Fact Checking: An empirical analysis on the effects of sanctuary city policy[1] (Preliminary)[2]

Research Thesis

Presented in partial fulfillment of the requirements for graduation with research distinction in Economics in the undergraduate colleges of The Ohio State University

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Abstract

Especially since the 2016 election, sanctuary city policy has been a vehemently debated topic. However, most people believe narratives without much causal evidence hence worsening the ideological struggle between different sides of society. Using data from the American Community Survey and Department of Homeland Security, I used fixed effect regressions to analyze the outcome of sanctuary city policy on the changes of demography and several economic characteristics. Demographically, my estimations suggest that both total and foreign population of a city decrease without affecting the ratio between them after a city becomes sanctuary, though the composition of the population regarding nativity was not shown to be associated with the policy. Economically, the percent of people in poverty status and the increase in unemployment rate decreased after the adoption of sanctuary city policy while both median income and the growth of median income increased.

Keywords: Sanctuary City, Migration, Unemployment

[1]I am indebted to Joyce Chen, Ryan Ruddy, and Rodrigo Perez-Silva for the completion of this paper. I am thankful for Rodrigo Perez-Silva for his help on data collection methods with ACS. I am grateful for the insightful discussions I had with Ryan Ruddy regarding regression design and data visualization. I especially appreciate the countless discussions with Joyce Chen regarding causality, identifier, general trend, and generally her advice on this paper.

[2]This analysis is preliminary. DO NOT cite without permission of the author.

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1 Introduction

In the political climate of 2018, media from all parts of the political spectrum create narratives and rhetoric that align with their interest to reinforce their ideology on their audiences. Liberal media tend to command sanctuary cities for being the symbol of progress while the conservative media tend to do the opposite. Such an environment makes it imperative to discuss the impact of sanctuary city policy. To do so, I needed to first define sanctuary cities, which surprisingly, does not have a legal or formal definition. Generally, sanctuary city policy refers to an ordinance or legislation that prevents local law enforcement from taking legal actions solely based on an individual's immigration status. This includes limiting the cooperation between local law enforcement and the Immigration and Customs Enforcement (ICE) such as not honoring a detention order issued by ICE or prohibiting officers from inquiring an individual's immigration status(Kittrie, 2006).

The first ever sanctuary city policy was enacted in Berkeley, CA in 1971 while Los Angeles passed an ordinance that prevents the Los Angeles Police Department (LAPD) from asking about immigration status about an arrested person. However, a city can be only sanctuary de jure, meaning that the city has the policy, but does not enforce it, adding in more variables in the situation. In 2017, President Donald Trump signed an executive order titled, "Executive Order: Enhancing Public Safety in the Interior of the United States" (Exec. Order No. 13742, 3 C.F.R., 2017))., requiring cities to comply with ICE or else they would lose eligibility of receiving federal grants, except when deemed necessary for law enforcement purposes. This order created waves of protests and lawsuits against the federal government while the supporters of the agenda claim that the executive order is necessary for public safety. That same year, the state of California became a sanctuary state with a few counties refusing and joining the federal government in a lawsuit against the state's legislation. In January 2018, Judge John A. Mendez ruled against the Trump administration and denied their request to suspend California's state-wide sanctuary policy, deeming it not an obstacle to ICE's actions.

Even though sanctuary cities now risk losing funding from the federal government, some local policy-makers think it is worth it to make a statement to show progress and unity by proving that they can provide a welcoming place for immigrants who are not welcomed at another city because of their immigration status. Both sides of the sanctuary city debate raise potential issues that counter with each other. Regarding safety, some suggest that limiting local law enforcement actions could cause an increase in crime, while others contend that reducing the risk of ICE action could encourage compliance with local law enforcement. The validity of the increase in crime narrative has been negated by empirical studies, with research showing that adopting sanctuary city policy either has no or negative effect on violent crime rates in a city (Gonzalez, Collingwood, & El-Khatib, 2017) On the economic side, oppositions claim that sanctuary city policy causes unemployment among natives due to its encouraging undocumented immigrants, who are more competitive since they are often forced or coerced into accepting lower wages (Capps, Passel, & Fix, 2004). However, research has shown that undocumented immigrants actually create more jobs than fill in existing jobs because their competitive wages created a different market and is actually beneficial to the native workers' situation (Albert, 2017). Similarly, proponents of the policy contend that the jobs that are employing undocumented immigrants are jobs that are not filled prior thus there was no crowding-out effect on the low-skilled job market.

Because of the events and narratives mentioned above, I want to look at whether the policy is effective, let alone being worth losing funding to, and also if the negative narrative is true. Hence, the two questions to ask are 1. Does the policy work? In other words, do cities with sanctuary city policies actually attract immigrants? 2. Does sanctuary cities actually have any effect on the city's unemployment rate or even any economic characteristics?

2 Data

For demographic changes and economic characteristics, I am using city-level data collected from the American Community Survey (ACS) 1-year estimates from 2006 to 2017. In consideration of consistent estimations and a balanced panel, the data set only includes Metropolitan Statistical Areas (MSAs) that consistently have more than 1 million population during the 12-year period. However, exceptions were made for Buffalo, NY, Memphis, TN, Louisville, KY, and Raleigh, NC in order to include more observations, which was already limited. This inclusion does not significantly affect the estimations[3]. The ACS data included select household economic, demographic, educational, and dwelling characteristics while separating groups based on nativity and citizenship statuses. The 3 categories of nativity are native, foreign-born naturalized citizens, and foreign-born non-citizens. An individual born to a parent who is a U.S citizen abroad is included in the category native. Since ACS is a self-reported survey, undocumented immigrants are less likely to be accounted for in the data. Some may claim that the estimates by ACS include said population, however, it is not used as a key outcome in this paper. Economic characteristics included in analysis are median household income, % opulation at different levels of poverty with respect to the poverty line, unemployment rate, etc. Demographic data includes race and ethnicity, age, sex, etc. Educational and dwelling characteristics records educational level of city residents as well as cost of owning/renting in relation to income.

For crime statistics, I collected data from Uniform Crime Report (UCR) from 2006 to 2017. These are reported crime data collected at the agency level and then aggregated at the MSA level by Federal Bureau of Investigation. The data set includes Crime rate per 100,000 population separated into violent crime and property crime and then subcategories. However, only the 2 main variables will be used as outcomes in this paper.

[3] Tables in the appendix sections show the estimation results excluding those cities in the estimation.

To identify sanctuary cities, I used sanctuary city de facto as provided in a report by ICE in 2018. The reports detailes the entity (city, county, and state), reason, time (month and year) an entity becomes sanctuary of the sanctuary city. I then match the each MSA with the counties they are in to generate the sanctuary tags. Out of the 52 MSAs with more than 1 Million in population, 18 are sanctuary cities in 2017. The repective year of becoming a sanctuary city are 2008, 2011, 2012, 2014, 2016, 2017. In 2014, both the state of California and the state of Conneticut become sanctuary states.

Table 1 below contains 12 figures describing the trends of the outcome variables used in the analysis and compare cities of different santuary types (cities that becomes a sanctuary city at one point in the time period versus cities that have never been a sanctuary city). Figure 1 shows the trend of the foreign population in a log scale separated by sanctuary type - whether a city has ever been a sanctuary city, and sanctuary status - whether a city is sanctuary at that year. Figure 2 shows the same comparison for Total population. Figure 3 shows the mean foreign population trend. Figure 4 shows the trend for %Hispanic in a city. FIgures 5 and 6 show respectively the income level and the growth of income trend. Figure 7 shows the trend for unemployment while figure 8 shows the trend for poverty level. Figure 9 and 10 shows the trend for cost of owning and cost of renting in a city. Finally, figure 11 and figure 12 show the trends for violent crime rate and property crime rate. There is a general trend of increase for both foreign and total population while %Hispanic has a trend of increase that was slowed down after 2011. The trends of income level seem to be parallel between the two types of cities, but there seem to be a difference in growth of income between 2011 and 2017. Unemployment trends are similar though sanctuary cities seem to bounce back faster after having a higher increase in unemployment rate. Trends of poverty are parallel between the two city types. The percentage of more affordable housing has an upward trend. Sanctuary cities seem to have lower crime rates overall while having similar trends. There seem to be a larger increase in crime in non-sanctuary cities starting in 2012.

On the other hand, there seem to be an increase in property crime at a small period and then the statistic decreased for sanctuary cities. Visually from the graph, sanctuary cities seem to be cities that are more economically well-off and have fewer crimes reported each year.

Table 2 is a brief summary of some of the key outcome variables. The 575 observations consist of 51 cities between 2006 and 2017 with certain observations dropping out due to lack of data. The mean of total and foreign population is about 3.44 million and 647 thousand respectively. The average % Hispanic in these MSAs is 16.18% with a vert large standard deviation of 13.29 showing a widely ranged distribution. The average median income is about 58.6 thousand dollars a year with a standard deviation of around 11 thousand dollars a year across all MSAs. On average, 50.88% of the population in a city are female, and 63.4% of the population are between the age of 18-65. The average unemployment rate across all years in all cities is 4.965%. The average percentage of people living under 200% of the poverty level is 30.09%. On average, 32.98% and 12.47% of a city have more than or equal to a college degree and less than a high school degree, respectively. On average, 71.18% of people who own the property they live in pay less than 30% of their income, while the same statistic for renters is 52.11%.

Table 1: Trends

Figure 1.

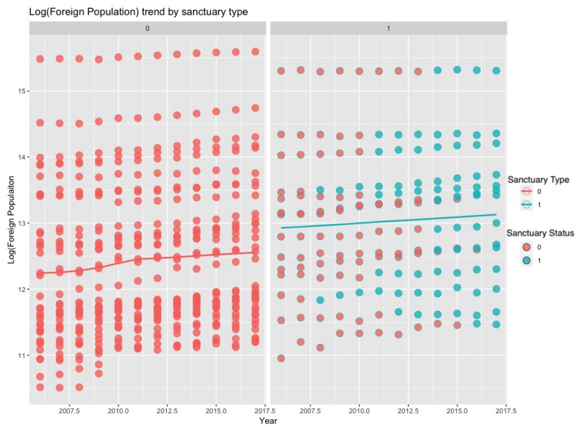


Figure 2.

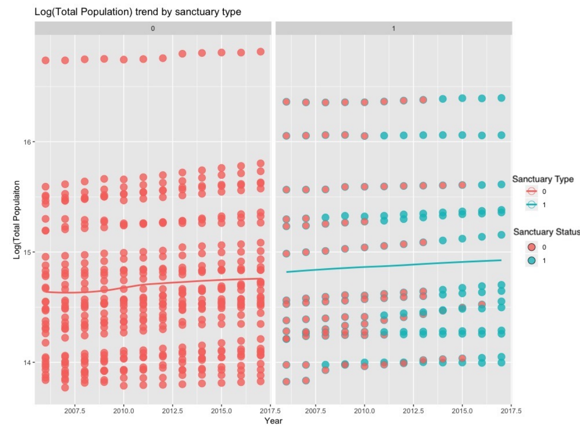


Figure 3.

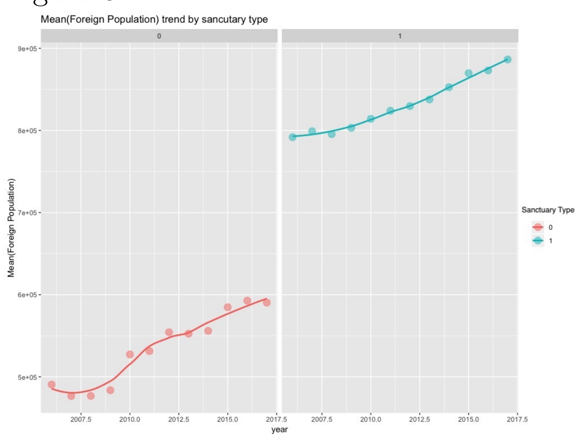
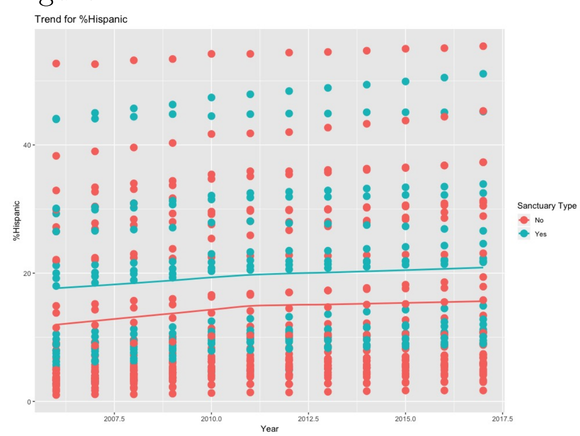


Figure 4.



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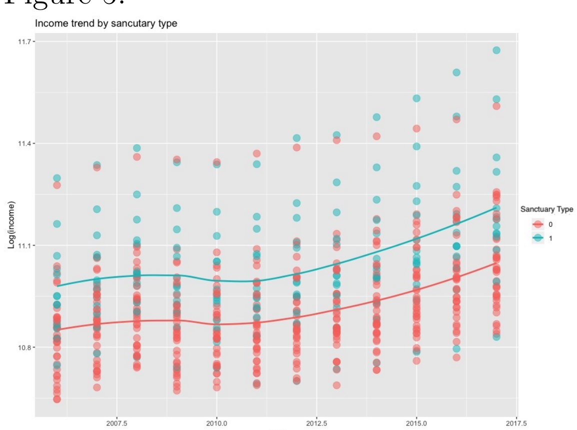

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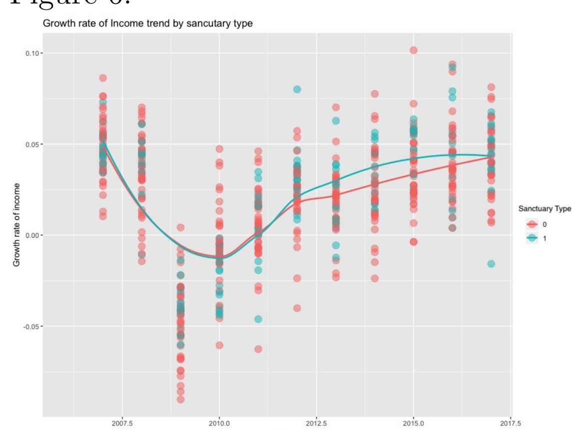


Figure 7.

Figure 8.

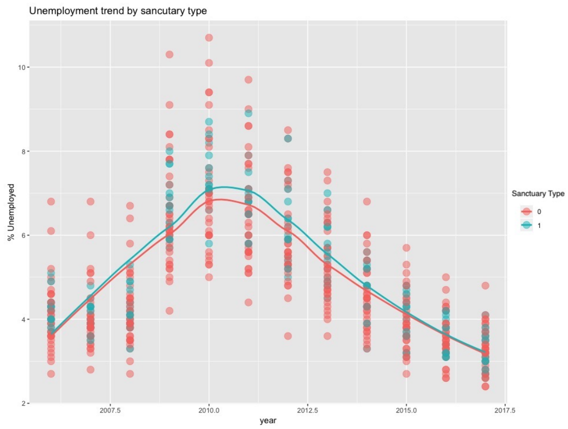
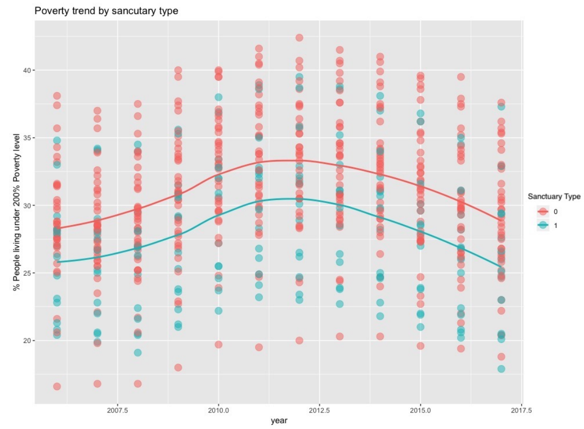


Figure 9.



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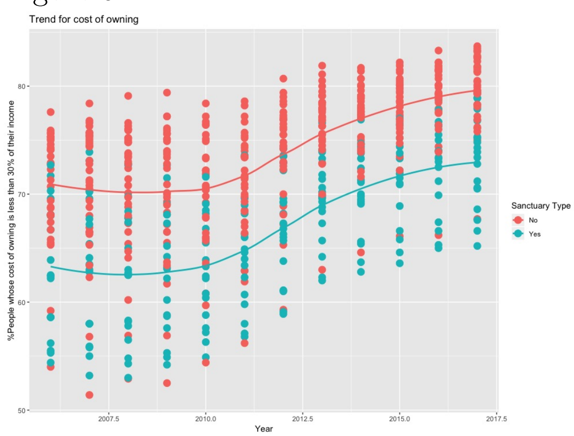
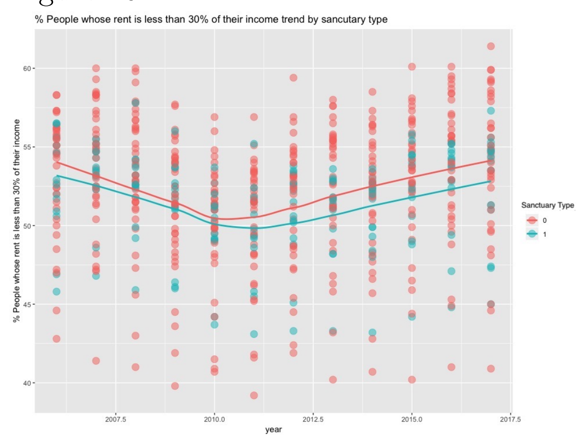


Figure 11.



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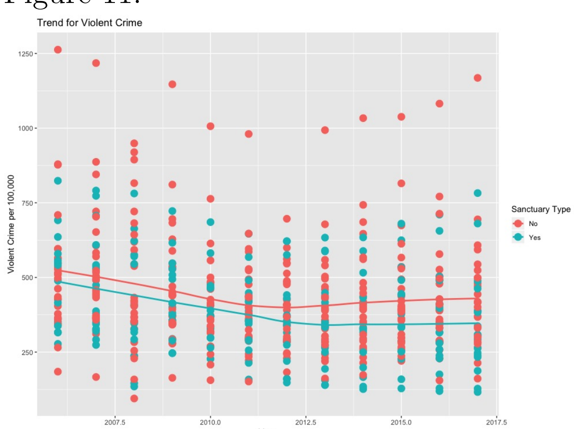

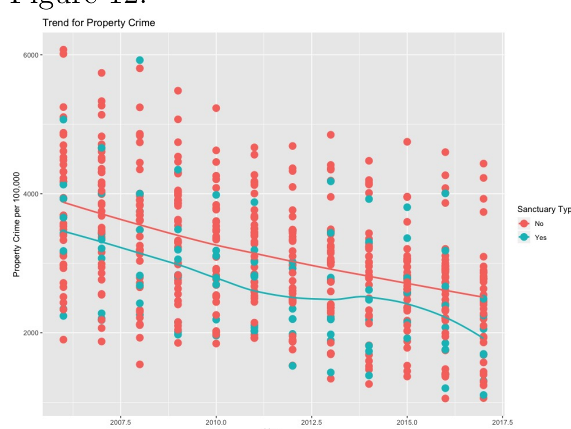

Table 2: Summary Statistics

	Mean (SD)		Mean (SD)
Total Population	3445728.9 (3253217.8)	Foreign Population	647059.7 (1034123.0)
%Hispanic	16.18 (13.29)	Median Household Income	58648.7 (10768.2)
%Female	50.88 (0.690)	%Working Age	0.634 (0.0142)
Unemployment rate	4.965 (1.550)	%People$\leq$200%Poverty Level	30.09 (5.16)
%Education$\geq$ to college	32.98 (6.109)	%Education $\leq$ High School	12.47 (3.278)
%Owning Cost$\leq$30%Income	71.18 (6.965)	%Renting Cost$\leq$30%Income	52.11 (4.066)
Observations	575	Observations	575

mean coefficients; sd in parentheses

3 Empirical Methodology

To examine the change in foreign population, I first estimated a naive regression using a regular OLS method for the correlation between the population and some economic characteristic as the following:

$$Foreign_{it} = \alpha_0 + \alpha_1 Sanctuary + \alpha_2 Income + \alpha_3 Education + \alpha_4 Unemployment + e_{it}$$

The results[4], for the most part, was what I expected. What was surprising though was that the coefficients for policy, education level, and unemployment, and working-age

[4]Results for this regression is reported as table 7 in the appendix.

percentage are not significant. To further examine if this was the case, I improved my regression by using a fixed-effects model including additional control variables, MSA-level fixed-effects, and year fixed-effects to try to capture omitted variables, resulting in the full regression:

$$Y_{it} = \beta_0 + \sum_{K=-10}^{+9} \gamma_{YS_K} KYearSince_{it} + \zeta_{control} X_{i,t-1} + \delta_t + \omega_i + \epsilon_{it}$$

i indicates individual MSAs and t indicates individual years. Outcome vairbables $Y_i t$ include **(1) Log(Total Population) (2)Log(Foreign Population) (3)%Foreign (4)Hispanic (5)Unemployment rate (6)Log(Median Household Income), (7)%Below 200% Poverty Level, (8)Violent Crime Rate, (9)Property Crime Rate**. (Note: $GrowthRate(Income)_{it} = (Income_{it} - Income_{i(t-1)})/Income_{i(t-1)}$)

Control variables $X_{i,t-1}$ include a combination of **Log(Income),Unemployment rate, %female, %WorkingAge, %Education≤HighSchool, %Education≥College, %Cost of Owning ≤30%Income, %Cost of renting≤30%Income**, while omitting the varible that is used as the outcome for specific regressions.

$YearsBefore/After$ represents how many years since a city became a sanctuary city and is zero for all other cases when a city is not a sanctuary city. *Sanctuary* is an identifier variable indicating whether the city is sanctuary in that specific year. For example, New York City became sanctuary de facto in 2014, so the $YearsBefore/After$ variable is 0 until the year 2015, and is 1 for the years 2015, 2016, and 2017 while *Sanctuary* is 0 through 2013 and 1 starting in 2014 and through. Then I generated individual dummies to indicate how many years a city is from adopting the policy. In the case of New York City, -8 to +3 years form policy adoption is 1, and the rest are 0. In my analysis, year zero (i.e the year the policy is adopted) is omitted to serve as a baseline comparison at zero. $\%WorkingAge$ is the percentage of people in the age bracket 18-65 years old with respect to population in the MSA.

I chose to use $Log(Total)Population)$, $Log(ForeignPopulation)$,$\%ForeignPopulation)$, and $\%Hispanic$ to capture the percentage change in population since the MSA size has a wide variation in the dataset making it more pertinent to look at percent change rather than level change. Originally, foreign population unemployment was included in the regression, but after a couple of estimations, it was not shown to be significant hence I omitted it from the regressions.

For economic characteristics, I wanted to examine unemployment rate, income, income growth rate, and poverty status. For income, I regressed on both $Log(Income)$ and the growth rate of income, $GR(Income)$. For unemployment rate and poverty, I did not perform any transformation since they are already in percents.

For crime, I used violent crime rate and property crime rate as outcomes of the main regression (9, 10). The results[5] showed that the policy seems to have null effect but a significant effect on property crime. To further investigate, I estimated the same regressions for property crime but restricting cities whose foreign population is in the top quartile in 2006 (11) and the other cities (12).

4 Results

Below are tables reporting the results of the regressions. Table 3 represents the results of regressions (1) through (4). Table 4 represents the results of regressions (5) through (8). Table 5 represents the results of regressions(8) through (12). Year level fixed effect was controlled for but not reported. Since the majority of the cities became a sanctuary city in

[5]In the results seciton

2014, I only report the coefficients of ± 3 years here. For other notes on the variables, consult notes right below table 5[6].

Table 3: Population Change Estimation

	(1) Log(Total Population)	(2) Log(Foreign Population)	(3) % Foreign	(4) % Hispanic
3 Years Before	0.0115*	0.0251**	0.00182	-0.00658
	(0.00584)	(0.0113)	(0.00146)	(0.128)
2 Years Before	0.0109**	0.0189	0.00125	0.00257
	(0.00466)	(0.0136)	(0.00151)	(0.106)
1 Year Before	0.00751**	0.00306	0.000895	0.0261
	(0.00332)	(0.00893)	(0.00141)	(0.0930)
Policy Adoption				
1 Year After	-0.00535	-0.0189*	0.000120	0.127
	(0.00459)	(0.0115)	(0.00139)	(0.0935)
2 Years After	-0.00991*	-0.0350***	-0.000427	0.161
	(0.00589)	(0.0123)	(0.00171)	(0.142)
3 Years After	-0.0189***	-0.0555***	-0.00244	0.118
	(0.00676)	(0.0174)	(0.00249)	(0.170)
N	556	556	556	550
R^2	0.667	0.745	0.483	0.770

Standard errors in parentheses; Notes are below Table 5

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Economic Characteristic Estimations

	(5) Log(Income)	(6) GR(Income)	(7) Unemployment	(8) Poverty Level
3 Years Before	-0.00616	-0.00626	0.204*	0.250
	(0.00712)	(0.00513)	(0.114)	(0.312)
2 Years Before	-0.00672	0.00287	0.149	-0.00634
	(0.00514)	(0.00679)	(0.113)	(0.223)

[6]The full tables with controlled balanced panel are reported in the appendix section. All tables in the appendix section are original table outputs of the full regression from Stata^{TM}.

1 Year Before	0.000841	0.000141	0.166*	0.0123
	(0.00664)	(0.00857)	(0.0951)	(0.268)
Policy Adoption				
1 Year After	-0.00179	-0.00114	0.0156	0.246
	(0.00779)	(0.00940)	(0.105)	(0.315)
2 Years After	-0.0000506	0.00906	0.0765	0.0530
	(0.00708)	(0.00730)	(0.106)	(0.287)
3 Years After	0.00886*	0.000852	-0.0374	-0.488
	(0.00528)	(0.00729)	(0.0900)	(0.315)
N	550	496	550	550
R^2	0.945	0.712	0.947	0.883

Standard errors in parentheses; Notes are below Table 5

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Crime Statistics Estimations

	(9) Violent Crime	(10) Property Crime	(11) Property Crime (Top 25 %)	(12) Property Crime (Bottom 75%)
3 Years Before	23.75	133.5	195.1	30.77
	(32.42)	(128.7)	(246.3)	(124.0)
2 Years Before	3.171	49.84	5.472	1.824
	(24.66)	(81.35)	(169.6)	(112.4)
1 Year Before	23.45	217.4	24.58	273.1
	(25.14)	(135.4)	(134.7)	(197.9)
Policy Adoption				
1 Year After	2.244	212.8*	432.2***	99.79
	(22.93)	(114.6)	(113.7)	(169.5)
2 Years After	23.95	241.6**	453.5***	161.7
	(24.64)	(110.4)	(105.5)	(166.6)
3 Years After	16.42	167.2	217.1	77.56
	(29.63)	(118.0)	(158.3)	(168.6)
N	494	486	126	360
R^2	0.170	0.460	0.661	0.454

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

Individual years are controlled for in these regressions but are not reported.
Full table is shown in the appendix section.
ln represents taking the natural log of the variable in paranthesis.
GR is an operator for growthrate of the variable in paranthesis.
Foreign stands for total foreign population in a city[7]
Total stands for total population in a city.
Unemployment is the unemplotment rate of peopel in labor force in a city.
Income is the median household income in a city.
Poverty is the percentage of people under 200% of poverty status.
Regression 11 and 12 differes in the sample separated by %Foreign in top quartile versus otherwise in 2006.
These are fixed effect regressions with robust standard errors.
Data collected from ACS 1-year estimates, 2006-2017, table S0501
Sanctuary city status are based on the report generated by ICE.
Crime Data collected from FBI Uniform Crime Report.

4.1 Population

For both total and foreign population, the policy has a negative, significant, and increasing effect on the population. In (1), there seems to be a general trend of decrease in total population throughout the policy year. The coefficient in (2) nearly tripled from $1YearAfter$ to $3YearsAfter$ showing a strong effect from the policy. Year fixed-effects are positive, significant, and increasing by year hence the coefficients here shows a slow in growth of both the total and the foreign population rather than a decrease in population. The coefficients in (3) show that the policy has no effect on the percentage of foreign individuals in a city which suggests a general slow of growth in population for sanctuary cities. Surprisingly, % Hispanic does not seem to have any correlation with Sanctuary city policy. This could be reflecting the assumption that this data set does not necessarily include undocumented immigrants, often largely composed of Hispanic population (Gorbachev, O'Flaherty, & Sethi, 2018).

[7] Foreign as defined by ACS represents individuals who are born abroad to non-US-citizen parents. Indiciduals born abroad to at least one US-citizen parent is considered native in this case.

4.2 Economy

Results (5) through (8) tell a compelling story about the relationship between sanctuary city policy and the economy of a city. For Log(Income), the effect seems random throughout the period and is only significant 3 years after the policy has been adopted. The estimates on the growth of income reaffirm the story by showing that the growth rate is not very much affected by sanctuary city policy. A similar explanation can be said about poverty level as none of the coefficients are significant so no effect of the policy can be inferred. Interestingly, in regression (7), even though there is no significance on the years after the policy is adopted, the coefficients are positive and significant in the years before. This shows that unemployment rate is decreased in a city the year it becomes a sanctuary city and stays at that level for at least the next 3 years, all else equal. These results combined yields lower unemployment while other major characteristics remain constant for sanctuary cities, holding all else equal.

4.3 Crime

Regressions (9) and (10) tell slightly different stories about the relationship between sanctuary city policy and crime. The estimation in (9) implies that there is no relationship between having sanctuary policy and the violent crime rate. However, the coefficients for property crime are positive and significant in the first two years. This relationship is further examined by regressions (11) and (12) as they show that in cities where there are more foreign people, having a sanctuary city policy has a positive and even more significant effect on property crime reported while not having an effect on cities that are not as high in percent of foreign population.

One explanation to the result is that sanctuary city policy can reduce the burden or risk of being questioned or detained when a foreign person chooses to report a property crime. With the policy, the cost of reporting would be greatly reduced and hence encourages foreign individuals to report. It is also possible that foreign peopel feel more welcomed in sanctuary cities by law enforecments and hence are more prone to cooperation and property crime reporting. This hypothesis also stands in the case of violent crime reported. Due to the cost of physical harm is likely to outweigh the cost of not reporting, and the fact that violent crimes are often more observable by bystanders, it is reasonable to suggest the encouragement of cooperation mainly corrects for reporting only in property crime.

The same regressions as (11) and (12) were estimated to examine whether the change in violent crime has a similar concentration in high foreign population MSAs but the results were insignificant and not reported here.

5 Robustness

In an attempt to confirm the robustness of my estimation and establish some causal relationship between instituting sanctuary city policy and change in demographic and economic characteristics, I conducted a placebo test. This procedure includes re-estimating regressions (1),(2),(7),(10),(11), and (12) while using the placebo year of policy adoption by making the policies adoptions 2 years earlier than in reality rather than the actual year the policy is instituted.

$$PlaceboYearofSanctuary = ActualSanctuaryYear - 2$$

With this model, if the estimated effects actually came from the sanctuary city policy, there should be no effects at the years that are not actually sanctuary but significant and have similar estimates at the years that are actually sanctuary. Year 3 of the placebo policy, equivalent to year 0 of the actual policy, is omitted in the analysis to establish the comparison baseline across the years to show consistency and robustness. The results in table 6 show a consistent estimate with table 3 through 5, validating that the results in the previous estimations are robust. The individual estimations have the same number order but with an asterisk denoting it the result of a placebo test.

Table 6: Placebo test results

	(1*)	(2*)	(7*)	(10*)	(11*)	(12*)
	Log(Total)	Log(Foreign)	Unemployment	Property	Property	Property
					Top 25% in %Foreign	Bottom 75% in %Foreign
Placebo Policy Adoption	0.0104*	0.0205*	0.204*	133.5	195.1	30.77
	(0.00588)	(0.0110)	(0.114)	(128.7)	(246.3)	(124.0)
1 Year Placebo	0.00855*	0.00905	0.149	49.84	5.472	1.824
	(0.00459)	(0.0121)	(0.113)	(81.35)	(169.6)	(112.4)
2 Years Placebo	0.00640*	-0.00166	0.166*	217.4	24.58	273.1
	(0.00340)	(0.00843)	(0.0951)	(135.4)	(134.7)	(197.9)
Actual Policy Adopted						
4 Years Placebo	-0.00648	-0.0237**	0.0156	212.8*	432.2***	99.79
	(0.00445)	(0.0108)	(0.105)	(114.6)	(113.7)	(169.5)
5 Years Placebo	-0.0109*	-0.0393***	0.0765	241.6**	453.5***	161.7
	(0.00587)	(0.0119)	(0.106)	(110.4)	(105.5)	(166.6)
6 Years Placebo	-0.0199***	-0.0596***	-0.0374	167.2	217.1	77.56
	(0.00674)	(0.0174)	(0.0900)	(118.0)	(158.3)	(168.6)
N	556	556	550	486	126	360
R^2	0.667	0.745	0.947	0.460	0.661	0.454

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion and future work

In conclusion, becoming a sanctuary city does not have a permanent impact on the level of foreign population. However, the negative correlations start to show after a year while the magnitude of the impact, increasing as much as tripling in 3 years. Total population also starts decreasing after one year of sanctuary city but this seems to be more of a trend than an effect of the policy. The results of the placebo test suggest a possible causal effect between sanctuary city policy and foreign population. My hypothesis in an attempt to explain this is a crowding-out effect on the foreign population. Admittedly, the data does not explicitly assume that all foreign individuals reported are documented immigrants. However, it is reasonable to make such an assumption, since ACS is a federally administered self-reporting survey, undocumented immigrants are less likely to be surveyed because it could mean risking detention and deportation. With this assumption, an elementary supply and demand theory can be used to analyze the crowding-out effect, in which case, because of the perceived increase in undocumented immigrants, documented immigrants could choose to move to a different city to separate themselves out in the society and in the labor market.

Economic-wise, my analysis showed that becoming a sanctuary city has no effect on income or poverty level. However, it does seem to reduce unemployment rate. This is an important result because this means that sanctuary city policy does not make cities worse off economically hence invalidating one of the big arguments against sanctuary city policy. Furthermore, since sanctuary city policy does not make a city worse off economically, one explanation to the increase in reported property crime is a correction to what was underreported before. If this hypothesis were true, then not only does sanctuary city not make a city unsafe, it would make it safer. Based on my estimation result, president Trump should revoke his executive order against sanctuary cities since he claims safety and economy was the reason behind it.

In the future, a study can be done to empirically analyze the relationship between the number of undocumented immigrants and the number of documented immigrants to examine whether the crowding-out effect explanation is plausible. Currently, due to limited data availability, it is difficult for such study to be done on the undergraduate level, but the data could be more available in the future when the political climate becomes more immigration friendly, enabling the Census Bureau to collect data on the subject. A study can also be done on what is causing the decrease in unemployment rate since researchers have shown that sanctuary cities are more progressive (Casellas & Wallace, 2018), they could have more accompanying social policies that helped lowered the increase in unemployment. Lastly, the hypothesis of increasing crime reporting is interesting and deserves to be looked into more. I am currently searching for data set available on victimization in order to make a comparative analysis to find out exactly why there is an increase in property crime reported following the policy.

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8 Appendix

Table 7: Naive regression

	(1)
	dm34
L.Sanctuary City	7094.9
	(25301.3)
L.ln(Income)	337552.2***
	(92855.9)
L.%High Education	-2991.3
	(4453.6)
L.UnemploymentRateloyment	2992.5
	(2341.0)
%Owning Cost $\leq$30%Income	7884.2***
	(2418.4)
%Renting Cost $\leq$30%Income	-4172.9**
	(2054.0)
L.%WorkingAge	1642252.3
	(1357942.6)
Constant	-4373819.8***
	(1474667.4)
N	547

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Full Version of Table 3

	(1)	(2)	(3)	(4)
	Log(Total)	Log(Foreign)	%Foreign	%Hispanic
10 Years Before	-0.000338	-0.0299	-0.00499	
	(0.0300)	(0.0356)	(0.00647)	
9 Years Before	-0.0475	-0.0298	-0.00273	-0.359
	(0.0413)	(0.0318)	(0.00494)	(0.355)
8 Years Before	-0.0148	-0.0466	-0.00469	-0.459*
	(0.0226)	(0.0337)	(0.00308)	(0.235)

7 Years Before	0.00379	0.0315	0.000479	-0.175
	(0.0134)	(0.0242)	(0.00295)	(0.303)
6 Years Before	0.00510	0.0335	0.000786	0.00242
	(0.0130)	(0.0253)	(0.00274)	(0.256)
5 Years Before	0.0123	0.0168	-0.000994	-0.0636
	(0.00928)	(0.0160)	(0.00216)	(0.236)
4 Years Before	0.0171**	0.0223	0.00129	0.0388
	(0.00744)	(0.0162)	(0.00196)	(0.155)
3 Years Before	0.0115*	0.0251**	0.000717	-0.0267
	(0.00584)	(0.0113)	(0.00131)	(0.124)
2 Years Before	0.0109**	0.0189	0.000287	-0.0150
	(0.00466)	(0.0136)	(0.00138)	(0.104)
1 Year Before	0.00751**	0.00306	-0.000356	-0.00749
	(0.00332)	(0.00893)	(0.00116)	(0.0905)
1 Year After	-0.00535	-0.0189*	-0.000769	0.105
	(0.00459)	(0.0115)	(0.00113)	(0.0848)
2 Years After	-0.00991*	-0.0350***	-0.00105	0.144
	(0.00589)	(0.0123)	(0.00157)	(0.132)
3 Years After	-0.0189***	-0.0555***	-0.00288	0.111
	(0.00676)	(0.0174)	(0.00237)	(0.166)
4 Years After	-0.0378***	-0.0879***	-0.00292	0.0734
	(0.00971)	(0.0202)	(0.00192)	(0.248)
5 Years After	-0.0427***	-0.0819***	-0.000839	0.127
	(0.0102)	(0.0188)	(0.00281)	(0.436)
6 Years After	-0.0460***	-0.109***	-0.00152	0.0796
	(0.0122)	(0.0209)	(0.00293)	(0.620)
7 Years After	-0.0527***	-0.0594***	0.00668***	0.943***
	(0.0110)	(0.0193)	(0.00215)	(0.275)
8 Years After	-0.0671***	-0.162***	-0.00507**	0.968***
	(0.0135)	(0.0204)	(0.00236)	(0.309)
9 Years After	-0.0767***	-0.132***	-0.00110	0.734**
	(0.0140)	(0.0249)	(0.00304)	(0.364)

L.%Female	0.0532***	-0.0102	-0.00384*	-0.373
	(0.0152)	(0.0222)	(0.00223)	(0.275)
L.Log(Income)	0.273**	0.280*	0.0252*	-2.863
	(0.125)	(0.160)	(0.0145)	(2.526)
L.%WorkingAge	-0.00658	-0.0155	-0.000296	0.208
	(0.00948)	(0.0133)	(0.00161)	(0.223)
L.%Education≤HighSchool	0.00754*	0.0101	0.000897	0.0548
	(0.00389)	(0.00749)	(0.000625)	(0.0926)
L.%Education≥College	-0.0107*	0.00384	0.000601	-0.181**
	(0.00639)	(0.00561)	(0.000591)	(0.0726)
L.UnemploymentRate	-0.00147	-0.0160**	-0.000701	0.0894
	(0.00575)	(0.00734)	(0.000704)	(0.0753)
L.%CostOfOwning≤30%Income	0.000628	-0.00256	0.000570**	0.0315
	(0.00132)	(0.00222)	(0.000268)	(0.0282)
L.%CostOfRenting≤30%Income	-0.00228**	-0.00470**	-0.000487**	-0.000386
	(0.000929)	(0.00192)	(0.000234)	(0.0279)
2008	0.0112	-0.00317	-0.00234**	0.546***
	(0.00702)	(0.0102)	(0.00115)	(0.127)
2009	0.0177*	0.0281	-0.00162	1.035***
	(0.0108)	(0.0176)	(0.00173)	(0.239)
2010	0.0358*	0.113***	0.00382*	1.357***
	(0.0207)	(0.0272)	(0.00206)	(0.308)
2011	0.0416*	0.139***	0.00544**	1.653***
	(0.0252)	(0.0295)	(0.00250)	(0.364)
2012	0.0565**	0.139***	0.00414*	1.882***
	(0.0254)	(0.0303)	(0.00235)	(0.365)
2013	0.0777**	0.171***	0.00305	2.237***
	(0.0314)	(0.0367)	(0.00269)	(0.420)
2014	0.0933***	0.193***	0.00328	2.587***
	(0.0321)	(0.0396)	(0.00294)	(0.464)
2015	0.0987***	0.207***	0.00358	2.994***
	(0.0324)	(0.0421)	(0.00324)	(0.522)

2016	0.111***	0.209***	0.00275	3.471***
	(0.0356)	(0.0481)	(0.00388)	(0.604)
2017	0.124***	0.228***	0.00301	4.092***
	(0.0392)	(0.0557)	(0.00489)	(0.721)
_cons	9.732***	11.12***	0.0311	54.12**
	(1.733)	(2.101)	(0.206)	(24.80)
N	556	556	556	550
R^2			0.510	0.773

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Full Version of Table 4

	(1) Log(Income)	(2) GR(Income)	(3) Unemployment	(4) Poverty
10 Years Before	-0.0104	-0.000682	0.209	0.282
	(0.0140)	(0.00824)	(0.237)	(0.360)
9 Years Before	-0.00764	-0.00962	0.0120	0.644
	(0.0117)	(0.0135)	(0.196)	(0.500)
8 Years Before	-0.0106	0.00723	-0.0565	0.729
	(0.0104)	(0.0113)	(0.214)	(0.645)
7 Years Before	-0.00893	-0.00613	-0.129	0.214
	(0.00937)	(0.00696)	(0.130)	(0.456)
6 Years Before	-0.0117	-0.00421	0.286**	0.496
	(0.00774)	(0.00848)	(0.111)	(0.376)
5 Years Before	-0.00762	-0.00425	0.0678	-0.0278
	(0.00535)	(0.00862)	(0.189)	(0.342)
4 Years Before	-0.00855	-0.00137	0.149	0.0498
	(0.00667)	(0.00609)	(0.118)	(0.331)
3 Years Before	-0.00616	-0.00626	0.204*	0.250
	(0.00712)	(0.00513)	(0.114)	(0.312)
2 Years Before	-0.00672	0.00287	0.149	-0.00634
	(0.00514)	(0.00679)	(0.113)	(0.223)
1 Year Before	0.000841	0.000141	0.166*	0.0123
	(0.00664)	(0.00857)	(0.0951)	(0.268)

1 Year After	-0.00179	-0.00114	0.0156	0.246
	(0.00779)	(0.00940)	(0.105)	(0.315)
2 Years After	-0.0000506	0.00906	0.0765	0.0530
	(0.00708)	(0.00730)	(0.106)	(0.287)
3 Years After	0.00886*	0.000852	-0.0374	-0.488
	(0.00528)	(0.00729)	(0.0900)	(0.315)
4 Years After	0.00391	0.000408	0.0732	-0.116
	(0.00922)	(0.00868)	(0.182)	(0.493)
5 Years After	0.00705	0.00737	0.0823	0.431
	(0.0116)	(0.00725)	(0.154)	(0.364)
6 Years After	0.0159	0.0218***	-0.0172	0.366
	(0.0104)	(0.00532)	(0.135)	(0.386)
7 Years After	0.0262***	-0.0277***	-0.203*	-0.715**
	(0.00736)	(0.00704)	(0.110)	(0.338)
8 Years After	-0.0232***	-0.0438***	-0.189*	1.711***
	(0.00715)	(0.00664)	(0.108)	(0.353)
9 Years After	-0.0555***	0	0.0671	2.315***
	(0.00768)	(.)	(0.104)	(0.335)
L.%Female	0.0119**	0.0144***	-0.319***	-0.480*
	(0.00447)	(0.00439)	(0.0926)	(0.249)
L.Log(Income)	0.655***	-0.111***	2.230**	-19.70***
	(0.0439)	(0.0397)	(0.855)	(2.154)
L.%WorkingAge	0.000892	-0.000556	-0.0114	-0.182
	(0.00201)	(0.00243)	(0.0515)	(0.190)
L.%Education≤HighSchool	0.00465***	-0.00261	0.0363	0.151
	(0.00162)	(0.00199)	(0.0392)	(0.0921)
L.%Education≥College	0.00313**	-0.00248	-0.00230	0.122
	(0.00135)	(0.00178)	(0.0339)	(0.0730)
L.UnemploymentRate	-0.0110***	0.00135	0.612***	0.791***
	(0.00202)	(0.00176)	(0.0425)	(0.102)
L.%CostOfOwning≤30%Income	-0.0000917	0.00214***	-0.0498***	0.0774**
	(0.000731)	(0.000565)	(0.0108)	(0.0314)

L.%CostOfRenting≤30%Income	-0.00217***	-0.00126*	-0.00639	0.0359
	(0.000648)	(0.000649)	(0.0144)	(0.0402)
2008	0.00361	-0.0719***	0.0394	0.985***
	(0.00431)	(0.00539)	(0.0761)	(0.198)
2009	-0.0629***	-0.0352***	2.216***	3.734***
	(0.00447)	(0.00613)	(0.128)	(0.245)
2010	-0.0223***	-0.0305***	1.489***	2.960***
	(0.00723)	(0.00586)	(0.131)	(0.350)
2011	-0.00912	-0.0170**	0.720***	3.137***
	(0.00806)	(0.00792)	(0.133)	(0.389)
2012	0.00664	-0.0249***	0.455***	3.596***
	(0.00755)	(0.00842)	(0.123)	(0.397)
2013	0.00396	-0.0157*	0.298**	3.885***
	(0.00871)	(0.00910)	(0.123)	(0.452)
2014	0.0135	-0.00576	-0.00325	3.982***
	(0.00971)	(0.00971)	(0.121)	(0.489)
2015	0.0242**	-0.00187	-0.140	3.770***
	(0.00969)	(0.0104)	(0.155)	(0.539)
2016	0.0341***	0.00363	-0.194	3.409***
	(0.0106)	(0.0120)	(0.166)	(0.581)
2017	0.0440***		-0.230	3.654***
	(0.0122)		(0.182)	(0.648)
_cons	3.143***	0.574	-2.483	261.5***
	(0.605)	(0.538)	(9.941)	(25.79)
N	550	496	550	550
R^2	0.945	0.712	0.947	0.883

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Full Version of Table 5

	(1) Violent Crime	(2) Property Crime	(3) Property Crime	(4) Property Crime
10 Years Before	44.79	291.7	0	240.6
	(51.22)	(315.1)	(.)	(352.7)
9 Years Before	66.07	965.7**	0	1005.1**
	(125.6)	(415.4)	(.)	(448.8)
8 Years Before	206.6*	716.9**	0	727.3*
	(110.5)	(325.7)	(.)	(385.6)
7 Years Before	27.10	70.62	-347.7	186.5
	(38.09)	(161.9)	(358.8)	(218.9)
6 Years Before	-6.301	688.2*	413.1	241.4
	(67.67)	(387.3)	(632.1)	(216.9)
5 Years Before	39.45	241.6	-262.1	351.7
	(38.34)	(163.5)	(238.5)	(230.6)
4 Years Before	-1.787	-3.946	-107.8	12.22
	(35.10)	(108.3)	(287.5)	(138.8)
3 Years Before	23.75	133.5	195.1	30.77
	(32.42)	(128.7)	(246.3)	(124.0)
2 Years Before	3.171	49.84	5.472	1.824
	(24.66)	(81.35)	(169.6)	(112.4)
1 Year Before	23.45	217.4	24.58	273.1
	(25.14)	(135.4)	(134.7)	(197.9)

1 Year After	2.244	212.8*	432.2***	99.79
	(22.93)	(114.6)	(113.7)	(169.5)
2 Years After	23.95	241.6**	453.5***	161.7
	(24.64)	(110.4)	(105.5)	(166.6)
3 Years After	16.42	167.2	217.1	77.56
	(29.63)	(118.0)	(158.3)	(168.6)
4 Years After	38.47	217.8	644.1**	114.9
	(44.19)	(145.9)	(262.3)	(204.1)
5 Years After	63.04	255.2*	753.8*	160.9
	(45.53)	(149.0)	(383.4)	(188.4)
6 Years After	43.44	344.5*	963.7*	237.0
	(37.32)	(183.9)	(517.7)	(216.5)
7 Years After	44.82	545.0***	0	410.0*
	(36.37)	(177.7)	(.)	(230.5)
8 Years After	42.02	712.7***	0	571.5**
	(38.05)	(168.2)	(.)	(213.4)
9 Years After	46.74	768.9***	0	701.2***
	(44.87)	(177.0)	(.)	(251.4)
L.%Female	12.01	-92.57	293.1	-154.2
	(29.55)	(168.0)	(209.6)	(230.8)
L.Log(Income)	127.3	208.0	-7.932	738.3
	(288.4)	(1231.0)	(3402.5)	(1430.8)
L.%WorkingAge	2.180	-77.88	-78.19	-55.88

	(17.07)	(98.56)	(179.4)	(113.7)
L.%Education≤HighSchool	-0.499	-24.90	-143.1	35.31
	(7.504)	(63.21)	(156.1)	(63.95)
L.%Education≥College	-11.96	-20.42	-104.5	-13.29
	(8.899)	(45.90)	(158.9)	(55.55)
L.UnemploymentRate	-10.87	-1.449	146.8	4.609
	(14.90)	(65.91)	(113.3)	(97.49)
L.%CostOfOwning≤30%Income	-0.297	23.76*	97.25**	14.82
	(4.848)	(13.00)	(36.71)	(20.38)
L.%CostOfRenting≤30%Income	-1.056	-29.37	-89.53*	-17.57
	(5.500)	(26.26)	(48.39)	(30.93)
2007	0	0	0	0
	(.)	(.)	(.)	(.)
2008	-50.34	-331.2	103.4	-426.7
	(50.81)	(224.9)	(534.9)	(260.0)
2009	-60.79**	-356.8**	-340.2	-314.9*
	(27.46)	(134.8)	(305.3)	(160.3)
2010	-49.55	-530.1***	-1238.0**	-435.1*
	(43.03)	(193.0)	(442.6)	(228.5)
2011	-63.40	-582.0**	-1796.7**	-451.8
	(51.65)	(235.0)	(605.4)	(276.7)
2012	-63.45	-699.5***	-1888.7***	-582.7**

	(54.38)	(246.1)	(571.2)	(280.8)
2013	-83.67	-889.0***	-2138.8***	-716.7**
	(63.40)	(278.1)	(697.3)	(295.0)
2014	-77.85	-1061.7***	-2460.0**	-873.7***
	(66.93)	(276.3)	(809.6)	(286.8)
2015	-66.40	-1197.5***	-2697.8**	-980.9***
	(68.56)	(303.1)	(892.6)	(299.0)
2016	-83.09	-1328.2***	-2701.6**	-1131.6***
	(77.51)	(344.3)	(988.6)	(358.1)
2017	-83.47	-1471.8***	-2635.9**	-1288.0***
	(88.75)	(387.7)	(1067.1)	(412.6)
_cons	-1150.7	11880.3	-2271.7	6853.0
	(3941.7)	(18455.0)	(38937.3)	(24124.9)
N	494	486	126	360
R^2	0.170	0.460	0.661	0.454

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Full Version of Table 6 Placebo Test

	(1) Log(Total)	(2) Log(Foreign)	(3) Unemployment	(4) Property Crime	(5) Property Crime	(6) Property Crime
7 Years Before Placebo	-0.00156	-0.0351	0.209	291.7	0	240.6
	(0.0299)	(0.0350)	(0.237)	(315.1)	(.)	(352.7)
6 Years Before Placebo	-0.0486	-0.0347	0.0120	965.7**	0	1005.1**

	(0.0412)	(0.0315)	(0.196)	(415.4)	(.)	(448.8)
5 Years Before Placebo	-0.0160	-0.0516	-0.0565	716.9**	0	727.3*
	(0.0225)	(0.0331)	(0.214)	(325.7)	(.)	(385.6)
4 Years Before Placebo	0.00263	0.0265	-0.129	70.62	-347.7	186.5
	(0.0133)	(0.0236)	(0.130)	(161.9)	(358.8)	(218.9)
3 Years Before Placebo	0.00397	0.0287	0.286**	688.2*	413.1	241.4
	(0.0128)	(0.0249)	(0.111)	(387.3)	(632.1)	(216.9)
2 Years Before Placebo	0.0111	0.0116	0.0678	241.6	-262.1	351.7
	(0.00930)	(0.0155)	(0.189)	(163.5)	(238.5)	(230.6)
1 Years Before Placebo	0.0159**	0.0173	0.149	-3.946	-107.8	12.22
	(0.00743)	(0.0159)	(0.118)	(108.3)	(287.5)	(138.8)
Placebo Year	0.0104*	0.0205*	0.204*	133.5	195.1	30.77
	(0.00588)	(0.0110)	(0.114)	(128.7)	(246.3)	(124.0)
1 Year After Placebo	0.00855*	0.00905	0.149	49.84	5.472	1.824
	(0.00459)	(0.0121)	(0.113)	(81.35)	(169.6)	(112.4)
2 Years After Placebo	0.00640*	-0.00166	0.166*	217.4	24.58	273.1
	(0.00340)	(0.00843)	(0.0951)	(135.4)	(134.7)	(197.9)
3 Years After Placebo	-0.00648	-0.0237**	0.0156	212.8*	432.2***	99.79
	(0.00445)	(0.0108)	(0.105)	(114.6)	(113.7)	(169.5)
4 Years After Placebo	-0.0109*	-0.0393***	0.0765	241.6**	453.5***	161.7
	(0.00587)	(0.0119)	(0.106)	(110.4)	(105.5)	(166.6)
5 Years After Placebo	-0.0199***	-0.0596***	-0.0374	167.2	217.1	77.56

	(0.00674)	(0.0174)	(0.0900)	(118.0)	(158.3)	(168.6)
6 Years After Placebo	-0.0389***	-0.0925***	0.0732	217.8	644.1**	114.9
	(0.00968)	(0.0199)	(0.182)	(145.9)	(262.3)	(204.1)
7 Years After Placebo	-0.0436***	-0.0860***	0.0823	255.2*	753.8*	160.9
	(0.0103)	(0.0187)	(0.154)	(149.0)	(383.4)	(188.4)
8 Years After Placebo	-0.0469***	-0.113***	-0.0172	344.5*	963.7*	237.0
	(0.0123)	(0.0208)	(0.135)	(183.9)	(517.7)	(216.5)
9 Years After Placebo	-0.0537***	-0.0634***	-0.203*	545.0***	0	410.0*
	(0.0110)	(0.0191)	(0.110)	(177.7)	(.)	(230.5)
10 Years After Placebo	-0.0679***	-0.166***	-0.189*	712.7***	0	571.5**
	(0.0135)	(0.0201)	(0.108)	(168.2)	(.)	(213.4)
11 Years After Placebo	-0.0775***	-0.135***	0.0671	768.9***	0	701.2***
	(0.0139)	(0.0246)	(0.104)	(177.0)	(.)	(251.4)
L.%Female	0.0532***	-0.0103	-0.319***	-92.57	293.1	-154.2
	(0.0152)	(0.0222)	(0.0926)	(168.0)	(209.6)	(230.8)
L.Log(Income)	0.273**	0.278*	2.230**	208.0	-7.932	738.3
	(0.125)	(0.161)	(0.855)	(1231.0)	(3402.5)	(1430.8)
L.%WorkingAge	-0.00658	-0.0155	-0.0114	-77.88	-78.19	-55.88
	(0.00948)	(0.0133)	(0.0515)	(98.56)	(179.4)	(113.7)
L.%Education≤HighSchool	0.00756*	0.0102	0.0363	-24.90	-143.1	35.31
	(0.00389)	(0.00748)	(0.0392)	(63.21)	(156.1)	(63.95)
L.%Education≥College	-0.0107*	0.00378	-0.00230	-20.42	-104.5	-13.29

	(0.00639)	(0.00560)	(0.0339)	(45.90)	(158.9)	(55.55)
L.UnemploymentRate	-0.00149	-0.0161**	0.612***	-1.449	146.8	4.609
	(0.00575)	(0.00734)	(0.0425)	(65.91)	(113.3)	(97.49)
L.%CostOfOwning≤30%Income	0.000609	-0.00263	-0.0498***	23.76*	97.25**	14.82
	(0.00133)	(0.00223)	(0.0108)	(13.00)	(36.71)	(20.38)
L.%CostOfRenting≤30%Income	-0.00227**	-0.00463**	-0.00639	-29.37	-89.53*	-17.57
	(0.000930)	(0.00192)	(0.0144)	(26.26)	(48.39)	(30.93)
2008	0.0112	-0.00324	0.0394	-331.2	103.4	-426.7
	(0.00702)	(0.0102)	(0.0761)	(224.9)	(534.9)	(260.0)
2009	0.0179*	0.0286	2.216***	-356.8**	-340.2	-314.9*
	(0.0108)	(0.0176)	(0.128)	(134.8)	(305.3)	(160.3)
2010	0.0360*	0.114***	1.489***	-530.1***	-1238.0**	-435.1*
	(0.0207)	(0.0272)	(0.131)	(193.0)	(442.6)	(228.5)
2011	0.0416*	0.139***	0.720***	-582.0**	-1796.7**	-451.8
	(0.0252)	(0.0295)	(0.133)	(235.0)	(605.4)	(276.7)
2012	0.0569**	0.141***	0.455***	-699.5***	-1888.7***	-582.7**
	(0.0254)	(0.0303)	(0.123)	(246.1)	(571.2)	(280.8)
2013	0.0779**	0.171***	0.298**	-889.0***	-2138.8***	-716.7**
	(0.0315)	(0.0367)	(0.123)	(278.1)	(697.3)	(295.0)
2014	0.0934***	0.193***	-0.00325	-1061.7***	-2460.0**	-873.7***
	(0.0321)	(0.0396)	(0.121)	(276.3)	(809.6)	(286.8)
2015	0.0990***	0.209***	-0.140	-1197.5***	-2697.8**	-980.9***

	(0.0324)	(0.0421)	(0.155)	(303.1)	(892.6)	(299.0)
2016	0.111***	0.210***	-0.194	-1328.2***	-2701.6**	-1131.6***
	(0.0356)	(0.0481)	(0.166)	(344.3)	(988.6)	(358.1)
2017	0.125***	0.229***	-0.230	-1471.8***	-2635.9**	-1288.0***
	(0.0392)	(0.0558)	(0.182)	(387.7)	(1067.1)	(412.6)
_cons	9.732***	11.14***	-2.579	11848.8	-2273.9	6851.7
	(1.732)	(2.097)	(9.952)	(18457.2)	(38910.2)	(24120.7)
N	556	556	550	486	126	360
R^2			0.947	0.460	0.661	0.454

Standard errors in parentheses   * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

Individual years are controlled for in these regressions but are not reported.

Full table is shown in the appendix section.

Log() represents taking the natural log of the variable in paranthesis.

GR is an operator for growthrate of the variable in paranthesis.

L. represents lagging the variable by 1 year

Foreign stands for total foreign population in a city[8]

Total stands for total population in a city.

Unemployment is the unemplotment rate of peopel in labor force in a city.

Income is the median household income in a city.

Poverty is the percentage of people under 200% of poverty status.

Regression 11 and 12 differes in the sample separated by %Foreign in top quartile versus otherwise in 2006.

These are fixed effect regressions with robust standard errors.

Data collected from ACS 1-year estimates, 2006-2017, table S0501

Sanctuary city status are based on the report generated by ICE.

Crime Data collected from FBI Uniform Crime Report.

[8]Foreign as defined by ACS represents individuals who are born abroad to non-US-citizen parents. Indiciduals born abroad to at least one US-citizen parent is considered native in this case.