Does Exposure to Migration Cause an Electoral Backlash? Evidence from the Mariel Boatlift*

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Abstract

Does exposure to a mass migration event cause citizens to vote against incumbents? I offer an answer to this question by focussing on one of the largest acute periods of migration in the US, the case of the Mariel Boatlift during which roughly 125,000 Cubans fled to South Florida. I estimate the effect of this migration using the synthetic control method and fixed effects regressions with a panel of county-level presidential election results and archival precinct-level election results. I find that, while Miami voters dramatically shifted to support Republican presidential candidates following the Boatlift, this shift was concentrated in overwhelmingly Cuban neighborhoods and that Cuban neighborhoods in a county with much less direct exposure increased Republican support to a similar degree. I also present evidence that this shift did not extend to voting in US House elections. These findings suggests that, in this case, direct exposure to migration did not translate into the large change in voting behavior predicted by the intergroup threat hypothesis and a number of economic models of voter behavior.

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"The refugee problem in Dade has set white against Cuban, black against Cuban, black against white, and in a sense, all of the above against Carter."

—The Washington Post, September 29, 1980[1]

1 Introduction

The concurrence of the Syrian refugee crisis and the rightward shift in European politics has many pundits arguing that immigration backlash is a key driver of native-born support for politicians on the right. Many believe immigration from Latin America has had a similar effect in the US. A large literature on intergroup threat and a number of models of economic voting support these views, finding that exposure to migration causes natives to adopt anti-migrant attitudes (see Hainmueller and Hopkins (2014) for a review).[2] But this literature also finds that the national political climate and the ethnic composition of the receiving population can minimize this effect (Hopkins 2010, 2011, 2012; Newman 2013). Taking all of this into account, should we expect exposure to migration to cause a drop in native-born support for incumbents?

Observing the relationship between where immigrants settle and support for incumbents is insufficient for answering this question—immigrants do not move at random, they tend to move where they have the best chance to fit in and build a good life. Surveys accordingly often report that support for anti-immigration candidates is lower where immigrants live (Irwin and Katz 2016; Hinojosa Ojeda, Wynnand, and Chen 2016). One way to overcome this challenge is to study cases in which the decision to migrate is driven by changes in the sending country instead of the receiving country (Becker and Fetzer 2016; Dinas et al. Forthcoming; Dustmann, Vasiljeva, and Damm Forthcoming; Steinmayr 2016; Tabellini 2018). In this paper, I study the Mariel Boatlift, a seven-month-long event in 1980 during which Fidel Castro allowed Cubans to flee and one of the most acute migration events in American history.[3] More than 120,000 left Cuba for the United States. Almost all of these Cubans passed through Miami for processing, the closest major city, and more than 70,000 were settled there by 1990.

[1] `https://www.washingtonpost.com/archive/politics/1980/09/29/floridas-top-issue/a5c316f1-82b8-4cc1-9240-7493a73edccc/`

[2] More recent work using creative identification strategies not discussed in the review include Cavaille and Ferwerda (2017) and Hangartner et al. (Forthcoming)

[3] For a discussion of the effects of the Boatlift on the Miami labor market, see Borjas (Forthcoming); Card (1990); Peri and Yasenov (Forthcoming).

I find that, even though the Boatlift was clearly a notable and disruptive event, direct exposure to the migration did not cause a large change in voter behavior. I reach this conclusion in two steps. First, I compare presidential voting in Miami-Dade to a weighted average of other counties with similar vote histories using the synthetic control method (Abadie, Diamond, and Hainmueller 2010). The synthetic control almost perfectly matches the pattern of Republican presidential support prior to the Boatlift, which is often provided as prima facie evidence that a synthetic control provides a trustworthy counterfactual. But Miami is unusual in one important way: its population was approximately 25% Cuban prior to the Boatlift, more than three times the per capita Cuban population of any other county in the US. This means that any national changes in Cuban-American politics will affect Miami-Dade more than any other county. I address this by gathering a new archival dataset of precinct-level election results in Miami-Dade County and Hudson County, New Jersey, the county with the second largest Cuban population in the US. In this second analysis, I use panel regressions to compare presidential election results before and after the Boatlift in Miami-Dade's Cuban neighborhoods to Hudson County's Cuban neighborhoods.

Using the synthetic control method, it appears as though Miami-Dade voted for Republicans at much higher rates after the Boatlift than counties with similar prior voting records. But this change was concentrated in Cuban neighborhoods and similar to a shift in Hudson County's Cuban neighborhoods. Since Hudson County received a much smaller share of the Boatlift migrants prior to the 1980 election, this suggests that the increased support for Reagan in Miami was not a backlash in response to immigration exposure.[4]

My results suggest that even a large, disruptive migration event may not cause an electoral backlash in the place most effected. This adds to a number of studies finding that the effects of migration exposure are context-specific. My results also highlight the value of testing difference-in-differences estimates using alternative comparison groups (Rosenbaum 2002).

[4] Hudson County ultimately received the second largest share of Boatlift migrants according to the 1990 Census. This is also consistent with newspaper accounts from late 1980, suggesting that approximately 7,000 Cubans resettled in New Jersey and New York after leaving processing facilities (Rand 1980).

2 Studying the Effect of Migration Exposure on Votes

2.1 A Wide Range of Theoretical Expectations

The expectations many have that migration changes the voting behavior of citizens in receiving communities typically arise from models in one of two classes. Political economy models imply that voters who compete with migrants in the labor market (Mayda 2006; Scheve and Slaughter 2001) or supply the tax base for services migrants consume (Hanson, Scheve, and Slaughter 2007) are less likely to support a candidate who favors higher rates of immigration. Including these preferences in a political agency framework, exposed voters may punish incumbents or their parties when they permit increased migration (Ashworth 2012; Fearon 1999). This punishment may be particularly stong when the signal is strong enough to be observed by voters, such as an unusually large migration event. But these models generally imply that the distance from the migration event should not meaningfully diminish its effect on voting behavior, meaning that the direct effect of exposure should be small while the effect on all citizens may be large. There is also a growing body of evidence that the substutability of native and migrant labor assumed for most results from these models may not be as great as predicted (Card 1990; Foged and Peri 2016; Peri and Yasenov Forthcoming). And some researchers dispute the size and sign of the effect the marginal migrant has on a government's budget.

Sociopsychological models suggest voters are more likely to develop anti-immigration attitudes following a migration event because of hightened concerns about national economic performance (Citrin et al. 1997), raised anxieties about cultural change (Sniderman, Hagendoorn, and Prior 2004), and fear of the now-salient out group (Brader, Valentino, and Suhay 2008). This change in attitudes can translate into prospective support for anti-immigration politicians or retrospective punishment of incumbents (Newman and Johnson 2012). Some evidence suggests that these changes can arise from relatively limited contact (Enos 2014), but other work suggests that the effect of exposure to a racial out group may decline rapidly as the expected number of interactions goes down (Enos 2016). Further, the national political context (Hopkins 2010) and the local ethnic composition (Newman 2013; Reny and Newman 2018) may limit the effect of a migration event.

These findings suggest that large, acute migration events are more likely to change voter behavior. But, even with such an event, the conditions under which the effects will be large, small, or nonexistent vary considerably based on the model.

2.2 Selective Migration Threatens Many Designs

Migrants choose whether to leave and where to settle by weighing how attractive their home is relative to alternatives abroad. Pure economic returns factor into this decision, but so do social and family ties and the political climate in potential receiving countries (Mahajan and Yang 2017; McKenzie and Rapoport 2010; Sjaastad 1962). The places migrants choose are likely to be among the most welcoming. This implies that migrants will tend to move to places that vote for candidates who endorse their presence. Even if exposure to migration provokes a political backlash, the places where migrants move may still be more supportive of pro-migration candidates than the places where migrants did not move. At the very least, the difference between receiving and non-receiving places will be an underestimate of the size of the backlash if one exists.

This logic extends to panel data as well. Standard difference-in-difference designs remove the confounding that arises from the fact that migrants move to places that are always better. But these designs still understate backlash if migrants move to the places that are improving the fastest or are becoming more attractive at the time they are making the decision. These types of violations are particularly plausible given the dynamic effects of migrant networks (Clemens 2017). More flexible panel techniques from the synthetic control literature find places that are on the same trajectory as places that receive migrants (Abadie, Diamond, and Hainmueller 2010; Doudchenko and Imbens 2016; Hazlett and Xu 2018; Xu 2017). The only remaining source of confounding is a change in receiving places that does not occur in places that do not receive migrants.

2.3 To Remove Selective Migration as a Confound, Study a Large, Exogenous Migration Event

One way to minimize the risk that migrants are moving because conditions have gotten much better in the receiving community is to find cases of forced migration. When a war breaks out or a natural disaster strikes, refugees may have to trade away quality for convenience in deciding where they go first. Their final destination may even be determined for them and selected based on availability rather than fit (Bansak et al. 2018). Accordingly, refugee flows offer a particularly plausible natural experiment for estimating the impact of migration on the votes of native-born citizens (Becker and Fetzer 2016; Dinas et al. Forthcoming; Dustmann, Vasiljeva, and Damm Forthcoming; Steinmayr 2016; Tabellini 2018).

The same logic holds for cases in which migrants who were previously unable to migrate are suddenly allowed to move. In this case, it is plausible that the migrant was not motivated to move by the quality of the labor market in their new home at the exact time they moved. Rather, they would have moved to this place at any time in recent years, but they were unable to due to a policy barrier.

2.4 Case: Mariel Boatlift When 125,000 Cubans Fled to US through South Florida

In this paper, I study the case of the Mariel Boatlift in which approximately 125,000 Cubans fled to South Florida following a change in Cuban domestic politics (Duany 1999; Garcia 1996). Between 1973 and 1980, only a small number of Cubans made it to the US. The constraints that the Cuban government placed on exit appear to have led to pent up demand. After thousands of Cubans seeking asylum took over the Peruvian embassy in the spring of 1980, the Cuban government opened the Mariel harbor, just west of Havana, to ships coming to pick up Cuban citizens. Roughly 125,000 Cubans—over 1% of the Cuban population at the time—fled to the US between April and September 1980, the vast majority of whom traveled through Key West and Miami, Florida for processing. 16% of all Cubans living in the US in 1990 arrived during this period. 60% of Boatlift migrants were living in Miami-Dade County as of 1990, and no other county received more than 4%. This massive influx of new Cuban residents in Miami-Dade County represented a roughly four percentage point increase in Miami-Dade's population.[5]

The fact that the Boatlift was a consequence of Cuban politics rather than changes in Miami-Dade makes it a good case. This makes it plausible that the migrants did not choose Miami-Dade because it had recently become much more attractive than other cities in the US. With this

[5]For a discussion of the economic conditions in Miami during this period, see Card (1990); Peri and Yasenov (Forthcoming).

assumption, estimates from a flexible panel technique that is able to identify the trajectory of Miami-Dade voting and find counties that are also on this trajectory should be unbiased.

I focuss my study on the effects the Boatlift had on the 1980 presidential election. The migrants came to the US at the height of the campaign. The president at the time of the Boatlift, Democrat Jimmy Carter, was facing a difficult reelection bid with a struggling national economy and intra-party competition from two popular politicians, Ted Kennedy and Jerry Brown. Carter faced former California Governor Ronald Reagan in the general election. Reagan positioned himself as the strong anti-communist candidate. As president, Carter was responsible for overseeing the national response to the Boatlift.

The fact that Carter was so closely tied to the national response to the Boatlift makes it a good case for testing the backlash, but the contrast between Carter and Reagan over international affairs adds a wrinkle. Since Miami-Dade had the largest Cuban population in the US prior to the Boatlift, if the national parties or candidates changed their stances on issues that are salient for Cubans in 1980, there are few counties that will be as impacted as Miami-Dade. The Boatlift received national media attention, became a campaign issue in 1980, and the incumbent president was on the ballot. This means a change in Miami-Dade's presidential voting could be part of a national Cuban-American response to Carter's handling of the event or of Reagan's proposals. Even the flexible panel techniques will likely not be able to adjust for this.

3 Miami's Republican Presidential Vote Increased After the Boatlift

3.1 County-Level Presidential Election Data

To study the effects of the Mariel Boatlift on presidential voting, I obtained results for every presidential election from 1960 through 2000 for nearly every county from the Congressional Quarterly elections results database. This data covers 3,060 of the 3,142 counties in the US, with 82 missing due to historical gaps in the data. I add to this dataset population estimates for each county based on the 1980 decennial census.

3.2 Design: Compare Miami After the Boatlift to Counties with Similar Vote Histories

Putting aside concerns about a national shift in Cuban-American politics for the moment, I begin by estimating the backlash with a number of flexible panel techniques. I break this into two steps. First, I select a set of counties that can act as a control pool. Miami-Dade County votes more like other urban counties throughout the US than other counties in Florida. Accordingly, I use population estimates from 1980 to rank counties based on how similar their population is to Miami-Dade's.[6] I then select a threshold for the number of counties to include. I use forward prediction error for the 1976 presidential vote share as a criterion, and select the error-minimizing candidate pool for my baseline estimate. I also report estimates based on a variety of population thresholds, including estimates using all counties.

Once I have a pool of candidate counties, I estimate the impact of the Mariel Boatlift on Republican presidential vote percentage using a panel regression with election and county fixed effects of the form

$$V_{it} = \tau M_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

where V_{it} is the Republican presidential vote percentage in county i at time t, M_{it} is a dummy variable that takes on the value one for Miami-Dade in 1980 and after and zero otherwise, α_i is a county fixed effect, γ_t is an election fixed effect, ϵ_{it} is a residual, and τ is the estimated backlash.

I also estimate the effect using the synthetic control method, which was designed with this type of case study in mind (Abadie, Diamond, and Hainmueller 2010, 2015). The synthetic control method constructs a weighted average of the vote patterns among the control counties. The weights are selected to minimize the difference between the weighted average of presidential vote in control counties and Miami-Dade before the Boatlift. The weights are restricted to fall between zero and one so that the synthetic control is not an extrapolation beyond the support of the control pool.

Formally, I consider a pool of N potential contributor counties to the synthetic control indexed by i where $i = 0$ represents Miami-Dade. I use T pre-treatment observations to select the weights. I represent the pre-treatment outcome data as a matrix K_0 for the control pool counties and a

[6] I leave the counties immediately bordering Miami-Dade out of this ranking since they may also be considered treated.

vector K_1 for Miami-Dade. I select the vector of weights W such that

$$W^* = \arg\min_W (K_1 - K_0'W)(K_1 - K_0'W)' \text{ subject to } \sum_{i=1}^{N} w_i = 1, w_i \in [0,1].$$

Using the moving average of squared forward prediction error for Republican presidential vote percentage in 1976 as my criterion, I select a threshold of 1,500 control counties for the fixed effects analysis and 555 control counties for the synthetic control method. I present the output from this analysis in the Appendix.

3.3 Fixed Effects Estimates

Table 1 presents the results of the fixed effects analysis. Each cell in the table reports an estimate of the effect of the Boatlift on Reagan's two-party vote share in 1980, the year in which the Boatlift took place. Columns one through four report estimates based on an ex ante plausible set of comparison counties: the 250 and 500 counties nearest to Miami-Dade in terms of population. I also adjust for county-specific time trends in columns two and four to account for differences in the paths that Miami-Dade and the comparison counties were on prior to the Boatlift. In columns five and six, I report the fixed effects estimates using 1,500 counties in the control pool, which minimized the forward prediction error for the 1976 presidential election, first without and then with county-specific time trends. In columns nine and ten, I present the estimates using all counties. And, in columns seven and eight, I report the fixed effects estimates after restricting the control pool to include only Florida counties. The last four columns report the least plausible estimates since many of the counties in the control pools are rural counties where political preferences tend to be quite different from those held by residents in Miami-Dade and where Republican support is increasing through this period. In the absence of meaningful analytic standard errors, I report where the estimated effect lies in the distribution of placebo effects (Abadie, Diamond, and Hainmueller 2010). This distribution of false effects comes from estimating a placebo effect for every county included in the analysis, using the same regression as I use to estimate the effect for Miami-Dade, but holding out Miami-Dade.

Despite the wide variety of control pools I use, all of my fixed effects estimates imply an increase in the percentage of Miami-Dade voters supporting Republicans over the six presidential elections

Table 1: **Increase in Republican Presidential Vote Share Following the Mariel Boatlift, Fixed Effects Estimates.**

	Rep Vote [0-1]									
Counties Included:	250		500		1500		Florida		All Counties	
Treatment Effect	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.04	0.03
	[0.91]	[0.92]	[0.88]	[0.89]	[0.86]	[0.81]	[0.87]	[0.89]	[0.77]	[0.67]
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Trends	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
# of Elections	6	6	6	6	6	6	6	6	6	6
# of Counties	250	250	500	500	1,500	1,500	61	61	3,060	3,060

Each cell reports an estimate of the increase in support for Ronald Reagan over Jimmy Carter in the 1980 presidential election. All estimates calculated holding out counties that border Miami-Dade. Columns 250, 500, and 1500 are estimated with the 250, 500, and 1500 counties most similar to Miami-Dade in terms of log population as of 1970. The share of the placebo distribution less than the effect estimate is reported in square braces.

after the Boatlift. Still, these estimates are noisy, and there is reason to think that the counterfactual trends implied by these estimates may not be right. This is particularly likely in the case of the Florida-only and all-county columns. In order to impute a more plausible counterfactual trend for Miami-Dade, I turn to the synthetic control method.

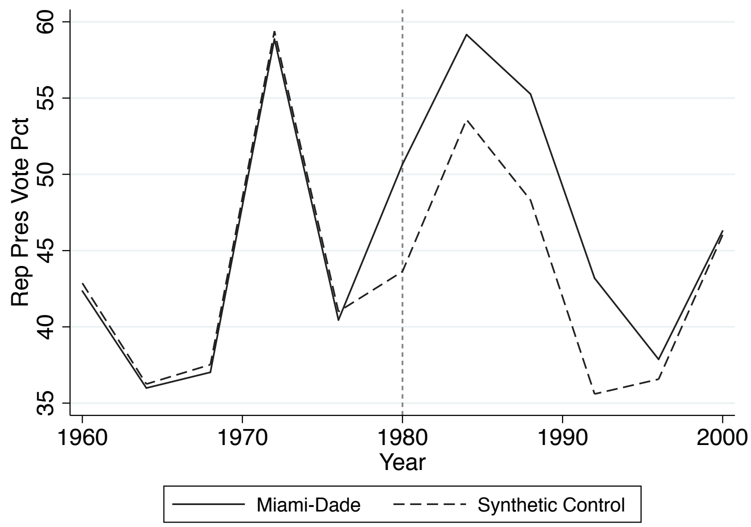
3.4 Synthetic Control Estimates

Figure 1 presents observed and synthetic Miami-Dade Republican presidential vote share from 1960 to 2000. As intended in the construction of the weights, the synthetic Miami-Dade is nearly identical to the true Miami-Dade prior to the election in 1980, at which point they separate.[7] This post-Boatlift split translates into a roughly 7-percentage-point increase in Republican presidential vote share in 1980.

As I described in the previous section, I conducted a placebo analysis for each of the remaining roughly 550 counties that I used in the construction of the Miami-Dade synthetic control, following the advice of Abadie, Diamond, and Hainmueller (2010). I find a synthetic control for each of these counties which allows me to construct a null distribution from the placebo impacts. In Figure 2, I present the results of this analysis. The dark line represents the synthetic-control-method-estimated impacts for Miami-Dade and the light grey lines reflect the placebo impacts for all of the remaining

[7] What may appear to be a separation between 1976 and 1980 is an artifact of the linear interpolation in the plot since no presidential election was held between 1976 and 1980.

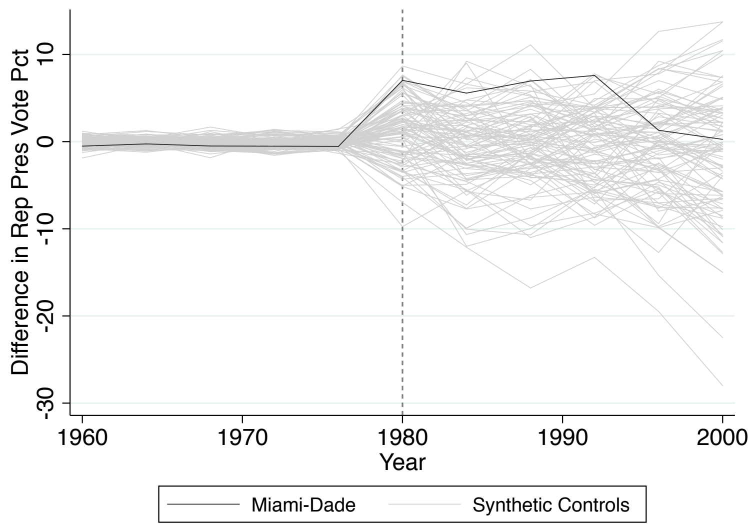
Figure 1: **Synthetic Control Method Estimate of Mariel Boatlift Impact on Republican Presidential Vote Share**



counties. This figure clearly shows that the impacts Miami-Dade experienced were near the edge of the range of null effects, particularly in the first few years after the Mariel Boatlift. The average estimated impact in Miami-Dade County across the six elections following the Boatlift is at the 96th percentile of the average placebo impacts represented in this figure, suggesting that these estimated impacts are very unlikely to be a purely chance event. I further infer from this analysis that the standard deviation of placebo treatment effects is 4.0 percentage-points, suggesting that, though this roughly 7-percentage point treatment effect is large relative to the null distribution, it is still a noisy estimate.

In Table A.1 in the Appendix, I report the estimated effects for all six of the presidential elections held after the Mariel Boatlift. In the first column, I present the synthetic control estimates based on a control pool of 250 counties. In the second column, I present the results based on the control pool size selected by minimizing a moving average of mean squared forward prediction error, which is 555. I find a 6.7 percentage-point shift toward Republicans in 1980 using the control pool of 250 counties, and a 7.0 percentage-point shift using a control pool of 555 counties. These fall in the 96th percentile of both of their empirical placebo distributions. I also find that this move toward Republicans is persistent, but the estimates are increasingly noisy as time goes on.

Figure 2: **Miami-Dade Synthetic Control-Estimated Impacts Against Distribution of Placebo Impacts**



As I indicated above, one important methodological concern I have about these analyses is that the synthetic control or fixed effects regressions may be fit on the wrong set of counties. To address this concern, I estimate the backlash using a large variety of control pools with both the synthetic control method and fixed effects regressions. Figures A.1 and A.2 in the Appendix present the results. The synthetic control estimates are noisy, but all of the estimates with both techniques are positive.

3.5 Threat to Validity: Uniquely-Large Cuban Population in Miami

The results above suggest that voters in Miami-Dade County supported Republican presidential tickets after 1980 more than we should expect based strictly on prior election results. Only a small number of similar counties moved more toward the Republican party at the same time. One plausible explanation for this shift is that white and black Miami-Dade residents punished Carter for permitting the Boatlift migrants to come. Workers who compete with the Marielitos for jobs may also have punished Carter. Or, perhaps more voters developed anti-migrant attitudes that they believed aligned better with Reagan's politics. These backlash explanations line up with much of the literature on the effects of forced migration on electoral outcomes that I described above. But white, black, and working-class backlash are not the only workable stories.

Miami's demographics offer an alternative explanation: Since Miami has a uniquely large Cuban population, might the unusually high support for Reagan reflect a Cuban political realignment unrelated to exposure to the Boatlift? Miami's Cuban-American population prior to the Boatlift was composed of disproportionately high earners and are less likely to consider Cuban refugees an out group, suggesting that these voters are least likely to punish incumbents for exposure to immigration under most models. But Jimmy Carter's response to events shortly preceding the election, including the Boatlift and Soviet troops being discovered in Cuba, could have led voters who cared a lot about Cuban-American relations to vote for Reagan. Any shift in Cuban-American politics will confound the estimates I reported above. If the shift is large enough, there could have been no backlash or even a negative backlash.

4 Increased Cuban-American Support for Republicans, Not Migration Exposure, Explains the Change in Miami

4.1 Estimating Neighborhood-Level Cuban Population and Republican Vote

As a first step in investigating whether a change in Cuban voting was responsible for the shift toward Reagan in Miami-Dade, I used public records requests to obtain historical precinct-level election results from the Miami-Dade County Elections Department. This data, which covers all Miami-Dade County elections from 1976 to 1992, allows me to allocate county-wide changes in voting to particular parts of town. Unfortunately, Miami-Dade does not use consistent or informative precinct labels. This means that often I cannot identify the same precincts or even neighborhoods from one election to the next. Fortuitously for this project, the precinct numbering system stayed the same from 1976 to 1980, and all precincts in nine neighborhoods housing approximately 65% of the city of Miami's residents are flagged with their neighborhood names.[8]

I pair my estimates of each neighborhood's two-party vote share with estimates of the Cuban, non-Latin black, non-Latin white, and total population. I construct these estimates by aggregat-

[8] Some neighborhoods have changed names over time, so I confirmed their historical names with an archivist at HistoryMiami, a Miami-based history museum.

ing block-level 1980 Census counts to the neighborhood level using Zillow's Florida neighborhood shapefile and the IPUMS NHGIS 1980 block shapefile (Manson et al. 2017).[9]

4.2 Within-Neighborhood Regression

If we assume that the estimates I report in the previous section are unbiased for the total shift toward Reagan due to backlash and Cuban-American politics, we can back out how large the change in Cuban-American voting would have to be for the backlash to be null. Only an exceptional shift in Cuban-American politics could produce such a large swing toward Republicans in Miami-Dade as a whole. Miami-Dade's synthetic control supported Reagan in 1980 by about 3 percentage points more than it did Ford in 1976. Miami-Dade supported Reagan by almost 10 percentage points more than Ford. Let us assume for simplicity that Cubans vote at about the same rate as other residents in Miami-Dade and that turnout did not change from 1976 to 1980. Let us also assume that Cubans were entirely responsible for the shift toward Reagan and that non-Cuban Miami-Dade voters followed the synthetic control. This would mean that 25% of the population would have to account for a 7-percentage-point change in the vote, implying that 28% of Cubans in Miami-Dade would have to switch from Carter in 1976 to Reagan in 1980.

I estimate the shift among Cubans using my neighborhood-level panel data. I run regressions of the form

$$V_{it} = \lambda C_{it} + \alpha_i + \gamma_t + X_{it}\beta + \epsilon_{it}$$

where V_{it} is the Republican presidential vote percentage in neighborhood i at time t, C_{it} is the Cuban share of the neighborhood's population, α_i is a neighborhood fixed effect, γ_t is an election fixed effect, X_{it} is a vector of time-varying controls, ϵ_{it} is a residual, and λ is the estimated shift among Cubans relative to other groups.

This regression compares the increased support for Republicans in more Cuban neighborhoods to that same increase in less Cuban neighborhoods. Putting aside concerns about ecological inference for the moment, by including controls, I change the comparison group. For example, including the interaction of a dummy variable for 1980 and the non-Latin white share of the neighborhood's population makes citizens who are not either non-Latin white or Cuban the comparison group.

[9] `https://www.zillow.com/howto/api/neighborhood-boundaries.htm`

Table 2: **Large Shift toward Republicans among Cubans in Miami.**

	Rep Vote [0-1]		
Cuban Share X 1980	0.26	0.24	0.26
	(0.03)	(0.07)	(0.05)
Neighborhood FE	Yes	Yes	Yes
Election FE	Yes	Yes	Yes
Black Share X 1980	No	Yes	No
White Share X 1980	No	No	Yes
Neighborhoods	9	9	9

Block bootstrapped standard errors from 1,000 samples are reported in parentheses below each estimate. All population share variables, including the Cuban population share, range from zero to one.

Figure 3: **Large Shift toward Republicans in Miami by Cuban Population.**

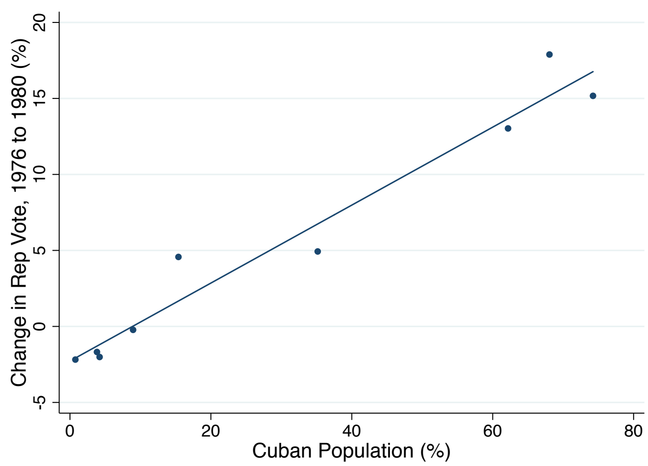


Table 2 presents the estimates from these regressions. I find that, relative to three groups of other Miami residents, a hypothetical neighborhood with 10 percentage points more of the population with Cuban backgrounds swung toward Republicans by about 2.5 percentage points. If white, black, or working-class backlash were responsible for the large swing in Miami-Dade, this effect should be negative. Instead, this shift in Cuban neighborhoods is so large that it is *consistent with no white, black, or working-class backlash.* Figure 3 further shows that this is being driven by neighborhoods that are overwhelmingly Cuban swinging to Reagan by massive margins.

4.3 Similar Increase in Republican Support Among Cubans in Miami and Elsewhere

Increased support for Republicans in Miami-Dade among Cubans rather than white, black, or working-class citizens could be a response to a changing political environment like Reagan's anti-communist stance or Carter's response to Cuban and Soviet behavior. But it could still be a response to exposure to the Boatlift migrants that is isolated among Cubans or in Cuban neighborhoods. To arbitrate between these two explanations—a local, exposure-driven change in Cuban voting versus a national political change that pushed Cubans toward Reagan—I compare the Cuban shift in Miami to the Cuban shift in the county with the second largest Cuban population in the US, Hudson County, New Jersey.

To make this comparison, I gathered precinct-level presidential election results for Hudson County from the New Jersey State Archives. I obtained the results for the 1976 and 1980 presidential elections. I also worked with the Hudson County Division of Planning to gain access to election district maps. I construct ward-level and city-level demographic estimates in Hudson County using the same procedure I use to construct neighborhood-level estimates in Miami. Since the ward boundaries may have changed in ways my maps do not account for, I run all analyses separately at the city level as a robustness check.

With this paired demographic and presidential election data, I estimate the difference in the shift toward the Republican presidential ticket among Cubans between Miami and Hudson County. I report these results in Table 3. In the first column, I find that if one city in Hudson County has a Cuban population that makes up five percentage points more of its total population than another ward, it should have shifted toward Republicans in 1980 by about one percentage-point more. This difference is slightly larger in Miami, where it only takes a four-percentage-point difference in Cuban population share to expect one-percentage point larger shift toward Republicans.

Since an increase in the Cuban population share means a decrease in some other population share, these regressions are estimating how much more a neighborhood with more Cubans, rather than non-Cubans, shifted toward Republicans in 1980. The non-Cuban population in the Miami neighborhoods I in my data may have a different demographic profile than the non-Cuban population in Hudson County. I deal with this in columns two and three by adjusting for the share of the

Table 3: **Similar Shift toward Republicans among Cubans in Miami and Hudson County.**

	Rep Vote [0-1]					
		Cities			Wards	
Miami X Cuban Share X 1980	0.06	0.07	-0.10	0.06	0.06	-0.05
	(0.13)	(0.22)	(0.38)	(0.06)	(0.11)	(0.17)
Cuban Share X 1980	0.20	0.17	0.36	0.20	0.18	0.31
	(0.12)	(0.11)	(0.38)	(0.03)	(0.03)	(0.03)
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
Election FE	Yes	Yes	Yes	Yes	Yes	Yes
Black Share Adjustment	No	Yes	No	No	Yes	No
White Share Adjustment	No	No	Yes	No	No	Yes
Miami Obs	9	9	9	9	9	9
Hudson County Obs	12	12	12	51	51	51

Adjustments for particular subpopulations is done by including two additional vairables in the regression: an interaction between the subgroup's population share with a flag indicating that the year is 1980 and separately the subgroup's population share interacted with a flag for 1980 and Miami. Block bootstrapped standard errors from 1,000 samples are reported in parentheses below each estimate. All population share variables, including the Cuban population share, range from zero to one.

neighborhood or city that identifies as non-Latin black and non-Latin white, respectively. Given the small sample, these adjustments make the estimates even noisier, but the results still consistent with Hudson County Cubans shifting toward Reagan by slightly less than Miami-Dade or perhaps even more than Miami-Dade. Columns four through six report estimates from the same regressions reported in columns one through three but using ward-level rather than city-level data in Hudson County. The results from these analyses are similar to the city-level results, but slightly less noisy.

These results suggest that the large shift toward Republicans in 1980 in Miami-Dade County may be an artifact of its unique demographics. This does not rule out the importance of the Boatlift as an event for Cuban politics in the US. But it suggests that Miami's unique exposure to the mass migration event was not the primary driver of this shift.

4.4 No Shift Toward Republicans in House Races

Using only the presidential election returns, it is not possible to distinguish general voting against the incumbent from a response to changes in the positions of presidenital candidates. If this switch in Cuban-American voting is indeed a response to a reallignment of presidential politics, it should

Table 4: **No Shift toward Republican House Candidates among Cubans in Miami.**

	Rep Vote [0-1]			
Cuban Share X 1980	-0.00	0.01	0.01	0.01
	(0.05)	(0.05)	(0.11)	(0.04)
Neighborhood X District FE	Yes	Yes	Yes	Yes
Election FE	Yes	No	No	No
Election X District FE	No	Yes	Yes	Yes
Black Share X 1980	No	No	Yes	No
White Share X 1980	No	No	No	Yes
Neighborhoods	9	9	9	9

Block bootstrapped standard errors from 1,000 samples are reported in parentheses below each estimate. All population share variables, including the Cuban population share, range from zero to one.

not extend to legislative races. To test this, I added US House election results to my precinct-level election data in Miami. In all three US House districts, Democrats held office in 1980, and had held the office since prior to 1976. This permits the same design as before: did Cuban parts of a US House district swing more toward Republicans in 1980 than less Cuban parts?

As I report in Table 4, I find that Cuban neighborhoods did not swing to Republican US House candidates more than other neighborhoos. This is markedly different from swing in presidential voting. This result rules out a general switch toward Republican candidates or against federal incumbents due to exposure to immigration. Instead, the switch in Cuban neighborhoods is something specific to the presidential race, potentially a distinctly anti-communist presidential candidate in Ronald Reagan.

4.5 Threat to Validity: Exposure Highest in Cuban Neighborhoods

Tables 2 and 3 make clear that neighborhoods in Miami and Hudson County shifted toward Reagan in proportion to the size of their Cuban population. I interpret this as evidence that the Cuban population itself was shifting. This is not the only explanation for the result. If non-Cubans living in Cuban neighborhoods shift toward Republicans, it is possible that this shift toward Republicans was driven by non-Cubans living in Cuban neighborhoods. I cannot rule this out using my aggregate data, and this explanation for the pattern is plausible. Many of the Boatlift migrants moved to or were processed in predominantly Cuban neighborhoods in Miami (Garcia 1996). Those that moved to Hudson County mostly did so with family members, meaning that they moved to cities or wards that housed many Cubans before the Boatlift. This means that exposure to the Boatlift migrants was highest in Cuban neighborhoods. White, black, or working-class backlash could, then, be largest in these neighborhoods. For this to be true, the effect of exposure on non-Cubans' propensity to switch to Republicans would have to increase dramatically between moderate and high levels of exposure. Also, the effect would have to be incredibly large: since neighborhoods that were nearly 80% Cuban shifted to Reagan by 15 percentage points, the effect would need to produce a nearly 75-percentage-point shift among white and black residents of Cuban neighborhoods. Given these facts, I attribute to Cubans the majority of this shift toward Reagan in Cuban neighborhoods.

4.6 Threat to Validity: Different Non-Cuban Populations Across Cities

Putting aside these concerns about ecological inference, one additional threat to the sub-county-level analysis is the difference in voting patterns of non-Cubans between Miami-Dade and Hudson County. This creates a problem because the regressions I am running estimate how much higher the shift toward Reagan is among more Cuban neighborhoods compared to less Cuban neighborhoods in the same county. If non-Cubans are meaningfully different in Miami and Hudson County, the within-county differences in the swing will be different as well. I take a small step toward addressing this in Table 3 by adjusting for the racial composition of the comparison group. Despite the noise in the estimates, these adjustments are still consistent with Cubans in Hudson County and Miami-Dade following similar paths. Still, there are likely remaining difference between the Cuban and non-Cuban populations across these parts of the country that influence the trend they are on, but I cannot adjust for this given the small number of periods I have in my data.

5 Final Remarks

Does exposure to migration cause native-born voters to vote against incumbents? In this paper, I present a case in which even large-scale migration likely did not produce a backlash by the group with which the migrants should compete economically or the majority racial group. I find that Miami-Dade voted for Reagan at a much higher rate than one would predict from prior election results, but that this change was likely due to a national change in Cuban-American politics. This change may be a response to the Boatlift, a platform change, Carter's performance, or some other change. Either way, my analysis does not support theories that predict a large electoral response to exposure to migration.

The evidence I have presented throughout is only suggestive—my precinct-level analysis is not a perfect design for estimating the effects of migration by subgroup. But the robustness checks also clarify a risk to many analyses of the effects of immigration: most immigrants move to places with unusually high concentrations of expatriates from their country, making it difficult for the analyst to rule out changes in that population's voting unrelated to the immigration.

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Appendix

Contents

A.1 Formal Synthetic Control Estimates

The formal synthetic control estimates are reported in Table A.1. The estimates suggest that Miami shifted toward Reagan in 1980 much more than similar counties (by 6.7 to 7.0 percentage points) and to a degree that was unusual among similar counties (in the 96th percentile). When compared to 250 other counties, this shift is sustained over time. When compared to 500 other counties, the increased support for Republicans drops off in 1996.

Table A.1: **Increase in Republican Presidential Vote Share After the Mariel Boatlift, Synthetic Control.**

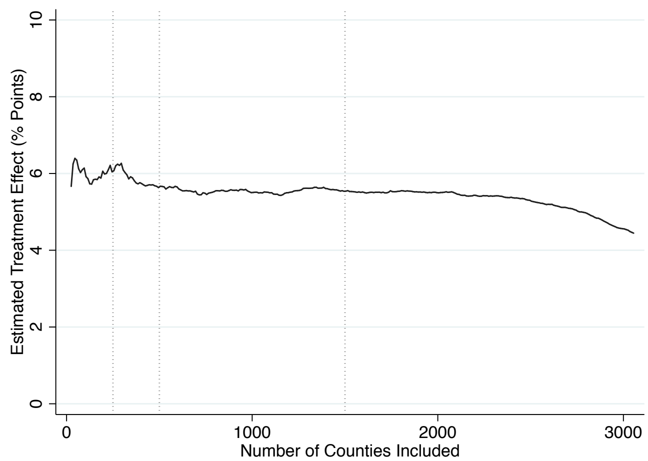
	Counties in Control Pool	
	250	555
All Years	7.4	4.8
	[96.3]	[90.0]
1980	6.7	7.0
	[96.3]	[96.0]
1984	7.5	5.6
	[96.3]	[93.0]
1988	8.5	7.0
	[96.3]	[95.0]
1992	9.2	7.6
	[97.8]	[98.0]
1996	4.2	1.3
	[72.6]	[63.0]
2000	8.4	0.3
	[81.5]	[56.0]

All estimates calculated holding out counties that border Miami-Dade. The 250 or 555 counties most similar to Miami-Dade in terms of 1978 population are included in the control pool. The percentile of the placebo distribution where Miami-Dade lands is reported in square brackets. The placebo distribution is found using the procedure discribed in Abadie et al (2010).

A.2 Sensitivity of Panel Estimates

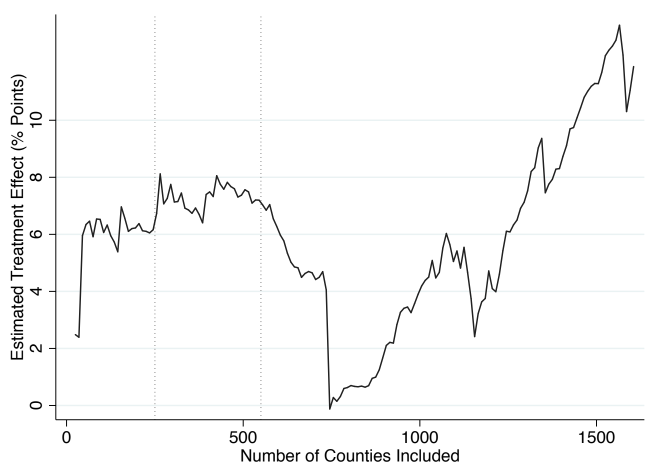
The fixed effects estimates decline as more counties are included in the analysis, up to roughly 1,000 counties. After that, the estimates stabilize and hover around 4 percentage points.

Figure A.1: **Sensitivity of Fixed Effects Estimate to Counties Included.**



The synthetic control estimates also generally decline as more counties are included in the analysis, but the estimates are less stable.

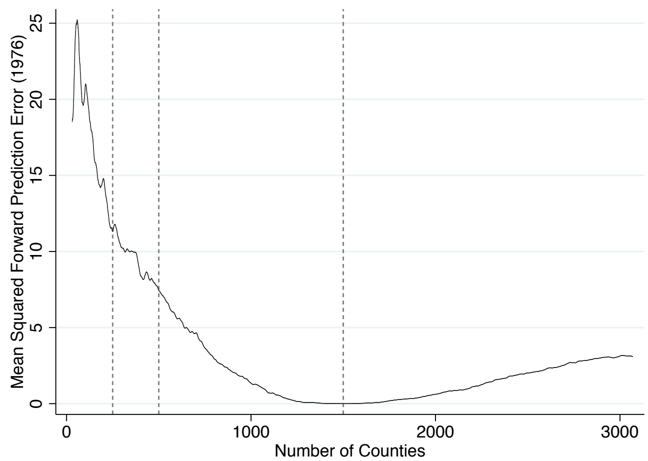
Figure A.2: **Sensitivity of Synthetic Control Estimate to the Number of Counties Included in the Control Pool.**



A.3 Procedure for Selecting Number of Counties

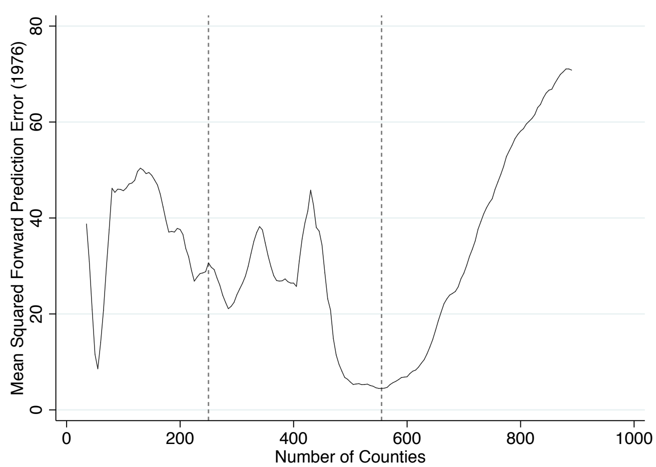
I find that the number of counties that minimizes a moving average of the squared forward prediction error for 1976 from a fixed effects regression is approximately 1,500. Given that I am predicting only one point, this may not be generally applicable to predicting other elections. This is just one rule by which to select the number of counties.

Figure A.3: **Mean Squared Forward Prediction Error for Selecting Number of Counties, Fixed Effects.**



I find that the number of counties that minimizes a moving average of the squared forward prediction error for 1976 from the synthetic control method is approximately 555.

Figure A.4: **Mean Squared Forward Prediction Error for Selecting Number of Counties, Synthetic Control.**



A.4 Data Collection Process for Hudson County, New Jersey

I gathered data for Hudson County that is similar to my data on Miami-Dade. I collected this data from a collection of historical New Jersey Department of State records in the New Jersey State Archives. Election results are reported for each district. Each district is housed in a single ward, and each ward is a mutually exclusive zone in a city. Because I have no information on the stability of the district boundaries, I only work with the ward and city boundaries.

A.5 Procedure for Estimating Neighborhood and Ward Demographics

I used three datasets to estimate neighborhood demographics in Miami. First, I downloaded a shapefile containing the block boundaries for the 1980 Census. I then overlaid a Miami neighborhood shapefile produced by the housing data company Zillow. I identified the portion of each block that fall within a given neighborhood's boundaries and stored that share as a column in a dataset indexed by neighborhood and block. Finally, I merged on 1980 population Census counts by block, multiplied that population count by the proportion of the block in each neighborhood, and summed up the population numbers for each neighborhood. I matched these neighborhoods to the neighborhoods tallied in Miami's 1981 precinct-level local election results.

I used a very similar procedure for ward demographics in Hudson County. The only change I made was to use a ward shapefile provided by the Hudson County Department of Planning. I was unable to confirm that the ward boundaries are approximately the same as in 1980. I was able to find articles referencing a change in the Jersey City boundaries in 2012. Accordingly, I re-ran all analyses dropping Jersey City, and the results did not substantively change. I also checked that every city in my analysis has the same number of wards as they had in 1980 and that the wards have similar population distributions—large ones in 2018 were also the large ones in 1980.

A.6 Shift toward Republicans in Miami by Cuban Population

In addition to the simple analysis of majority Cuban neighborhoods in the body of the letter, I present here a more formal analysis of the shift to Republicans among Cubans. I show these results in Table 2 and Figure 3. I find that, relative to other Miami residents, a hypothetical neighborhood with 10 percentage points more of the population with Cuban backgrounds swung toward Republicans by 2.5 percentage points.

A.7 Similar Shift toward Republicans among Cubans in Miami and Hudson County

As I presented in the paper, I find that, relative to other neighborhoods in their city, Cuban neighborhoods increased support for Reagan over Carter by about the same amount in Miami-Dade and Hudson County. This is evident in the parallel lines and boulstered by the fact that the lines are relatively close to one another.

Figure A.5: **Similar Shift toward Republicans among Cubans in Miami and Hudson County.**