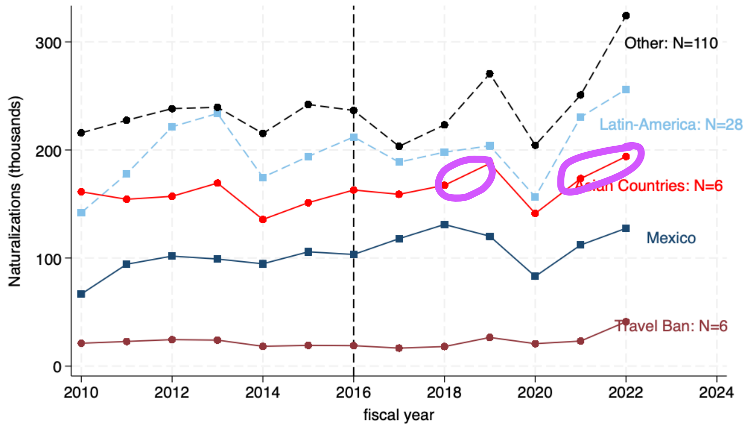
Figure 3 shows yearly total naturalization counts added across all states and group of interest. Note that all data are according to fiscal year, which runs from October 1 to September 30 of the given year. The first group (not in order of naturalizations) consists of those born in Mexico, the second group is made up of those born in other Latin-American countries (excluding Mexico). The third group includes those born in 6 majority-Muslim countries targeted by Trump's 2017 travel ban. The fourth group includes those born in China (PRC), Philippines, Vietnam, Japan, India and Korea. The fifth group all other countries not mentioned and serves at the initial control group.

As Figure 3 shows, those from Mexico account for a large share of the naturalizations. [16] There is an increase in Mexican nationalization requests after 2016, which is not seen by other nationalities. During 2020, the number of naturalization dropped drastically, but recovered significantly for all nationalities in the past four years.

Table **??** shows pre- and post-2016 means of naturalizations across countries by group of interest. At the state-level there were on average 1,837 (2,316 & 2,109) yearly naturalizations of

[16] Although not shown in the graph, naturalizations are thought to have spiked around 2008 as a response to an increase in naturalization fees on that were enacted in July of 2007 and as a result of campaigns prior to the 2008 presidential election (Blizzard & Batalova, 2019). Since there is a delay between application and naturalization time and sharp increases may create backlogs, many of the 2008 naturalizations correspond to petitions filed in 2007.

Figure 1 – Total Naturalizations by Groups of Interest: Country-of-birth-State-Year Level, 2010-2023



Notes: Latin-America excludes Mexico and Puerto Rico (whose citizens are automatically U.S. citizens) and includes the following countries of birth: Argentina, Aruba, Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Dominica, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, Uruguay, Venezuela. Naturalizations of Muslim countries included in the 2017 were those of people born in the following countries: Iran, Libya, Somalia, Sudan, Syria, Yemen. Asian countries include: China (PRC), Philippines,Vietnam, Japan, India and Korea (the Korean peninsula countries). Other includes those naturalized citizens born in all other countries whose observations are balanced.

individuals born in Mexico in the pre (post 2016) period. The average yearly state-level number of naturalizations across non-treated countries was 41 (42 & 46) in the pre (post) period. In general, Mexico has a much larger level of average naturalizations than other countries.

Table 1 – State-wide Naturalizations by Grouped Country of Birth

Country of Birth	Years 2010-2015			Years 2016-2019			Years 2020-2023		
	Mean	StD	Obs	Mean	StD	Obs	Mean	StD	Obs
Mexico	1,837	(5,854)	306	2,316	(7,311)	204	2,109	(6,575)	153
Latin America Countries*	133	(845)	8,568	141	(889)	5,712	150	(1,055)	4,284
Iran, Libya, Somalia, Sudan, Syria, Yemen	71	(364)	1,836	66	(310)	1,224	93	(408)	918
China, Philippines, Vietnam, India, Korea, Japan	506	(1,515)	1,836	553	(1,583)	1,224	554	(1,601)	918
Other countries	41	(153)	33,660	42	(150)	22,440	46	(172)	16,830

Notes: Standard deviations in parenthesis. Observations at the country-of-birth state-year level. Samples consists of balanced panels.

Table 2 shows 2015-2016 and 2017 means of state ICE arrest per 100,000 capita across for the top 4 arrest countries. Figure A1 in the Appendix plots the yearly number of arrest separately by state and country of birth, showing variation across states and time.

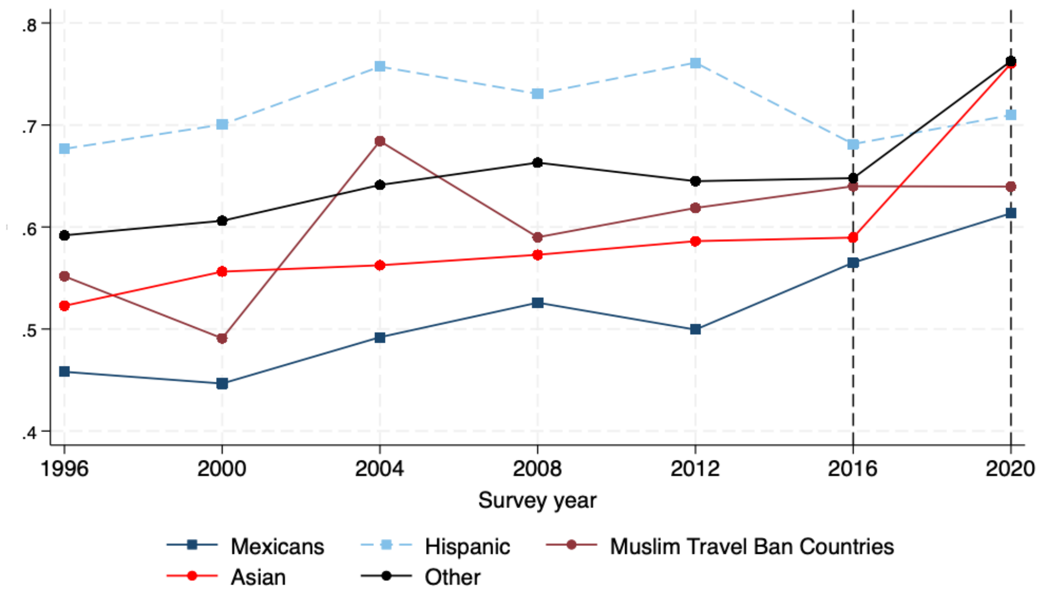
Table 2 – Pre and Post: State-Level ICE Detention Means per 100,000 State Capita of Nationals of Top 4 Countries

	Fiscal Year 2014-2016			Fiscal Years 2017-2019		
	mean	sd	obs	mean	sd	obs
Mexico	16	(20)	153	21	(22)	153
Guatemala	2	(2)	150	4	(3)	149
Honduras	2	(2)	142	3	(3)	151
El Salvador	1	(2)	143	2	(3)	142

Notes: Standard deviations in parenthesis. Observations at the country-of-birth state-year level.

Figure 2 shows Current Population Survey reported voting turnouts of U.S. naturalized citizens for presidential elections. Naturalized Mexican and Asian-born US citizens have in general lower reported turnouts than all other groups, although there is a sustained increased over time. The turnout for Mexican-identified seems to have risen more than other groups in 2016. However, the biggest increase in 2020 is seen for Asian-born.

Figure 2 – Presidential Voting Turnout in CPS Sample by Groups of Interest



Notes: Sample consists of naturalized citizens. Mexicans and Hispanics are Self-Identified. Naturalized citizens of Muslim countries included in the 2017 Travel Ban were people born in the following countries: Iran, Libya, Somalia, Sudan, Syria, Yemen. Asian countries include: China (PRC), Philippines,Vietnam, Japan, India and Korea.

VII. Naturalization Results

Table 3 shows the results of the coefficient on the post*mexican treatment indicator. Across specifications, there is a consistent positive effect of the naturalization of those immigrants born in Mexico relative to those of other non-targeted countries (excluding the countries in the other potentially treated groups). The effect is positive and statistically significant for the post-group period, but as can be seen by the bottom panel of 3, when broken down by years this effect is negative in fiscal year 2016 but positive in 2017 on. Fiscal year 2016 is from October 1st 2015 till September 30th 2016, so while Trump had already targeted Mexicans in his campaign, he had not yet been voted as president and the threat might have been empty at that point. Furthermore, as can be seen by specifications (6) and (7), the level of clustering has some effect on the standard errors, with a few specific years at the beginning and end no longer being statistically significant. In the base specifications (1)-(5), we cluster at the country of birth level, which is the level of the treatment here and as was done by (Fouka, 2019). We further test the robustness of the results when using only state or both multi-way clusters at the state and country of birth level. Interpreting the first panel of 3, nationalizations for those born in Mexico increased by 277 on average in the post period relative to those born in other countries. This is about 13% increase relative to the 2004-2015 state average of 2,036. As can be seen by the bottom panel of 3, this effect seems to take effect starting in 2017 and peak in 2018, with a coefficient of 532. When using only Latin American countries as a control group, the results are very similar, as can be seen in 6

Interestingly, for other Latin Americans, there is no effect in the grouped post period but when broken down by years, it seems that there are some increases only in 2016, in the opposite direction than that of Mexicans, as can be seen in Table 4. For countries subject to the travel ban, the coefficients for the grouped period are negative but not statistically significant. When broken down by years, the direction is negative, except for 2019, although not consistently statistically significant, as seen in Table 5.

Table 3 – Coefficients on Interaction of Mexico, Post Year and 2016-2019 Dummies

	(1)	(2)	(3)	(4)	(5)	(6)
	natural_norm	naturalizations mexico	naturalizations mexico	naturalizations mexico	naturalizations mexico	naturalizations mexico
post*mexico	-0.0477	186.3***	186.3***	186.3***	186.3***	186.3
	(0.0668)	(2.676)	(2.676)	(2.678)	(2.678)	(139.6)
post	0.0733***	-3.366				
	(0.00618)	(2.071)				
mexico	0.0176	1970.8***	1970.8***			
	(0.0406)	(12.77)	(12.77)			
Observations	113373	113373	113373	113373	113373	113373
linear trend		Yes				
year f.e.			Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes
state f.e.					Yes	Yes
s.e. clustering	country	country	country	country	country	state

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations
2016*mexico	-13.12***	-12.26***	-12.61***	-12.61***	-12.61***	-12.61	-12.61
	(2.550)	(2.193)	(2.070)	(2.072)	(2.072)	(159.4)	(82.15)
2017*mexico	273.3***	273.6***	279.9***	279.9***	279.9***	279.9***	279.9***
	(2.550)	(2.424)	(2.385)	(2.386)	(2.387)	(93.59)	(63.25)
2018*mexico	530.7***	530.4***	532.7***	532.7***	532.7***	532.7***	532.7***
	(2.550)	(2.682)	(2.609)	(2.611)	(2.612)	(195.7)	(131.5)
2019*mexico	317.9***	317.1***	308.8***	308.8***	308.8***	308.8	308.8***
	(2.550)	(2.959)	(4.202)	(4.205)	(4.206)	(303.6)	(6.759)
Observations	98736	98736	98736	98736	98736	98736	98736
linear trend		Yes					
year f.e.			Yes	Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes	Yes
state f.e.					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	state	state & country

Notes: Observations at the country-of-birth-year-state level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for specifications (6) clustering at the state level, and (7) multi-way clustering at the country of birth and state level. Pre-years include 2004-2015. Sample consists of balanced panel which naturalization state counts from birth countries with data all throughout 2004-2019. Other countries in Latin America and those subject to the 2017 travel ban excluded from control group. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4 – Coefficients on Interaction of Latin-American Country of Birth, Post Year and 2016-2019 Dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations
post*LatinAm.	9.040	9.040	9.040	9.040	9.040	9.040**	9.040
	(7.402)	(7.402)	(7.402)	(7.407)	(7.408)	(4.241)	(6.939)
post	2.703	-5.813**					
	(2.548)	(2.591)					
latin	65.65**	65.65**	65.65**				
	(28.17)	(28.17)	(28.17)				
Observations	120768	120768	120768	120768	120768	120768	120768
linear trend		Yes					
year f.e.			Yes	Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes	Yes
state f.e.					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	state ~~& country~~	state & country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations
2016*LatinAm.	17.01**	18.63**	17.52**	17.52**	17.52**	17.52**	17.52*
	(8.418)	(8.625)	(8.286)	(8.291)	(8.293)	(7.224)	(9.724)
2017*LatinAm.	0.695	1.235	7.291	7.291	7.291	7.291	7.291
	(5.595)	(5.612)	(5.521)	(5.525)	(5.526)	(4.802)	(6.356)
2018*LatinAm.	7.170	6.630	9.141	9.141	9.141	9.141	9.141
	(7.926)	(7.895)	(7.946)	(7.950)	(7.952)	(6.847)	(8.644)
2019*LatinAm.	11.29	9.668	2.209	2.209	2.209	2.209	2.209
	(10.40)	(10.29)	(10.93)	(10.93)	(10.93)	(7.636)	(10.91)
Observations	120768	120768	120768	120768	120768	120768	120768
linear trend		Yes					
year f.e.			Yes	Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes	Yes
state f.e.					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	state	state & country

Notes: Observations at the country-of-birth-year-state level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for specifications (6) clustering at the state level, and (7) multi-way clustering at the country of birth and state level. Pre-years include 2004-2015. Sample consists of balanced panel which naturalization state counts from birth countries with data all throughout 2004-2019. Mexico and those countries subject to the 2017 travel ban excluded from control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 – Coefficients on Interaction of Travel-Banned Muslim Country of Birth, Post Year and 2016-2019 Dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations
post*TravBanMusl.	-5.857	-5.857	-5.857	-5.857	-5.857	-5.857**	-5.857
	(5.589)	(5.589)	(5.589)	(5.593)	(5.594)	(2.888)	(4.537)
post	2.703	-1.131					
	(2.550)	(1.771)					
travelbanmus	5.556	5.556	5.556				
	(30.71)	(30.71)	(30.71)				
Observations	102816	102816	102816	102816	102816	102816	102816
linear trend		Yes					
year f.e.			Yes	Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes	Yes
state f.e.					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	state	state & country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations	naturalizations
2016*TravBanMusl.	-9.556*	-8.855*	-9.046*	-9.046*	-9.046*	-9.046***	-9.046**
	(4.945)	(4.771)	(4.716)	(4.719)	(4.720)	(2.557)	(4.394)
2017*TravBanMusl.	-16.88**	-16.64**	-10.28	-10.28	-10.28	-10.28**	-10.28
	(7.564)	(7.528)	(7.510)	(7.514)	(7.516)	(4.214)	(6.768)
2018*TravBanMusl.	-12.28	-12.52	-10.31	-10.31	-10.31	-10.31**	-10.31
	(8.027)	(8.064)	(8.047)	(8.052)	(8.054)	(4.862)	(6.980)
2019*TravBanMusl.	15.29***	14.59**	6.211	6.211	6.211	6.211	6.211
	(5.525)	(5.670)	(6.456)	(6.460)	(6.462)	(3.999)	(4.494)
post	2.703	-1.036					
	(2.550)	(1.769)					
travelbanmus	5.556	5.556	5.556				
	(30.71)	(30.71)	(30.71)				
Observations	102816	102816	102816	102816	102816	102816	102816
linear trend		Yes					
year f.e.			Yes	Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes	Yes
state f.e.					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	state	state & country

Notes: Observations at the country-of-birth-year-state level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for specifications (6) clustering at the state level, and (7) multi-way clustering at the country of birth and state level. Pre-years include 2004-2015. Sample consists of balanced panel which naturalization state counts from birth countries with data all throughout 2004-2019. Mexico and countries in Latin America and excluded from the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I now run the estimation using Mexico as a treatment group and only countries in Latin America as a control group. Table 6 shows the results of this and the results are very similar to those using only the non-treated countries as a control. The average effect estimated suggest that nationalizations for those born in Mexico increased by 268 on average in the post period relative to those born in other Latin American countries. This is again about 13% increase relative to the 2004-2015 state average of 2,036.

Table 6 – Coefficients on Interaction of Mexican and Post Year and 2016-2019 Dummies Using Only Latin America as a Control Group.

	(1) naturalizations	(2) naturalizations	(3) naturalizations	(4) naturalizations	(5) naturalizations	(6) naturalizations	(7) naturalizations
post*mexico	268.2***	268.2***	268.2***	268.2***	268.2***	268.2**	268.2***
	(7.049)	(7.049)	(7.051)	(7.055)	(7.062)	(131.0)	(16.48)
post	11.74	-21.40***					
	(7.049)	(7.203)					
mexico	1907.3***	1907.3***	1907.3***				
	(25.67)	(25.67)	(25.67)				
Observations	23664	23664	23664	23664	23664	23664	23664
linear trend		Yes					
year dummies			Yes	Yes	Yes	Yes	Yes
country dummies				Yes	Yes	Yes	Yes
state dummies					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	country	state & country

	(1) naturalizations	(2) naturalizations	(3) naturalizations	(4) naturalizations	(5) naturalizations	(6) naturalizations	(7) naturalizations
2016*mexico	-22.16***	-16.16***	-30.13***	-30.13***	-30.13***	-30.13	-30.13
	(7.049)	(5.800)	(8.141)	(8.145)	(8.154)	(159.0)	(95.81)
2017*mexico	264.3***	266.3***	272.6***	272.6***	272.6***	272.6***	272.6***
	(7.049)	(6.601)	(5.053)	(5.056)	(5.062)	(93.33)	(70.18)
2018*mexico	521.7***	519.7***	523.5***	523.5***	523.5***	523.5***	523.5***
	(7.049)	(7.522)	(7.615)	(7.620)	(7.628)	(195.1)	(145.7)
2019*mexico	308.9***	302.9***	306.6***	306.6***	306.6***	306.6	306.6***
	(7.049)	(8.526)	(10.23)	(10.24)	(10.25)	(302.4)	(9.124)
Observations	23664	23664	23664	23664	23664	23664	23664
linear trend		Yes					
year f.e.			Yes	Yes	Yes	Yes	Yes
country f.e.				Yes	Yes	Yes	Yes
state f.e.					Yes	Yes	Yes
s.e. clustering	country	country	country	country	country	state	state & country

Notes: Observations at the country-of-birth-year-state level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for specifications (6) clustering at the state level, and (7) multi-way clustering at the country of birth and state level. Pre-years include 2004-2015. Sample consists of balanced panel which naturalization state counts from birth countries with data all throughout 2004-2019. Only countries in Latin America included in the control group.

VIII. ICE Interior Arrests Results

In this section we focus on state naturalization and arrests of those from Mexico. Given that this group seems to have increased their naturalization numbers, in this section we explore how the number of ICE arrest might be related to the number of naturalizations in the post period relative to the average of 2015-2016, the last two years of the Obama administration. To do this, we focus on state-level variation of ICE arrests. We expect these arrest to have a spillover effect to non-deportable permanent residents eligible for naturalization, either through erroneous ICE encounters or arrest of community members, which may increase the fear for those that are not yet citizens. In general, we find that after controlling for year and state fixed effects, an increase in 1 arrests per 100,000 capita on average in the post period increases the number of naturalizations by 27 for Mexican nationals, relative to the pre-period. There were on average an increase of 3 arrests per 100,000 capital. States with higher post-period arrest are therefore expected to have more naturalizations in the post period. This coefficient, however, is only statistically significantly different than zero at the 10% level.

Table 7 – Coefficients on Interaction of Avg.Period Ice Arrest and Post Year Dummies. Mexican Nationals.

	(1) naturalizations	(2) naturalizations	(3) naturalizations
Post*AvgIceArrests	10.71	10.71	27.14*
	(22.15)	(22.28)	(14.84)
Post	-443.9	0	0
	(368.0)	(.)	(.)
AvgIceArrests	159.6**	159.6**	-14.15
	(67.85)	(68.26)	(36.67)
Observations	255	255	255
year f.e.		Yes	Yes
state f.e.			Yes

Notes: Observations at the country-of-birth-year-state level. Sample restricted to observations from Mexico. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the state level. Pre-years include 2015-2016 and post-years 2017-2019.

IX. Voting Turnout Results

In this section, we look at the results of a linear probability model of having voted for the sample of all naturalized citizens in the CPS. We find that there was a positive and statistically significant effect on the reported probability of voting of naturalized Mexicans in the 2016 election, as can be seen in Table 8 but no effect for the 2018 midterm (see Appendix Table A2). Each additional specification adds a staggered set of controls and the final specifications change the level of clustering of the standard errors. The coefficeint of 0.04 suggests an increase of about 4 percentage points in the voting turnout of Mexicans relative to those of other nationalities for the 2016 election. Relative to the pre-post presidential election turnout of .49 for Mexicans, this is about a 8 percent increase.

I find no consistent significant effect on the probability of having voted for naturalized citizens of Muslim countries targeted by Trump's travel ban and those identifying as non-Mexican Hispanic (see Appendix Tables A3 and A4). We find some effect on the probability of voting in the 2018 Midterm election for non-Mexican Hispanics but only after having controlled for year of immigration.

Table 9 shows the results of the treatment effect for Mexicans using only individuals that identify as Hispanics as the control group, a more similar set. The effect is now about an increase in turnout by 7 percentage points, about a 15% increase relative to the .49 mean, an even greater effect than when using all other nationalities as a control group.

Table 8 – Linear Probability Model Coefficients on 2016*Mexican. Effect on Reported Voting Turnout in 2016 Presidential Election.

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2016*mexican	0.0594***	0.0443***	0.0446***	0.0446*	0.0446
	(0.0114)	(0.0135)	(0.0134)	(0.0227)	(0.0298)
postyearmex=2020	-0.00558	-0.0194	-0.0220	-0.0220	-0.0220
	(0.0154)	(0.0147)	(0.0145)	(0.0417)	(0.0438)
mexican	-0.131***				
	(0.0456)				
N. of observations	30236	30236	30236	30236	30236
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	state & country

Notes: Observations at the individual-year level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for the last 2 specifications. Pre-years include election years 1996-2012. Sample is restricted to naturalized citizens that answered yes/no to having had voted (excludes non-responses and missings). Excludes Non-Mexican self-reported Hispanics and those born in Muslim countries affected by the 2017 travel ban. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 – Linear Probability Model Coefficients on 2016*Mexican. Effect on Reported Voting Turnout in 2016 Presidential Election Using Other Hispanics as a Control Group.

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2016*mexican	0.0886***	0.0710**	0.0694**	0.0694**	0.0694*
	(0.0300)	(0.0288)	(0.0289)	(0.0295)	(0.0404)
mexican	-0.200***				
	(0.0178)				
N. of observations	8124	8124	8124	8124	8124
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	country & state

Notes: Observations at the individual-year level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for the last 2 specifications. Pre-years include election years 1996-2012. Control group is other Hispanics. Sample is restricted to naturalized citizens that answered yes/no to having had voted (excludes non-responses and missings). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

X. Robustness Checks: Including years 2020 through 2022

In this section, we provide an update of some results using data from 2020 through 2022. As it is apparent, the main issue here is the COVID-19 pandemic, which severely affected the dynamics of political participation, naturalization, and migration. As a result, we include the results with caution, even if they are mostly robust for the period.

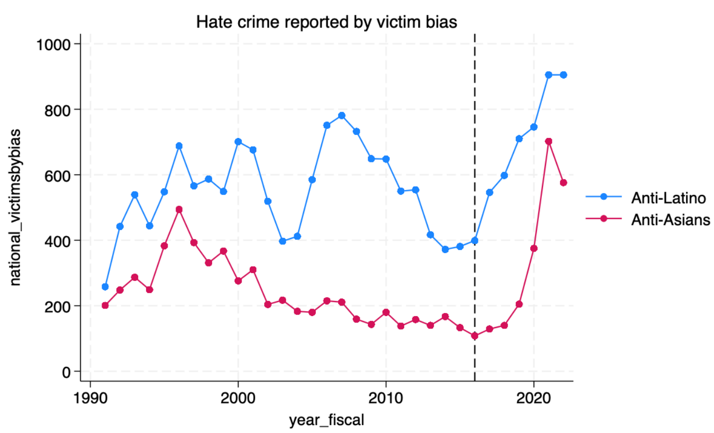
[From Chan: The association of China with COVID-19 manifested in a rise of antipathy toward Asian Americans. Evidence shows that there was a clear spike in reported hate crimes against Asian Americans by April 2020, with further academic research showing a growth in anti-Asian sentiment among the American public (Jeung et al., 2021; Lu et al., 2021; Lu et Sheng, 2020; Tessler, Choi, and Kao 2020; Chan, Leung, and Kim 2021). Asian Americans were simultaneously struggling with not only the threat of public health but also the racial targeting aimed at their community.]

[From Kim: To advance research in this area, the current study examines how a diverse, "pan-ethnic" Asian group can function as a cohesive collective using evidence from a behavioral game, an innovation in this area of research. I show that an inclusive common ingroup can be forged and cohesion attained when shared threats of exclusion that cut across subgroup distinctions are made salient. I demonstrate this using original experimental data that allow me to examine behavioral measures of group cohesion, as well as policy support for different subgroups. Results show the existence of co-ethnic bias among Asians in the US towards those who share their ethnic background. They also show the power of salient shared exclusionary discrimination to overcome this bias by increasing ingroup cohesion in a one-shot economic game and enhancing support for policies that benefit Asians as a group. Taken together, this study highlights unique conditions of group-based threats under which Asians in the US achieve political cooperation—particularly across South and East Asian lines—due to substantial heterogeneity within the group category.]

During this period, we could differentiate several dynamics: (1) A shift of contentiousness of ethnic targeting from Mexican and Latinos to Asians, as presented in Figure XXXX. Hence, we consider a fourth group, "Asians", as being treated on and after 2020. [17], (2) A slow-down of ICE arrests and detentions due to COVID restrictions, and, (3) a systemic, up-ward shift in voter turn-out in the 2020 elections.

However, the first dynamic falls outside of the scope of this paper, as we....

Figure 3 – Total Hate crimes reported by Victim bias



Notes: Thkdhsdjk

Naturalization

The analysis of naturalization indicates that Asians did not increase their rate post-2020 [Mexican results are robuts].

[17]For this definition we follow the rationale of Chan et al. (2024) and include naturalized citizens born in China, Vietnam, the Philippines, Korea, India, and Japan.

[Table with results here]

Voting

The most interesting result is related to voting turnout, as Asian changed their voting behaviour at an incredible pace. This has been documented by several autors. Chan et al. (2024) use the Multiracial Post-Election Survey to shed light on the voting behaviour of Asians (including naturalized citizens and).

Kim on the other hand, uses the concept of pan-Asian identity Chan et al. (2024); Kim (2023); Zhang (2023).

Hate Crime

As presented in figure XXX 2020 saw a massive uptick in hate crimes towards asian victims

ICE detentions

The dyamics of ice arrests are too convoluted during the period (???)

XI. Robustness Checks: Event Study Analysis

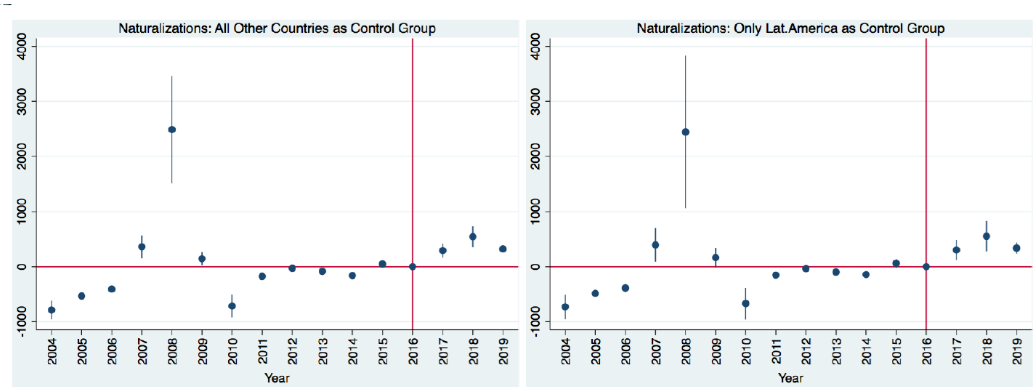
******* PROBABLY NOT NECESSARY WITH THE SDID METHODOLOGY

In this section, we analyze the plausibility of parallel trends using an event study framework. This is done by estimating 1, but with a full set of time leads and lags, using the year 2016 as the base year. The specification is the one with the fullest set of controls, a full set of year dummies, country-of-birth dummies, and state dummies. Standard errors are clustered multi-way at the country of birth and state levels to test the sensitivity of these. We focus on Mexicans as a treatment group, and use two control groups 1) the full set of countries that were not previously used a a treatment group (non Latin America, non Travel Ban), and as a plausibly better control 2) other countries in Latin America.

Table 10 shows the coefficients and Figure 4 plots these coefficients. In general, using all of the non-treated countries as a control group gives very similar results to using countries in Latin America as a control group. As shown in Table 10, the lead coefficients are almost statatistically significantly different than zero, which is problematic for the parallel trends assumption. This seems to be the case particularly because the coefficients are very precisely estimated given their small standard errors. In the specification with the largest standard errors, the one clustering only at the state level, this no longer seems to be the case, although post-treat coefficients also lose significance.

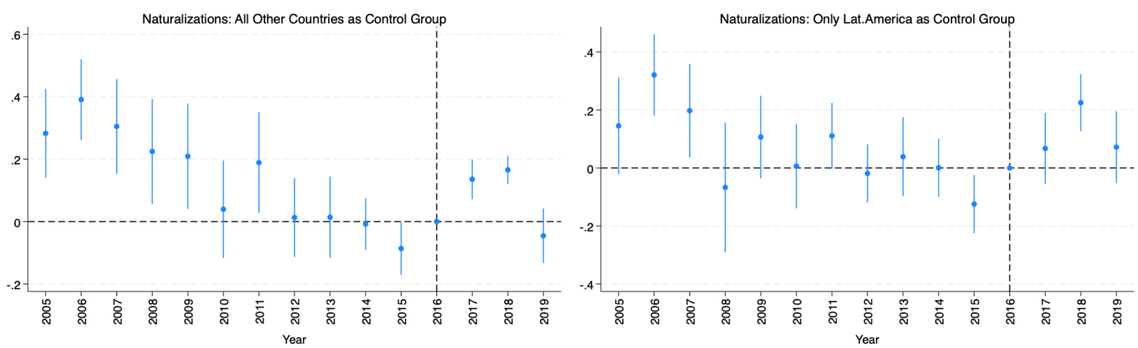
The coefficients from 2010-2014 are all negative, which seems to point that for these years, naturalizations for Mexico were consistently below that of the control group, and there does not seems to be a particular upward or downward trend, at least from years 2011 onwards. In contrast, the coefficients in the post period are all positive, suggesting that there was a shift from a negative to positive effect. In the future, we would have to research what can be done given the nonzero leads and potentially find more controls that could explain this. However, when using the most conservative set of errors (clustering at state level) where there seem to be no pre-treatment effects, the results still show robust positive effects in the post period, as was shown by specifications (6) in both Table 3 and Table 6 .

Figure 4 – Lead Lag Coefficients: Control Group 1) "Others" and 2) Latin American Countries after Normalizing by the Number of eligible to Naturalize



Notes:

Figure 5 – Lead Lag Coefficients: Control Group 1) "Others" and 2) Latin American Countries after Normalizing by the Number of eligible to Naturalize



Notes:

Table 10 – Event Study Coefficients

	Control: All			Control: Lat.America		
	(1) naturalizations	(2) naturalizations	(3) naturalizations	(4) naturalizations	(5) naturalizations	(6) naturalizations
mex2004	-786.6***	-786.6***	-786.6***	-729.3***	-729.3**	-729.3***
	(82.65)	(278.2)	(3.908)	(108.4)	(275.1)	(18.22)
mex2005	-532.9***	-532.9**	-532.9***	-485.4***	-485.4**	-485.4***
	(22.06)	(199.9)	(3.926)	(22.67)	(198.0)	(16.54)
mex2006	-408.0***	-408.0**	-408.0***	-388.0***	-388.0*	-388.0***
	(29.82)	(196.0)	(3.091)	(38.40)	(194.9)	(11.27)
mex2007	361.5***	361.5	361.5***	395.1**	395.1	395.1***
	(104.2)	(386.1)	(3.015)	(149.2)	(383.9)	(14.43)
mex2008	2488.2***	2488.2	2488.2***	2443.8***	2443.8	2443.8***
	(484.3)	(1575.4)	(5.856)	(677.7)	(1566.4)	(16.21)
mex2009	144.2**	144.2	144.2***	165.2*	165.2	165.2***
	(59.40)	(236.5)	(2.812)	(86.51)	(235.7)	(9.225)
mex2010	-714.8***	-714.8**	-714.8***	-669.5***	-669.5**	-669.5***
	(103.9)	(324.9)	(3.475)	(139.6)	(321.4)	(16.07)
mex2011	-174.5***	-174.5*	-174.5***	-153.5***	-153.5*	-153.5***
	(21.92)	(90.01)	(2.276)	(26.49)	(88.14)	(10.99)
mex2012	-28.91***	-28.91	-28.91***	-36.19**	-36.19	-36.19***
	(5.336)	(41.72)	(2.405)	(14.73)	(43.89)	(5.141)
mex2013	-84.46***	-84.46	-84.46***	-98.16***	-98.16	-98.16***
	(3.210)	(57.74)	(1.518)	(11.67)	(59.03)	(8.365)
mex2014	-161.1***	-161.1***	-161.1***	-143.0***	-143.0***	-143.0***
	(6.558)	(50.20)	(2.296)	(13.19)	(50.72)	(7.363)
mex2015	48.78*	48.78	48.78***	60.39	60.39	60.39***
	(27.58)	(91.69)	(1.260)	(38.03)	(90.36)	(5.498)
mex2016						
mex2017	292.5***	292.5	292.5***	302.7***	302.7	302.7***
	(64.41)	(222.9)	(1.699)	(90.54)	(222.5)	(4.753)
mex2018	545.3***	545.3*	545.3***	553.7***	553.7*	553.7***
	(93.76)	(292.8)	(1.580)	(133.4)	(293.0)	(5.604)
mex2019	321.5***	321.5	321.5***	336.8***	336.8	336.8***
	(33.68)	(219.5)	(3.243)	(50.08)	(219.2)	(6.509)
Observations	98736	98736	98736	23664	23664	23664
linear trend						
year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
state f.e.	Yes	Yes	Yes	Yes	Yes	Yes
s.e. clustering	state & country	state	country	state & country	state	country

Notes: Observations at the country-of-birth-year-state level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level. Pre-years include 2004-2015. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

XII. Discussion

Political engagement at the electorate level is an important step in the integration process of immigrants, and whose pre-requisite in most countries is naturalization. Naturalization has been shown to develop political integration by increasing formal political participation, political knowledge, and political efficiency Hainmueller, Hangartner, and Pietrantuono (2015). Furthermore, naturalization grants foreign born individuals nearly all the benefits, rights, and responsibilities as native born citizens, including the right to vote and full protection from deportation. In the case where immigrants may perceive discrimination, it is not straightforward whether this will hinder or increase their political participation and likelihood on integrating into the electorate.

In this paper, we test the hypothesis that those that are more directly targeted by anti-immigrant rhetoric increased voting turnout in 2016 and their naturalization numbers during the Trump administration. We find that the only significant effect was for Mexicans, one of the most targeted and largest immigrant groups that has been previously shown to become the most politicized by Trump's rhetoric.

I further use ICE arrests, since this is likely to also lead to spillover effects to permanent residents, and can be used as a measure of threat. The effect of this is not clear ex-ante, since encounters with ICE might lead to fear and anxiety which may decrease the probability of wanting to engage in the formal procedure of naturalization. Using state variation in the pre and post period, we find that Mexican nationals are more likely to naturalize in states where arrest increased, when adding state fixed effects.

Finally, we find a positive effect in voting turnout of Mexicans in 2016 relative to other immigrant groups, even when using other self-identified Hispanics as a control group.

These results are in line with a social identity theory in which the most salient and politically targeted group, i.e. Mexicans, increased their voting turnout in a political campaign in which their identity became more politicized. It also indicates that increases in naturalizations may have been used in order to provide some protection from the potential consequences of Trump's presidency. Surprisingly, the effect does not seem to have spilled over to other closely related immigrant groups from other Latin American countries, perhaps because their identity was not particularly triggered or become salient from Trump's attacks, since most of these were specific to Mexicans and Mexico. Additionally, the null effects found for individuals belonging to Muslim countries could be due to the fact that this group of countries that was banned from traveling to the U.S was not clearly defined, and nationalities kept being added and removed from this group throughout Trump's presidency. On the other hand, if this group faced both political systematic discrimination (which is hypothesized to increase political behavior) and interpersonal discrimination (e.g. in the form of personal hate crimes, which is hypothesized to decrease political behavior) (Oskooii, 2016), the net effect may be null.

A limitation of this study is that we do not observe who immigrants vote for. Furthermore, naturalizations should account for past immigration increases unrelated to Trump's presidency and election.

XIII. Potential Revisions and Extensions / Questions

- Data
  - Naturalizations (priority): we need to divide number naturalized by number of eligible to naturalize for each country to have more of a naturalization rate and avoid increases due to increases in past migration waves.
  - Voting turnout: Add 2020 Current Population Survey Voting Turnout Data. Also, use CPS weights that take into account potential

  - ~~Should add naturalization costs/fees by year, since increases in these from one year to the other can also drive spikes in naturalization (although it's the same effect for all groups, so may not necessarily change the results so much if year f.e. are included)~~
  - ~~Other covariates?~~

- Research Design
  - ~~Catch up on all of the new DID literature to make sure the type of DID we am doing still makes sense. Add necessary identification checks.~~
  - Think more carefully about the definition of treatment/control groups. Particularly, what nationalities make up the appropriate treatment/control group. What nationalities make up the control group? As of now, everyone else who is not from Latin America/ Muslim travel ban country, but potentially need to also remove Asians if they have also been targeted? Or maybe use Europeans or others that were not targeted.
  - Need to check heterogeneity within Latin Americans: Cubans are not the same as those from El Salvador/Guatemala/Honduras and this may be resulting in effects canceling out? Need to make sure results are robust to omitting certain countries (e.g. Cubans?)
  - Need to more carefully think about building appropriate Travel Ban group... Many countries were added and removed throughout the presidency....
  - Try to take into account potential geographical heterogeneity or measure some more direct effect (in a way this is what we try to do with arrests/hate crimes...). We saw a study that uses Trump's twitter data and some exogenous variation based on his presidential schedule to look at the effect of Trump's rhetoric on hate crimes for Muslims/Arabs.
  - Question: What is going on with the event study? In 2008 there is a huge spike for some potential reasons: 1) 2007 anti-immigration legislation/ huge protests that resulted in 2008 naturalizations, 2) Presidential Campaign of Barack Obama potentially driving naturalizations to be eligible to vote 3) Increase in naturalization fees, making everyone want to naturalize before spikes. Since naturalization takes a while, this is only visible in 2008. Why are the standard errors so small?

Other

- At what level should the standard errors be clustered? "Treatment" here is at the country of birth level, so does it make sense to cluster also at the state level?
- Revise the literature section to only focus on the relevant literature and to make it clear which specific literature we am contributing to.
- Does voting turnout of individuals change based on their year of naturalization? this will be interesting to see if more recent immigrants are more likely to respond and there is data on this on CPS.

- Do ICE arrests and hate crimes change voter turnout?
- Look at voting turnout of immigrants relative to non-immigrants

References

Abrajano, M., & Hajnal, Z. L. (2017). *White backlash: Immigration, race, and American politics*. Princeton University Press.

Ahmed, A. M., & Hammarstedt, M. (2008). Discrimination in the rental housing market: A field experiment on the internet. *Journal of Urban Economics*, *64*(2), 362–372.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021, December). Synthetic difference-in-differences. *American Economic Review*, *111*(12), 4088-4118. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aer.20190159 doi: 10.1257/aer.20190159

Armenta, B. E., & Hunt, J. S. (2009). Responding to societal devaluation: Effects of perceived personal and group discrimination on the ethnic group identification and personal self-esteem of Latino/Latina adolescents. *Group Processes & Intergroup Relations*, *12*(1), 23–39.

Ayers, J. W., & Hofstetter, C. R. (2008). American muslim political participation following 9/11: Religious belief, political resources, social structures, and political awareness. *Politics and Religion*, *1*(1), 3–26. doi: 10.1017/S1755048308000023

Baker, B. (2019). *Estimates of the lawful permanent resident population in the united states and the subpopulation eligible to naturalize: 2015-2019.* Department of Homeland Security Office of Immigration Statistics. Retrieved 2021-04-26, from https://www.dhs.gov/sites/default/files/publications/immigration-statistics/Pop_Estimate/LPR/lpr_population_estimates_january_2015_-_2019_v2.pdf

Barreto, M. A., Manzano, S., Ramírez, R., & Rim, K. (2009). Mobilization, participation, and solidaridad: Latino participation in the 2006 immigration protest rallies. *Urban Affairs Review*, *44*(5), 736-764. Retrieved from https://doi.org/10.1177/1078087409332925 doi: 10.1177/1078087409332925

Berry, J. A., Cepuran, C., & Garcia-Rios, S. (2022, May). Relative group discrimination and vote choice among Blacks, Latinos, Asians, and Whites. *Politics, Groups, and Identities*, *10*(3), 410–429. Retrieved 2024-04-17, from https://www.tandfonline.com/doi/full/10.1080/21565503.2020.1842770 doi: 10.1080/21565503.2020.1842770

Blizzard, B., & Batalova, J. (2019). Naturalization trends in the United States. *Migration Policy Institute*. Retrieved from https://www.migrationpolicy.org/article/naturalization-trends-united-states

Bosch, M., Carnero, M. A., & Farre, L. (2010). Information and discrimination in the rental housing market: Evidence from a field experiment. *Regional science and urban Economics*, *40*(1), 11–19.

Branscombe, N. R., Schmitt, M. T., & Harvey, R. D. (1999). Perceiving pervasive discrimination among African Americans: Implications for group identification and well-being. *Journal of personality and social psychology*, *77*(1), 135.

Budiman, A., Noe-Bustamante, L., & Lopez, M. H. (2020). Naturalized citizens make up record one-in-ten u.s. eligible voters in 2020. *Pew Research Center*. Retrieved from https://www.pewresearch.org/hispanic/2020/02/26/naturalized-citizens-make-up-record-one-in-ten-u-s-eligible-voters-in-2020/

Bursztyn, L., Egorov, G., & Fiorin, S. (2017, May). *From Extreme to Mainstream: How Social Norms Unravel* (NBER Working Papers No. 23415). National Bureau of Economic Research, Inc. Retrieved from https://ideas.repec.org/p/nbr/nberwo/23415.html

Cantor, G., Ryo, E., & Humphrey, R. (2019). *Changing patterns of interior immigration enforcement in the United States, 2016 -2018* (Tech. Rep.).

Carlsson, M. (2010). Experimental evidence of discrimination in the hiring of first-and second-generation immigrants. *Labour*, *24*(3), 263–278.

Chan, N., Kim, J. Y., & Leung, V. (2022, June). COVID-19 and Asian Americans: How Elite Messaging and Social Exclusion Shape Partisan Attitudes. *Perspectives on Politics*, *20*(2), 618–634. Retrieved 2024-04-17, from https://www.cambridge.org/core/product/identifier/S1537592721003091/type/journal_article doi: 10.1017/S1537592721003091

Chan, N., Nguy, J. H., & Masuoka, N. (2024). The asian american vote in 2020: Indicators of turnout and vote choice. *Political Behavior*, *46*(1), 631–655.

Crandall, C. S., Miller, J. M., & White, M. H. (2018). Changing norms following the 2016 u.s. presidential election: The Trump effect on prejudice. *Social Psychological and Personality Science*, *9*(2), 186-192. Retrieved from https://doi.org/10.1177/1948550617750735 doi: 10.1177/1948550617750735

Dancygier, R. M., & Laitin, D. D. (2014). Immigration into europe: Economic discrimination, violence, and public policy. *Annual Review of Political Science*, *17*(1), 43-64. Retrieved from https://doi.org/10.1146/annurev-polisci-082012-115925 doi: 10.1146/annurev-polisci-082012-115925

DeSipio, L. (2002). Immigrant organizing, civic outcomes: Civic engagement, political activity, national attachment, and identity in Latino immigrant communities. *Center for the Study of Democracy*. Retrieved from http://www.u.arizona.edu/~jag/POL596A/desipioimmig.pdf

Disha, I., Cavendish, J. C., & King, R. D. (2011). Historical events and spaces of hate: Hate crimes against arabs and muslims in post-9/11 america. *Social problems*, *58*(1), 21–46.

Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. R. (2020). *Integrated Public Use Microdata Series, Current Population Survey: Version 7.0.* IPUMS, Minneapolis, MN. Retrieved from https://doi.org/10.18128/D030.V7.0

Fouka, V. (2019). How do immigrants respond to discrimination? the case of germans in the us during world war i. *American Political Science Review*, *113*(2), 405–422.

Garcia-Rios, S., Pedraza, F., & Wilcox-Archuleta, B. (2019). Direct and indirect xenophobic attacks: Unpacking portfolios of identity. *Political Behavior*, *41*(3), 633–656.

Glaeser, E. (2002, 09). The political economy of hatred. *The Quarterly Journal of Economics*, *120*. doi: 10.2139/ssrn.336264

Gutierrez, A., Ocampo, A. X., Barreto, M. A., & Segura, G. (2019). Somos mas: how racial threat and anger mobilized Latino voters in the Trump era. *Political Research Quarterly*, *72*(4), 960–975.

Hainmueller, J., Hangartner, D., & Pietrantuono, G. (2015). Naturalization fosters the long-term political integration of immigrants. *Proceedings of the National Academy of Sciences*, *112*(41), 12651–12656.

Hobbs, W., & Lajevardi, N. (2019). Effects of divisive political campaigns on the day-to-day segregation of Arab and Muslim Americans. *American Political Science Review*, *113*(1), 270–276.

Jasinskaja-Lahti, I., Liebkind, K., Jaakkola, M., & Reuter, A. (2006). Perceived discrimination, social support networks, and psychological well-being among three immigrant groups. *Journal of cross-cultural psychology*, *37*(3), 293–311.

Jiménez, T. R. (2010). *Replenished ethnicity: Mexican Americans, immigration, and identity*. Univ of California Press.

Jones-Correa, M. (2001). Institutional and contextual factors in immigrant naturalization and voting. *Citizenship Studies*, *5*(1), 41–56.

Kalkan, K. O., Layman, G. C., & Uslaner, E. M. (2009). "bands of others"? attitudes toward muslims in contemporary american society. *The Journal of Politics*, *71*(3), 847–862.

Kim, S. (2023). Under threat we unite: How shared marginalization shapes cohesion and political cooperation among asian americans. *Political Behavior*, 1–22.

Lajevardi, N., & Oskooii, K. A. (2018). Old-fashioned racism, contemporary islamophobia, and the isolation of muslim americans in the age of Trump. *Journal of Race, Ethnicity and Politics*, *3*(1), 112–152.

Loftin, C., & McDowall, D. (2010). The use of official records to measure crime and delinquency. *Journal of Quantitative Criminology*, *26*(4), 527–532.

Masuoka, N. (2006, December). Together They Become One: Examining the Predictors of Panethnic Group Consciousness Among Asian Americans and Latinos *. *Social Science Quarterly*, *87*(5), 993–1011. Retrieved 2024-04-17, from https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6237.2006.00412.x doi: 10.1111/j.1540-6237.2006.00412.x

McDonald, M. P. (2019). Cps vote over-report and non-response bias correction. *United States Elections Project*. Retrieved from http://www.electproject.org/home/voter-turnout/cps-methodology

McVeigh, R., Welch, M. R., & Bjarnason, T. (2003). Hate crime reporting as a successful social movement outcome. *American Sociological Review*, 843–867.

Miles, T. J., & Cox, A. B. (2014). Does immigration enforcement reduce crime? evidence from secure communities. *The Journal of Law and Economics*, *57*(4), 937–973.

Newman, B. J., Shah, S., & Collingwood, L. (2018). Race, place, and building a base: Latino population growth and the nascent Trump campaign for president. *Public Opinion Quarterly*, *82*(1), 122–134.

Oskooii, K. A. (2016). How discrimination impacts sociopolitical behavior: A multidimensional perspective. *Political Psychology*, *37*(5), 613–640.

Pantoja, A. D., & Gershon, S. A. (2006). Political orientations and naturalization among Latino and Latina immigrants. *Social Science Quarterly*, *87*(5), 1171–1187.

Pantoja, A. D., Ramirez, R., & Segura, G. M. (2001). Citizens by choice, voters by necessity: Patterns in political mobilization by naturalized Latinos. *Political Research Quarterly*, *54*(4), 729–750.

Pascoe, E. A., & Smart Richman, L. (2009). Perceived discrimination and health: a meta-analytic review. *Psychological bulletin*, *135*(4), 531.

Pérez, E. O. (2015a). Ricochet: How elite discourse politicizes racial and ethnic identities. *Political Behavior*, *37*(1), 155–180.

Pérez, E. O. (2015b). Xenophobic rhetoric and its political effects on immigrants and their co-ethnics. *American Journal of Political Science*, *59*(3), 549–564.

Pierce, S. (2019). *Immigration-related policy changes in the first two years of the Trump administration* (Tech. Rep.).

Rumbaut, R. G. (2008). Reaping what you sow: Immigration, youth, and reactive ethnicity. *Applied development science*, *12*(2), 108–111.

Sanchez, G. R. (2006, July). The Role of Group Consciousness in Political Participation Among Latinos in the United States. *American Politics Research*, *34*(4), 427–450. Retrieved 2024-04-17, from http://journals.sagepub.com/doi/10.1177/1532673X05284417 doi: 10.1177/1532673X05284417

Schildkraut, D. J. (2005). The rise and fall of political engagement among Latinos: The role of identity and perceptions of discrimination. *Political Behavior*, *27*(3), 285–312.

Schmitt, M. T., Branscombe, N. R., Postmes, T., & Garcia, A. (2014). The consequences of perceived discrimination for psychological well-being: A meta-analytic review. *Psychological bulletin*, *140*(4), 921.

Shanmugasundaram, S. (2018). Hate crimes, explained. *Southern Poverty Law Center*. Retrieved from https://www.splcenter.org/20180415/hate-crimes-explained

Szaflarski, M., & Bauldry, S. (2019). The effects of perceived discrimination on immigrant and refugee physical and mental health. *Advances in medical sociology*, *19*, 173.

Tajfel, H., Turner, J. C., Austin, W. G., & Worchel, S. (1979). An integrative theory of intergroup conflict. *Organizational identity: A reader*, *56*, 65.

Takyar, D. (2019). When interest doesn't turn into action: Discrimination, group identification, and muslim political engagement in the post-9/11 era. *Social Psychology Quarterly*, *82*(3), 231–253.

Transactional Records Access Clearinghouse (TRAC). (2018). *Ice arrests in the interior of the u.s.* Retrieved 2021-01-18, from https://trac.syr.edu/phptools/immigration/arrest/

Treyger, E., Chalfin, A., & Loeffler, C. (2014). Immigration enforcement, policing, and crime: Evidence from the secure communities program. *Criminology & Public Policy*, *13*(2), 285–322.

Trump, J. D. (2015). Donald trump announces a presidential bid. *The Washington Post*. Retrieved 2020-06-07, from https://www.washingtonpost.com/news/post-politics/wp/2015/06/16/full-text-donald-trump-announces-a-presidential-bid/

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory.* Basil Blackwell.

United States Census Bureau. (2020). *U.s. populaiton estimates.* Retrieved 2020-06-07, from https://www2.census.gov/programs-surveys/popest/datasets/

Valentino, N. A., Brader, T., Groenendyk, E. W., Gregorowicz, K., & Hutchings, V. L. (2011). Election night's alright for fighting: The role of emotions in political participation. *The Journal of Politics*, *73*(1), 156 - 170. Retrieved from http://0-search.ebscohost.com.lib.unibocconi.it/login.aspx?direct=true&db=edsjsr&AN=edsjsr.10.1017.S0022381610000939&site=eds-live&scope=site

Valentino, N. A., Brader, T., & Jardina, A. E. (2013). Immigration opposition among us whites: General ethnocentrism or media priming of attitudes about Latinos? *Political Psychology*, *34*(2), 149–166.

White, A. (2016). When threat mobilizes: Immigration enforcement and Latino voter turnout. *Political Behavior*, *38*(2), 355–382.

Zaykowski, H. (2010). Racial disparities in hate crime reporting. *Violence and victims*, *25*(3), 378–394.

Zepeda-Millán, C. (2014). Perceptions of threat, demographic diversity, and the framing of illegality: Explaining (non) participation in new york's 2006 immigrant protests. *Political Research Quarterly*, *67*(4), 880–888. Retrieved from https://doi.org/10.1177/1065912914536470

Zepeda-Millán, C. (2017). *Latino mass mobilization: Immigration, racialization, and activism*. Cambridge University Press.

Zhang, Y. (2023). Spatial segregation and voting behavior among asian americans in 2020 general election. *Social Science Research*, *116*, 102929.

Zschirnt, E., & Ruedin, D. (2016). Ethnic discrimination in hiring decisions: a meta-analysis of correspondence tests 1990–2015. *Journal of Ethnic and Migration Studies*, *42*(7), 1115-1134. Retrieved from https://doi.org/10.1080/1369183X.2015.1133279 doi: 10.1080/1369183X.2015.1133279

N. Appendix

Table A1 – List of Countries of Birth of Naturalized Citizens Included in Sample

Afghanistan	Colombia	India	Netherlands	Switzerland
Albania	Congo, Democratic Republic	Indonesia	Netherlands Antilles (former)	Syria
Algeria	Congo, Republic	Iran	New Zealand	Taiwan
American Samoa	Costa Rica	Iraq	Nicaragua	Tajikistan
Angola	Cote d'Ivoire	Ireland	Niger	Tanzania
Anguilla	Croatia	Israel	Nigeria	Thailand
Antigua and Barbuda	Cuba	Italy	Norway	Togo
Argentina	Cyprus	Jamaica	Oman	Tonga
Armenia	Czech Republic	Japan	Pakistan	Trinidad and Tobago
Aruba	Czechoslovakia (former)	Jordan	Palau	Tunisia
Australia	Denmark	Kazakhstan	Panama	Turkey
Austria	Djibouti	Kenya	Papua New Guinea	Turkmenistan
Azerbaijan	Dominica	Korea	Paraguay	Turks and Caicos Islands
Bahamas	Dominican Republic	Kuwait	Peru	Uganda
Bahrain	Ecuador	Kyrgyzstan	Philippines	Ukraine
Bangladesh	Egypt	Laos	Poland	United Arab Emirates
Barbados	El Salvador	Latvia	Portugal	United Kingdom
Belarus	Eritrea	Lebanon	Qatar	Uruguay
Belgium	Estonia	Liberia	Romania	Uzbekistan
Belize	Ethiopia	Libya	Russia	Venezuela
Benin	Fiji	Lithuania	Rwanda	Vietnam
Bermuda	Finland	Luxembourg	Saint Kitts and Nevis	Yemen
Bolivia	France	Macau	Saint Lucia	Zambia
Bosnia and Herzegovina	French Polynesia	Macedonia	Saint Vincent and the Grenadines	Zimbabwe
Botswana	Gabon	Madagascar	Samoa	
Brazil	Gambia	Malawi	Saudi Arabia	
Brunei	Georgia	Malaysia	Senegal	
Bulgaria	Germany	Mali	Serbia and Montenegro (former)	
Burkina Faso	Ghana	Malta	Seychelles	
Burma	Greece	Mauritania	Sierra Leone	
Burundi	Grenada	Mauritius	Singapore	
Cabo Verde	Guatemala	Mexico	Slovenia	
Cambodia	Guinea	Micronesia, Federated States	Somalia	
Cameroon	Guinea-Bissau	Moldova	South Africa	
Canada	Guyana	Mongolia	Soviet Union (former)	
Cayman Islands	Haiti	Montserrat	Spain	
Central African Republic	Honduras	Morocco	Sri Lanka	
Chad	Hong Kong	Mozambique	Sudan	
Chile	Hungary	Namibia	Suriname	
China, People's Republic	Iceland	Nepal	Sweden	

Notes: In the analysis, only countries at the observation level that are present throughout the whole time period in their respective samples are used.

Table A2 – Linear Probability Model Coefficients on 2018*Mexican. Effect on Reported Voting Turnout in 2018 Midterm Elections.

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2018*mexican	-0.00287	-0.0215*	-0.0207*	-0.0207	-0.0207
	(0.0120)	(0.0110)	(0.0116)	(0.0213)	(0.0289)
mexican	-0.108***				
	(0.0165)				
N. of observations	35066	35066	35066	35066	35066
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	country & state

Notes: Observations at the individual-year level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level,except for the last 2 specifications. Pre-years include election years 1994-2014. Sample is restricted to naturalized citizens that answered yes/no to having had voted (excludes non-responses and missings). Excludes Non-Mexican Hispanics and those born in Muslim countries affected by the 2017 travel ban. * p < 0.10, ** p < 0.05, *** p < 0.01.

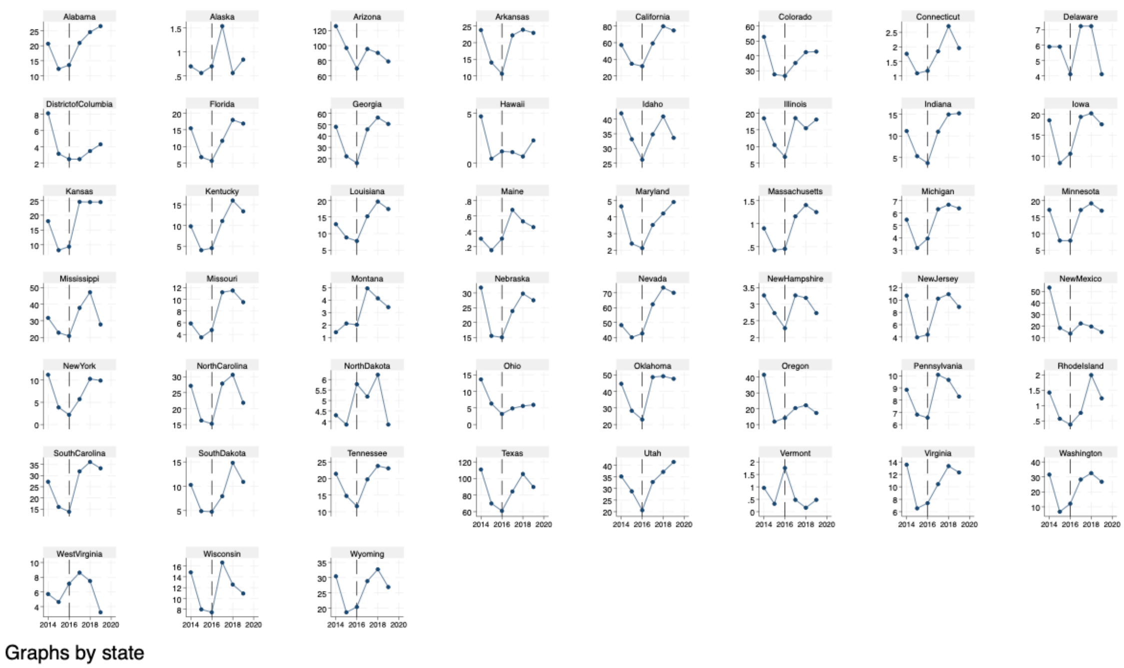
Table A3 – Linear Probability Model Coefficients on 2016/8*Hispanic. Effect on Reported Voting Turnout in 2016 Presidential Election and 2018 Midterm Election.

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2016*hispanic	-0.0288	-0.0405	-0.0375	-0.0375	-0.0375
	(0.0328)	(0.0298)	(0.0296)	(0.0274)	(0.0370)
hispanic	0.0604**				
	(0.0239)				
N. of observations	23024	23024	23024	23024	23024
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	country & state

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2018*hispanic	0.0401	0.0199	0.0232	0.0232	0.0232
	(0.0269)	(0.0242)	(0.0243)	(0.0253)	(0.0353)
hispanic	0.00135				
	(0.0305)				
N. of observations	27397	27397	27397	27397	27397
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	country & state

Notes: Observations at the individual-year level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for the last 2 specifications. Pre-years include election years 1996-2012. Sample is restricted to naturalized citizens that answered yes/no to having had voted (excludes non-responses and missings). Excludes Mexican Hispanics and those born in Muslim countries affected by the 2017 travel ban. * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure A1 – ICE Arrest Per Country of Birth per 100,000 State Capita: 2015-2017 Mexico and Other Top Countries



Notes:

Table A4 – Linear Probability Model Coefficients on 2016/8*MuslimTravelBan. Effect on Reported Voting Turnout in 2016 Presidential Election and 2018 Midterm Election.

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2016*TravelbanMusl	0.0273	0.0216	0.0279	0.0279	0.0279
	(0.0409)	(0.0391)	(0.0387)	(0.0396)	(0.0470)
TravelbanMusl	-0.0317				
	(0.0280)				
N. of observations	19367	19367	19367	19367	19367
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	country & state

	(1)	(2)	(3)	(4)	(5)
	voted	voted	voted	voted	voted
2018*TravelbanMusl	0.0846	0.0410	0.0412	0.0412	0.0412
	(0.0526)	(0.0315)	(0.0357)	(0.0484)	(0.0517)
TravelbanMusl	-0.0568*				
	(0.0299)				
N. of observations	23086	23086	23086	23086	23086
year dummies	Yes	Yes	Yes	Yes	Yes
country-of-birth dummies		Yes	Yes	Yes	Yes
state dummies			Yes	Yes	Yes
s.e. clustering				state	country & state

Notes: Observations at the individual-year level. Heteroskedasticity-robust standard errors clustered and shown in parenthesis at the country of birth level, except for the last 2 specifications. Pre-years include election years 1996-2012. Sample is restricted to naturalized citizens that answered yes/no to having had voted (excludes non-responses and missings). Excludes Mexican and Non-Mexican Hispanics. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

N.1 Hate Crime

I use hate crime data from the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) program, which complies data on hate crime, particularly crimes that manifest evidence of prejudice based on race, ethnicity, religion, sexual orientation, disability, gender, or gender identity[18]. The types of offenses that are collected as hate crime include: crimes against persons and crimes against property such as robbery, burglary, larceny-theft, motor vehicle theft, arson, and destruction/damage/vandalism. There are several weaknesses of this data, particularly that participation in the FBI UCR Program is mandated for federal law enforcement agencies, but is voluntary for local, state, and tribal law enforcement agencies, thus the number of hate crimes may be undercounting crimes that are not voluntarily reported by non-federal law enforcement agencies. Other critiques of using this data include that in many cases victims never report crimes to the police, many law enforcement agencies do a poor job of consistently collecting and categorizing hate crime data (Loftin & McDowall, 2010; Shanmugasundaram, 2018; Zaykowski, 2010). McVeigh et al. (2003) report that hate crimes are more likely to be reported in counties with a legislative mandate for data collection, in counties with resourceful civil rights organizations, and in counties

[18] Data from https://crime-data-explorer.fr.cloud.gov/downloads-and-docs.

with more political party competition.[19] Furthermore, another large drawback from this data in this analysis is that there is no indication of whether a victim was an immigrant, and it includes hate crimes committed towards all members of a group, not just those that are foreign-born immigrants.

Hate crime data is available at the incident level and includes the exact date and reporting agency. We compile the data at the fiscal year-state level, to create measures that are consistent with the naturalization data. This gives me region-specific variation in hate crimes committed towards the groups of interest. Furthermore, for the state analysis, we use U.S. Census[20] population estimates to create a measure for hate crimes per capita (per 1,000) in each state. We further use the 2010 Hispanic population in each state as a control in part of the analysis. We focus on hate crimes based on race and ethnicity and particularly those targeted against Hispanics/Latinos, Muslims and Arabs. Arabs and Muslims come from various different countries, and while not all Arabs are Muslim and refering to them together might be imprecise, their identity is often stereotyped into one and both of these groups have been targeted in similar manners, particularly post 9/11. While FBI reports anti-Muslim and anti-Arab hate crimes separately, we combine these two as is done in research that studies hate crimes towards these groups, for example, Disha, Cavendish, and King (2011); Hobbs and Lajevardi (2019). It is important to mention that the anti-Arab category was removed from 2004-2014.[21].

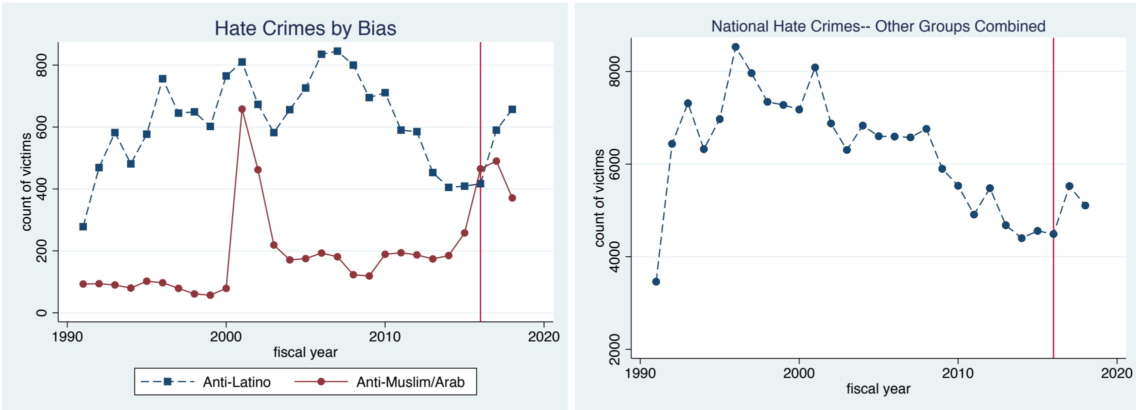
Figure A2 shows total hate crimes toward groups of interest aggregated at the fiscal-year (fiscal years run from October 1st of the previous year to September 30th of the current year) level to match the time frames of the naturalization observations. The red vertical line marks fiscal year, 2016. The left figure shows hate crimes towards Muslims/Arabs rose sharply following 9/11 and again from 2015-2016, while hate crimes toward Latinos rose rapidly for the years 2017-2018. In general, hate crimes towards other groups also rose sharply in 2017 as shown by the right figure of A2. Hate crimes include victims other than immigrants or permanent residents, so these measures are taken to be an admittedly imperfect proxy for hate crimes experienced by immigrants eligible to naturalize in these groups.

[19] In a next step we can try to compare hate crime data with report from the U.S. Justice Department's Bureau of Justice Statistics, which estimates its numbers from its National Crime Victimization Survey.

[20] United States Census Bureau (2020). From: https://www2.census.gov/programs-surveys/popest/datasets/

[21] I have to run robustness checks to see if omitting the anti-Arab category makes a difference.

Figure A2 – Hate Crimes By Groups of Interest



Notes: Note different y-scales of graphs. Other Groups victim counts excludes Latino and Arab/Muslim hate crimes and includes following types of hate crimes: Anti-American Indian or Alaska Native, Anti-Asian, Anti-Black or African American, Anti-Jewish, Anti-Multiple Race Group, Anti-White, and Anti-Other Race/Ethnicity/Ancestry.