Economic Impacts of Sanctuary and ICE Policies
Inclusive and Exclusive Institutions

Alexander D. Natanson

Using county-level census data and Immigration and Customs Enforcement (ICE) data on economic indicators, this study exploits quasi-experimental variation in the time and space of policy implementation to isolate the effects of local immigration policies on U.S. counties. These policies range from areas where immigrants are strictly regulated via collaboration with ICE compared to those that provide protections. The study finds evidence that providing protections to immigrants increases overall per capita income, wages, GDP, and total employment, while unemployment experienced a decline. Meanwhile, the data show that punitive measures have no statistically significant effect on income and unemployment but adverse effects overall on GDP, total employment, and the proportion of the foreign-born population. These results support a model of immigration policy as an institution that can either support or suppress productivity, and they confirm that immigrant labor is a positive driver of economic well-being at the local and regional level.

Keywords: Inclusive & Exclusive Institutions, Postmatching, Fixed Effect, Time Trend, Regression Discontinuity, Difference and Difference, Randomization Inference

Introduction

Opinions on the economic effects of immigration are political and controversial. Economic studies generally concentrate on the negative aspect of increasing the supply of labor, thus excluding native workers, and in politics fear drives the show. This paper focuses on the effect of sanctuary and ICE policies on local economies. "Sanctuary cities" refers to municipal jurisdictions that limit their cooperation with the federal government efforts to enforce immigration. Opponents of sanctuary policies allege that they come at an economic cost by arguing that they drive down wages for native workers and strain taxpayers and the national budget through immigrant utilization of social services. In contrast, proponents of sanctuary policies argue that anti-immigrant policies (ICE policies) only harm immigrant rights through surveillance and the threat of deportation because immigrants only respond to the availability of jobs (Harris 2006).

This paper examines the local effects of policy towards immigrants on economic outcome. To assess the impact of a county's openness to immigrants on the local economy, I use U.S. Census data on income, GDP, unemployment, and employment combined with newly digitized information on county-level immigration policies from 2006 to 2018. The econometric approach uses quasi-experimental variation in adopting policies that are both welcoming and restricting to undocumented immigrants. The circumstances for analysis create a staggered difference in difference environment. The analysis includes fixed effects, time-variant covariates, and time trends. Results are robust to nearest-neighbor matching, random assignment of treatment, and a regression discontinuity model comparing bordering counties with opposite policies.

I begin by classifying all counties by sanctuary, ICE, or neutral counties. Then, I estimate the impact of policies comparing sanctuary and ICE counties to neutral counties for each year in the data. In separate regressions using only those counties that ever end up with a sanctuary city or ICE designation, I restrict the sample to counties that ever chose to adopt either policy. This approach uses the variation in policy timing to address the possibility that sanctuary counties might be fundamentally different from non-sanctuary counties or ICE counties might be different from non-ICE counties. I also examine heterogeneity by urban, rural, educational attainment, gender, white, black, Latino population, and economic quintiles. Pre-trends suggest that the counterfactual groups in each setting are plausible, and various robustness checks confirm the results. Finally, I repeat this analysis using a geographical regression discontinuity model with counties that share a common border with opposing policies.

The evidence demonstrates that providing protections to undocumented immigrants increases economic activity. The estimates show increases in per capita income ranging from 3.1 to 7.2, median wages between 1.7 to 2.6, and GDP between 2.4 to 4.1 percent. In terms of labor, sanctuary counties saw an increases in total employment between 2.3 to 4 percent, and the decline in unemployment rate ranged from 12 to 17 percent. The data further shows that punitive measures have no statistically significant effects on income, median wages, or GDP, but adverse effects on total employment with declines from 1 to 2 percent, mostly in rural counties, and an increase in unemployment of around 7 percent in urban counties. In addition, I find a decline in the foreign-born population in ICE counties, but no changes in sanctuary counties. The study also finds similar results for sanctuary counties when separating the data between urban, rural, educational attainment, gender, ethnic groups, and economic quintiles. Meanwhile, most ICE counties show no significant effects except for the foreign-born population who appear to leave these areas. To sum, inclusive policies show positive effects on economic outcomes with no evident increase in population. In order to make sense of these results, my hypothesis proposes that inclusive immigration policies play an essential role in conditioning the effect of immigration by decreasing uncertainties and constraints for immigrants' interaction in their communities. By doing so, policies reduce the cost from fear of deportation or the constant fear of criminalization, optimize their human capital, and increase efficiency in the economy.

Studies on the economic effects of immigration in local economies have mainly concentrated on the effects on wages and income for native workers. Evidence on the impact of immigration on the U.S. economy is mixed. Theory suggests that an increase in the labor supply will increase total employment, decrease wages, and increase unemployment. Empirical evidence shows lower wages for certain subgroups, including high school dropouts (Borjas 2003, 2006) and workers in the below the 20th percentile (Dustmann et al. 2013). While other show no impact (Card 1990, Lalonde and Topel 1991). Studies on the economic effects of local immigration policies, such as this paper, are scarce. All of the existing studies focus only on punitive institutions (to my knowledge). Bohn et al. (2017), examine the effect of 287(g) policy on employment and wages, and found no effect on all industries combined. 287(g) is an ICE immigration policy which turns local police into immigration agents, and it is included in this study.

This paper also contributes to the discussion around the mechanisms through which immigration could increase productivity. The general equilibrium narratives suggest that as immigrants increase diversity and consumption, they supply work that natives are less willing to supply and provide a renovated entrepreneurial spirit. This view suggests that immigration to the United States should be associated with economic development due to productivity growth (Peri 2012, Model 2008). Further, immigration impacts productivity per worker because migrant skills often complement the existing populations. Immigration increases the percentage of working-age people in a country because migrants tend to fall within this age bracket and increase the employment to working-age population ratio (Jaumotte et al. 2016). The immigrant advantage is also explained by the circumstances of migration because not all people migrate; instead, only individuals who self-select themselves due to their exceptional internal drive for success, resilience, and resourcefulness (Model 2008, Borjas 1987, Bencivenga et al. 1997).

When studies look at productivity growth given local immigration policies, Ifft et al. (2017) found that after the 287(g) implementation, farms experienced statistically significant increases in labor and fuel expenses, while adjacent counties experienced lower costs. Hence, the 287(g) policy is driving a decline in farm profitability in implemented counties, while adjacent counties benefit. Likewise, Pham et al. (2010) found that local anti-immigration laws reduce employment from 1 to 2 percent and a payroll drop between 0.8 to 1.9 percent. The findings of the current paper are consistent with these stories.

One explanation for the small, measured effects of immigration is the small number of immigrants relative to the entire population. According to the U.S. Census Bureau, the net foreign-born migration into the U.S. averaged 790,000 people per year for the last ten years for both authorized and unauthorized immigrants. 2019 added only 595,000 people, and the rate has been declining since 2016. This number represents only a 0.15 percent increase in the total U.S. population per year, and only a portion of that becomes part of the U.S. labor market. The number of foreign-born individuals entering the U.S. labor market each year introduces the question of whether the addition of these individuals indeed constitutes a shock to the labor market. This question notwithstanding, it is worth noting that immigrants are not distributed uniformly across the U.S. landscape; some areas have a much higher concentration of immigrants, as is the case in sanctuary counties, shown in Table 1 in the appendix. Immigrants' location choice can be driven by border enforcement (Bohn and Pugatch 2015), local policies (Watson 2013), or economic opportunities (Cadena 2013). The data used for my analysis shows no statistically significant evidence of an increase in the foreign-born population after counties adopt sanctuary policies and finds a 4 percent decline in the foreign-born population when countries adopt policies to criminalize undocumented immigrants. Similarly, Watson (2013) finds that the 287(g) ICE policy nearly doubles the propensity for immigrants to relocate within the United States; however, the most significant effects are observed among non-citizens with college or higher education.

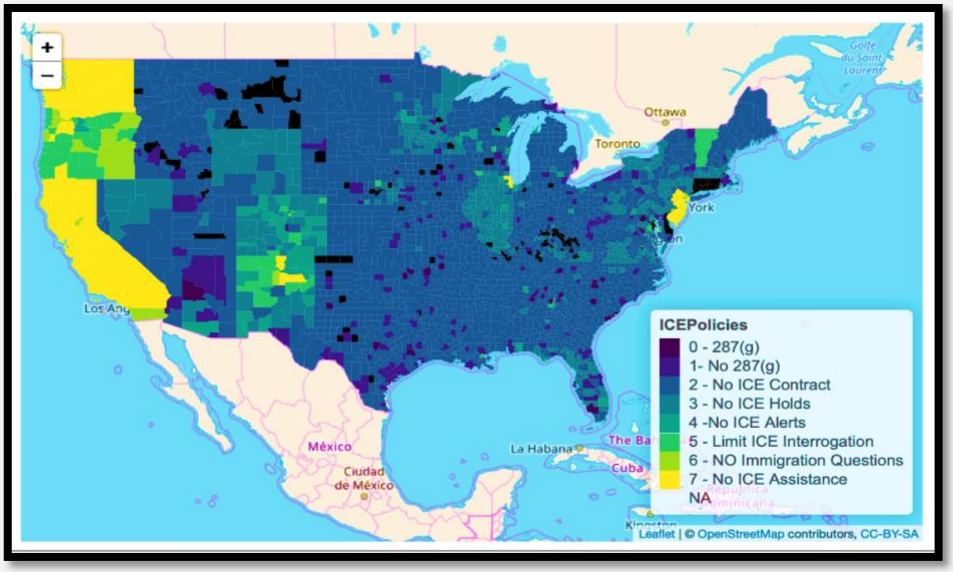
This paper adds to the current literature by examining both inclusive and exclusive local immigration policy, and no existing study uses a data set comparable in scope. The comprehensive data set in the present study accounts for 85.1% of the U.S. population by the end of our study period.

2. Data and Summary Statistics

This study compiles data on sanctuary policies from 2006 to 2018 from the Immigration and Customs Enforcement Agency (ICE) and the Immigrant Legal Resource Center (ILRC). The data integration helps characterize counties as sanctuary counties, neutral counties, or counties cooperating with ICE to identify and detain undocumented immigrants. Our sample of 797 counties consists of all U.S. counties with a population of 65,000 or more, accounting for 85.1% of the U.S. population by the end of our study period.

For clarity, "sanctuary city" is the commonly used term, but there can be either sanctuary cities or counties in terms of jurisdictions. The term "sanctuary counties" will be used in this paper to include both sanctuary cities and counties. While some cities designate themselves as sanctuary cities, the term "sanctuary city" is, in many cases, more symbolic than actual. Stated differently, "sanctuary city" is an umbrella term for locations with an expressed pro-immigrant stance. However, sanctuary cities differ in the extent to which the city's sanctuary status reflects the city's resource allocation and formal policies regarding collaboration with ICE. Consequently, our sanctuary city definition is based on the ILRC classification of seven policies.

Figure 1 **ICE Policies**



The ILRC policy classification in 2019

The ILRC has been tracking counties' policy data on immigration since 2013 and created an index based on the extent of local, county-level assistance to immigration enforcement across the country, shown in Figure 1. The ILRC defines sanctuary cities by county jails' policies regarding assistance with deportations; these policies govern how immigrants may be profiled and funneled into the deportation pipeline (ILRC report) (Avila et al. 2018). Seven central policies characterize county-level cooperation with immigration enforcement along an eight-point spectrum from zero to seven. The assignment of a "zero" on this spectrum indicates that county-level authorities go out of their way to spend local resources on immigration enforcement. Conversely, a "seven" on the spectrum denotes the counties with the most comprehensive immigrants' protection. Since not all are immigrant-friendly policies, the index regards the non-adoption of a policy, as a policy itself, as in the case of counties' non-adoption of 287(g) contracts and declination of a No ICE Detention policy. The descriptions of the seven policies are as follows:

Table 1 Regularity of immigration county policy throughout our study period

7 Policies	Description	Out of 10166 Observations & 797 Counties		
		Observations	Counties	Percentage
No 287(g)	The non-adoption of the 287(g) agreement with ICE. This agreement turns local police into immigration agents; hence local public safety officials become a direct route to deportation.	9687	782	95.3%
No ICE Detention	The non-adoption of detention contract. This contract between ICE and a local jail where ICE pays the jail to hold immigrants in detention during their deportation Proceedings.	8917	746	87.6%

Limiting ICE Detainers (No ICE Holds	ICE hold is a request from ICE to a local jail or law enforcement agency to hold a person for longer than what is lawful to allow ICE to come and take custody.	3207	338	32.2%
Restrictions to ICE about the release dates or other information	ICE asks local agencies to give them advance notice of when immigrants will be released from custody so that ICE can come and arrest them upon release.	698	127	6.75%
Limits on ICE access to local jails and ICE interrogation of detainees	Requires ICE to have a judicial warrant to access limited areas, and enact procedural protection for immigrants, so they can refuse to be interrogated by ICE agents.	431	101	4.13%
Prohibitions on Inquiries into immigration status	Prohibits their officers or employees from inquiring into immigration status or place of birth.	322	99	3.1%
General prohibitions on participating in immigration enforcement	Prohibits the use of local resources in assisting with immigration enforcement, such as joint task forces with ICE.	248	95	2.38%

Since the data consists of 797 counties and 13 years, we have a total of 10166 observations. The observations column represents the number of observations that each policy has. The counties column represents the number of counties that ever ended up with that policy throughout our study period.

Table 1 gives the name of the seven policies, their description, the number of observations (a data point at a specific county and a specific year) that have adopted that policy, the numbers of counties that adopted the related policies at any point in the thirteen years under study, and the percentage of times that the policy appeared in our sample size. According to our sanctuary county definition and by using this sample, 134 counties ended up with a sanctuary city designation throughout our study period, 132 counties were counties that ultimately endorsed explicit contracts to collaborate with ICE, and 531 counties where always assigned as neutral counties (NC) during the same period. When a county attains at least four of these policies in a given year, I assign it a 1 for sanctuary status. Notably, the seven policies that make up the ILRC system did not emerge simultaneously. While ICE detention contracts and the 287(g) policies began in 2006, many of the sanctuary-relevant policies that make up the ILRC spectrum were introduced to different counties before or throughout our sample period. Nevertheless, there was an inflection in the data in 2014 (Figure 1), as many counties adopted those policies that year, and the number of sanctuary counties more than doubled.

Given that the ILRC has been tracking sanctuary policy information since 2013, and our data started in 2006, I used ICE Declined Detainer Reports (DDR) to supplement ILRC data for the seven years that preceded ILRC's data collection beginning in 2013. DDR reports a list of jurisdictions that enacted policies restricting cooperation with ICE, including the type of restrictions and the years and months when counties enacted the policies. Hence, ICE information was crucial to ascertain changes in policy adoption from 2006 to 2013. The ICE-authored DDR reports continue from this span through 2018, and this data overlaps with comparable ILRC data from the same timeframe. In cases where counties appeared in documentation by both organizations, the ILRC's characterization coincided with ICE. Such corroboration was possible in most cases; for a small number of counties, data were available from only one source. In short, I synthesized information from both sources to construct the information detailed in Figures 2 and 3.

Fig. 2 Sanctuary Counties

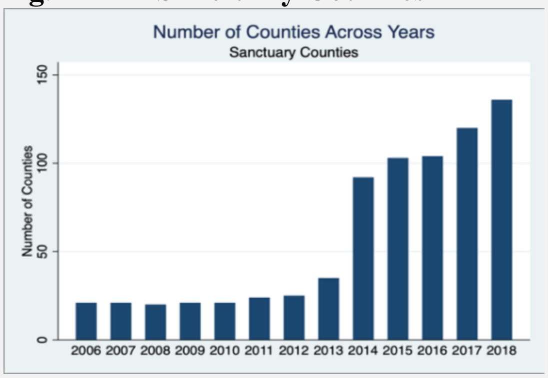
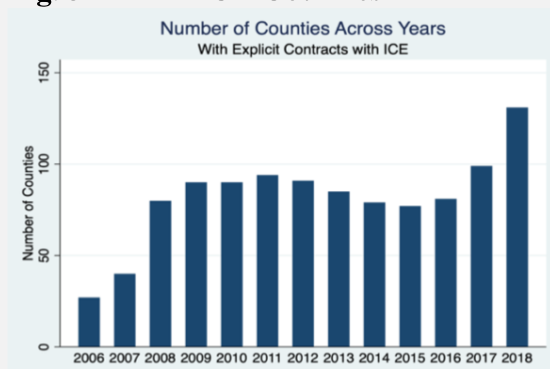


Fig. 3 ICE Counties

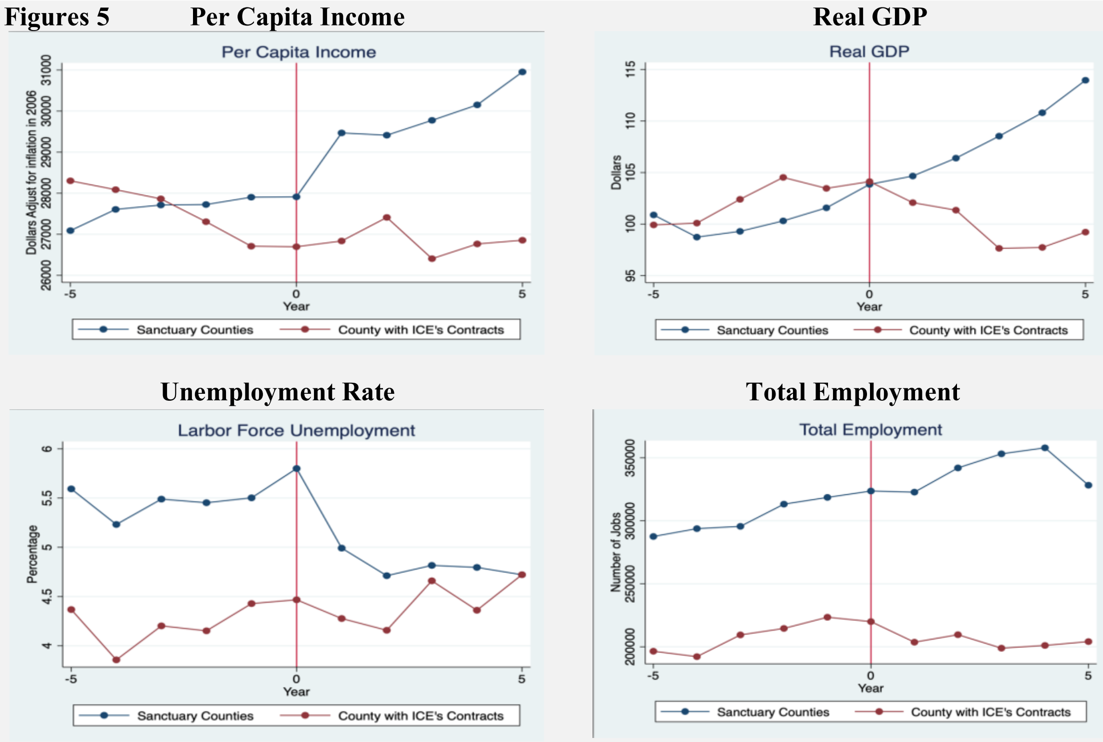


Ultimately, the study uses U.S. Census data (BEA, SE), combined with this newly digitized information on county-level immigration policy, to test whether development outcomes vary according to immigration policies. To summarize the data, Table 1.1-A in the appendix explores the differences in demographics that do not change significantly over time and shows the difference in economic indicators. These comparisons between SC, ICE, and NC, use the mean before and after 2013. The mean population among sanctuary counties suggests that such counties are mostly in metropolitan areas. Sanctuary counties show a much higher population density and a lower ratio of rural counties than ICE and neutral counties (NC) counties, but for all designations, rural counties are predominant with around 70 to 80 percent of all observations.

Additionally, sanctuary counties have a more diverse community with a higher rate of Latino-origin and foreign-born residents. However, all these indicators are also higher in ICE counties compared to NC. Some features of ICE counties may be attractive to immigrants (despite the ICE status of these counties). More likely, the higher presence of immigrants in SC and ICE counties motivate ICE initiatives to implement collaboration agreements in the first place. Similarly, ICE justifies its presence by the higher presence of immigrants in a county from a cost-benefit analysis perspective, which explains the absence of county-level policies concerning immigration enforcement in NC counties. Interestingly, ICE counties are the only designation with an observable drop in the mean-level population of the foreign born.

To visualize the difference between counties, I aligned the change in policies at a fixed period for all counties when a county became SC or ICE, as shown in Figure 5, describing the change in economic indicators over immigration policies' impact at the beginning of the fixed year zero. Sanctuary counties perform better than ICE counties starting at year zero according to the per-capita income and the unemployment rate. However, they performed better across times according to the real GDP and the total employment.

Figures 5



All event graphs show 5 years before and after the adoption of the immigration policy for SC and ICE counties.

In Figure 5-A in the Appendix, data show similar results according to the unemployment rate for women, white and Latino population, and similar results according to the average family income. The initial visualization of the data concurs with the assumption that inclusive institutions that invest in people and allow people to mobilize their talents and skills harness their potential human capital into the social system.

3. Empirical model

The basic strategy for this study is a panel difference in differences approach with fixed effects. The outcomes of interest are income, real GDP, the unemployment rate, median wages, and total employment. The specification equation has three approaches to reduce the problems of selection. First, I estimate the impact of policies comparing sanctuary and ICE counties versus neutral counties. Second, using only those counties that ever end up with a sanctuary city designation and only the variation in sanctuary designation timing, I addressed the criticism that sanctuary counties might be fundamentally different from non-sanctuary counties. In the third subsample, I repeat the last procedure with only counties that ever collaborate with ICE. I test for differential pre-trends between ever-sanctuary and never-sanctuary counties, as well as between early and late implementers, and economic attributes. I repeat these processes with each economic indicator and separate rural and urban areas. Finally, I estimate the impact of policies on median family income across education levels and economic quintiles, and the unemployment rates by gender and ethnic categories. The first estimation that includes the full sample is:

$$EI_{it} = \alpha + \beta_1 SC_{it} + \beta_2 ICE_{it} + \gamma_i + \sum_{i=1}^{8} \varphi_i Reg_i * Y_t + Y_t + \theta' X_{it} + \epsilon_{it} \quad (1)$$

For only sanctuary counties, we use:

$$EI_{it} = \alpha + \beta_1 SC_{it} + \gamma_i + \sum_{i=1}^{8} \varphi_i Reg_i * Y_t + Y_t + \theta' X_{it} + \epsilon_{it} \quad for\ all\ i\ \in SC \quad (2)$$

And for only ICE counties the estimation is:

$$EI_{it} = \alpha + \beta_2 ICE_{it} + \gamma_i + \sum_{i=1}^{8} \varphi_i Reg_i * Y_t + Y_t + \theta' X_{it} + \epsilon_{it} \quad for\ all\ i\ \in ICE \quad (3)$$

EI_{it} is the dependent variable that stands for economic indicator (EI) at county i and in period t. The following two treatment groups, SC and ICE, are dummy variables for sanctuary cities and counties with explicit contracts with ICE, where 1 is a treatment county, and 0 is a control county or neutral county (NC). These treatment groups will also be time-variant, as counties become SC or ICE. The omitted group will be neutral counties in equation 1. The county fixed effects control for the time-invariant effect of county-specific characteristics is γ_i. The equations include eight economic region time trends ($Reg*Y_t$), and a continuous year time trend, and time-varying controls X_{it} . The latter includes political variables that would influence sanctuary counties' assignments, such as diversity, population density, rural or not, percentage of the foreign population, and an education index.

The study also explores specific labor markets according to people's educational attainment, gender, ethnicities, and economic quintiles. As a robustness check, we pre-process the data using nearest neighbor matching based on counties' economic attributes, demographics, regions, whether the county is rural or urban, education index, and the percentage of minority populations. Moreover, for an additional robustness check, the study analyzes the results using rural or urban counties, and a geographical regression discontinuity using only counties that share a border. All regressions use robust standard error clustered at the state level. Finally, the study applies a randomization inference test for the main regressions with each dependent variable. Randomization inference takes the set of study subject as fixed and regards only the treatment assignment as a random draw. Hence, it is based on resampling the variable of interest. Then, randomization inference tests the estimate β_1 obtained by comparing the means of the coefficient estimates from the regressions, by randomly changing the treatment status SC or ICE a thousand times.

4. Parallel Pre-Trend Assumption

Each of these models relies on different versions of the parallel trend assumption. Equation 4 requires that sanctuary, ICE, and neutral counties would have maintained parallel trends in the absence of policies change, while equations 5 and 6 use late policy-adopters as the counterfactual for early ones. This section presents tests on the pre-policy implementation to see if they suggest that this assumption holds. The estimation equations are:

$$EI_{it} = \alpha + \sum_{t=1}^{8} \delta_t Y_t * Ever_{SC_i} + \sum_{t=1}^{8} \theta_t Y_t * Ever_{CEC_i} + X_{it}\Gamma + \gamma_i + \epsilon_{it} \quad (4)$$

For only sanctuary counties,

$$EI_{it} = \alpha + \sum_{t=1}^{8} \delta_t Y_t * Ever_{SC_i} + X_{it}\Gamma + \gamma_i + \epsilon_{it} \quad (5)$$

For only ICE counties,

$$EI_{it} = \alpha + \sum_{t=1}^{8} \theta_t Y_t * Ever_{CEC_i} + X_{it}\Gamma + \gamma_i + \epsilon_{it} \quad (6)$$

This approach allows us to see the differences in the change in economic indicators between the affected and counterfactual groups across time. As above, the dependent variable is $\boldsymbol{EI_{it}}$, and the treatment groups are ever sanctuary or ever ICE county. The interaction of the treatment groups with $\boldsymbol{Y_t}$ becomes the test for the difference in trends prior to the change in policies, which are the year-specific dummy variables from 2006 to 2013 for equation 4. When using late policy adopters as the counterfactual for early ones for equations 5 and 6, the equation uses every year, and the first year becomes the base.

Table 2 Pre-Trend Test using Per Capita Income

	Ordinary Least Squares		Fixed Effects	
Sanctuary County in 2007	0.021**	(0.01)	-0.0019	(0.01)
Sanctuary County in 2008	0.032**	(0.01)	0.0089	(0.01)
Sanctuary County in 2009	0.0075	(0.02)	-0.017	(0.01)
Sanctuary County in 2010	0.0030	(0.02)	-0.011	(0.01)
Sanctuary County in 2011	-0.000043	(0.02)	-0.021	(0.02)
Sanctuary County in 2012	0.012	(0.03)	-0.012	(0.03)
Sanctuary County in 2013	-0.0054	(0.03)	-0.017	(0.02)
ICE County in 2007	0.019	(0.01)	0.0093	(0.01)
ICE County in 2008	0.033	(0.02)	0.035***	(0.01)
ICE County in 2009	0.028	(0.03)	0.0028	(0.02)
ICE County in 2010	0.023	(0.03)	-0.011	(0.02)
ICE County in 2011	0.036	(0.03)	-0.00021	(0.01)
ICE County in 2012	0.034	(0.03)	0.018	(0.02)
ICE County in 2013	0.029	(0.02)	-0.0062	(0.01)
Observations	9351		9351	
Adjusted R-squared	0.437		0.240	
Pre-trend test for sanctuary counties, using early adopter as counterfactual				
Sanctuary County in 2007	-0.048	(0.03)	0.00058	(0.03)
Sanctuary County in 2008	-0.020	(0.05)	-0.00064	(0.03)
Sanctuary County in 2009	0.016	(0.06)	0.0023	(0.04)
Sanctuary County in 2010	0.075	(0.06)	0.024	(0.03)
Sanctuary County in 2011	0.089	(0.05)	0.025	(0.04)
Sanctuary County in 2012	0.036	(0.07)	-0.00084	(0.04)
Sanctuary County in 2013	0.024	(0.07)	-0.036	(0.03)
Observations	1846		1846	
Adjusted R-squared	0.525		0.338	
Pre-trend test for ICE counties, using late policy adopter as counterfactual				
ICE County in 2007	0.011	(0.03)	-0.011	(0.02)
ICE County in 2008	-0.0064	(0.05)	-0.021	(0.02)
ICE County in 2009	-0.0081	(0.06)	-0.0058	(0.02)
ICE County in 2010	0.0022	(0.04)	0.012	(0.03)
ICE County in 2011	-0.030	(0.04)	-0.016	(0.02)
ICE County in 2012	-0.021	(0.04)	-0.020	(0.02)
ICE County in 2012	-0.0062	(0.04)	0.017	(0.02)
Observations	1779		1779	
Adjusted R-squared	0.465		0.279	

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01 All regressions contain robust standard errors clustered by county ID, time trends and time variant covariates.

Using per capita income, Table 2 suggests that all ordinary least squares, fixed effects, and time-varying controls do support a parallel pre-trend assumption: most years show no statistically significant change in per capita income between the treatment and the control groups. These results are also consistent when using late policy adopters as counterfactuals for sanctuary and ICE counties. I also estimate the same test for the labor unemployment rate, real GDP, median wages, and the total employment per county, shown in Tables 2.1, 2.2, and 2.3 in the appendix. These results are also consistent except for the real GDP when comparing sanctuary counties to neutral counties, and total employment only for late policy adopters in sanctuary (using the OSL regression) and ICE counties (using the fixed effects regression). All of them show a statistically significant change in at least three years out of seven.

This study was written with a comparison paper that examines the choice of pro- or anti-immigrant policies by county. This paper's goal is to find out whether the economic circumstances predict county's policy choice. The policies are the same, the collaboration with Immigration and Customs Enforcement (ICE) and the sanctuary policies that provide legal protections (Natanson 2021). However, by placing the independent variable as the dependent one, if the economic factors influence immigration policy preferences, we will inevitably have a problem of reverse causality. However, the comparison analysis shows that, in a fixed effects setting, economic factors do not determine adoption of local immigration policies.

5. Results

All regressions contain eight regional time trends, a time dummy, and a matrix of control for population density, foreign population, elections results per county, voting turn out, rural or urban, and an education index. They include robust standard errors and are clustered by county. The first column shows the ordinary least square regression, the second column shows the fixed effects model, and the third column combines fixed effects and the nearest neighbor matching. The nearest neighbor matching is based on counties' economic attributes, an education index, family income, and region. The fixed effect model in the second column is the primary regression since it contains the most variation. Table 3 presents results using the log of per capita income as the dependent variable. The omitted group is the neutral counties. Using equation 1, the point estimate for sanctuary counties is statistically significant in most models with magnitudes ranging from 3.1 to 7.2 percent increase in per capita income in sanctuary counties. There are no significant effects of ICE counties in any of the models.

Table 3	Natural log of Per Capita Income			
Model	(1) Ordinary Least Squares,	(2) Fixed Effects	(3) Fixed Effects & Matching	
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1				
Sanctuary County	0.072***	0.031***	0.043***	
	(0.02)	(0.01)	(0.01)	
P- value from Randomization Inference	0.014	0.000	0.008	
ICE County	0.00044	-0.0013		-0.0015
	(0.02)	(0.01)		(0.01)
P- value from Randomization Inference	0.51	0.324		0.569
Observations	10147	10147	3705	3095
Adjusted R-squared	0.444	0.234	0.347	0.283
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	0.0045	0.017*	0.013	
	(0.02)	(0.01)	(0.02)	
Observations	1846	1846	1326	
Adjusted R-squared	0.762	0.355	0.409	

Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3			
ICE County	-0.0051	-0.0061	-0.0086
	(0.01)	(0.01)	(0.01)
Observations	1778	1778	1751
Adjusted R-squared	0.654	0.298	0.329

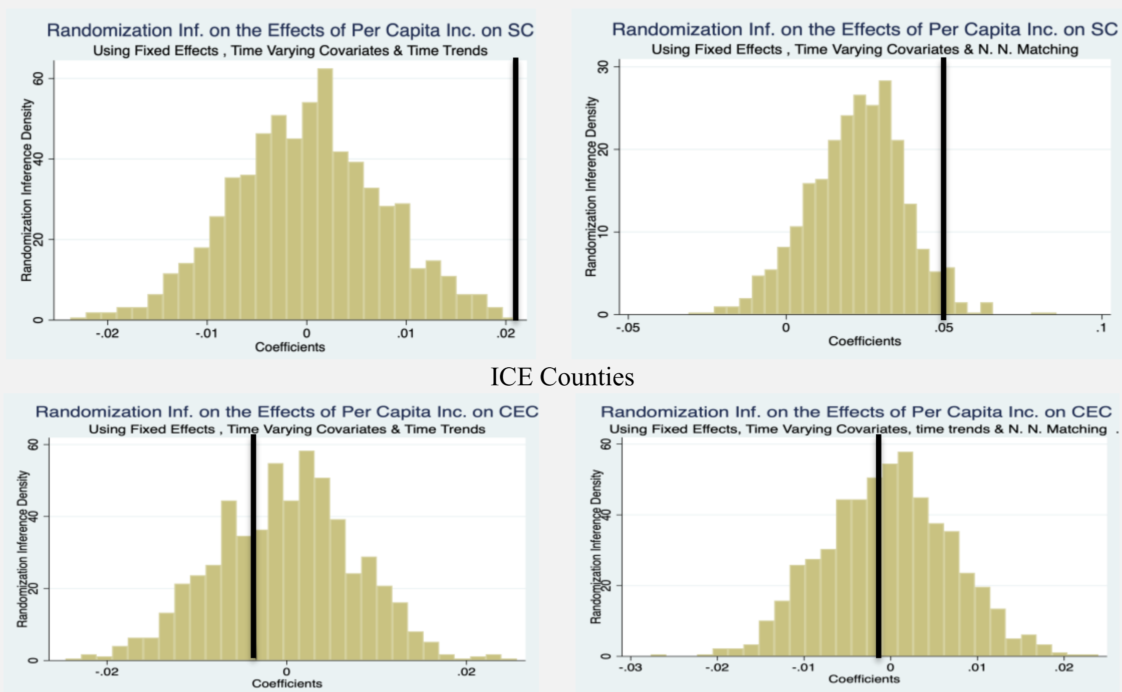
* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. All regressions contain robust standard errors clustered by county, time trends, and time variant covariant. Nearest – neighbor matching is based on counties' economic attributes, education index, family income, and region.

All statistically significant results are also significant after testing for randomization inference (RI) regarding the treatment assignment as random. Using RI, I regressed all the models, randomly assigning the treatment a thousand times. The results for RI are the P-values below the standard of errors for each regression using Equation 1. The significance is based on the statistical difference between the mean of all thousand coefficients using RI and the main results. The bell distributions of the randomization inference for the fixed effects models and the matching models are shown in Figure 6. The locations of the main results from Table 3 are also shown, and it is visible to see that the sanctuary counties' significant results are located further away from the median of the bell. The results are the same for all other outcomes.

Figure 6 Randomization Inference for Per Capital Income

Sanctuary Counties

Fixed Effect6 Fixed Effects & Matching



In the second section, using only those counties that ever end up with a sanctuary city designation (equation 2), and therefore using only the variation in sanctuary designation timing, I addressed the possible criticism that sanctuary counties might be fundamentally different from non-sanctuary counties. Here, results are similar but with less variation in magnitude, with a 1.7 percent increase in per capita income in Sanctuary counties using our primary regression. With Equation 3, ICE counties again show no significant effects in any of the models. The contrast in the results between the sanctuary and ICE counties is interesting. It suggests that while providing protections to immigrants increases economic activity, punitive measures do not improve economic outcomes for natives.

In Table 4, I repeat all three equations using only the fixed effect model, but now I separate urban and rural counties. In this way, I address the likelihood that urban counties may be different from rural counties. Starting by using the urban and rural neutral counties as control groups, urban sanctuary counties show an increase in per capita income of 2.5 percent and a 3.2 increase in rural counties, while there is no effect in ICE counties for rural or urban. In addition, using late policy adopters as controls, I find an increase in per capita income of almost 2 percent in rural sanctuary counties.

Table 4	Natural log of Per Capita Income			
Mode 2: Fixed Effects	Equation 1		Equation 2	Equation 3
	Urban	Rural	Urban using only Sanctuary Counties	Rural using only ICE Counties
Sanctuary County	0.025**	0.032***	0.0057	0.019*
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1292	7811	472	1374
Adjusted R-squared	0.415	0.225	0.513	0.361
ICE County	0.0015	-0.0030	0.0023	-0.0044
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1286	8118	301	1478
Adjusted R-squared	0.370	0.226	0.445	0.302

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Table 3.1 in the appendix shows the impact of immigration policies on the labor force unemployment rate. All models are statistically significant, with magnitudes ranging from 12 to 17 percent declines in the unemployment rate in sanctuary counties but no significant effect on ICE counties. The same result appears when dividing the data amount late policy adopters and rural counties in Table 4.1, with a decrease in unemployment in rural sanctuary counties by around 12 percent. However, the data shows an increase in unemployment in urban ICE counties ranging between 6.4 to 8.1 percent. Table 3.2 shows the impacts on real GDP. The results in most models are statistically significant positive for sanctuary counties with magnitudes ranging from 2.5 to 4.1 percent increase. This time for ICE counties, the study detects a small but significant decline in GDP using only the OLS model. When using late policy adopters as the control groups (with equations 2 and 3), I find consistent results, and that is also the case when separating the data between rural and urban counties in Table 4.2.

Table 3.3 shows the total employment growth after adopting sanctuary policies between 2.3 to 4 percent, while the adoption of ICE policies decreases the total employment per county. Results are the same after I restrict the data to later policy adopters, and rural and urban counties as shown in Table 4.3. Finally, with similar results, Table 3.4 shows an increase in median wages after adopting sanctuary policies and after restricting the data to rural, urban, and late policy adopters between 1.7 to 2.6 percent. There are not policy effects on ICE counties.

Thus, using per capita income, unemployment rate, real GDP, total employment, and median wages, the study finds strong evidence that protecting people increases efficiency in the economy. Hence, the results show evidence supporting the hypothesis that immigrants' human capital benefits ought to be more prominent in regions where institutions are inclusive, and conversely, punitive measures are detrimental to economic outcomes.

How do immigrants respond to these policies? In Table 3.5, I test for the effects of local migration policies on immigrants' population or mobility due to policy changes, and using Equation 1, I find no effect for sanctuary or ICE policies. These results contradict the basic intuition that the protection of immigrants would increase the immigrant population in sanctuary counties. No change in the foreign-born population enforces the idea that local immigration policies only harm immigrant rights because immigrants only respond to the availability of jobs. However, when comparing counties with similar characteristics using only the variation in ICE county designation timing, I find a decline in the foreign-born population by 4 percent. In this case, ICE policy institutions do produce their intended effect by creating some incentive for immigrants to leave ICE counties.

Lastly, I examine heterogeneity in impact across different populations by educational attainment, the economic quintiles, gender, and ethnic groups. Using the fixed effects model, Table 5 shows the effect on median earnings among educational attainment. Results are positive and significant at all educational attainment in sanctuary counties except at the college level. However, more interesting is that contrary to the literature, I obtain favorable outcomes for workers without a high school diploma. Similarly, punitive measurements in ICE counties show no significant effects.

Table 5 **Natural log of Median Earning by Educational Attainment**

	No High School	High School	College	Bachelor	Graduate School
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1					
Sanctuary County	0.038*	0.027**	0.0097	0.026***	0.019*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
ICE County	0.015	0.0056	-0.0048	-0.0053	-0.0038
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	10147	10147	10147	10147	10147
Adjusted R-squared	0.049	0.085	0.082	0.111	0.084
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	0.023	0.021**	0.0038	0.023**	0.025**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1846	1846	1846	1846	1846
Adjusted R-squared	0.116	0.119	0.102	0.141	0.156
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	0.012	0.0028	-0.0048	-0.0097	-0.0042
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1779	1779	1779	1779	1779
Adjusted R-squared	0.058	0.106	0.097	0.156	0.123

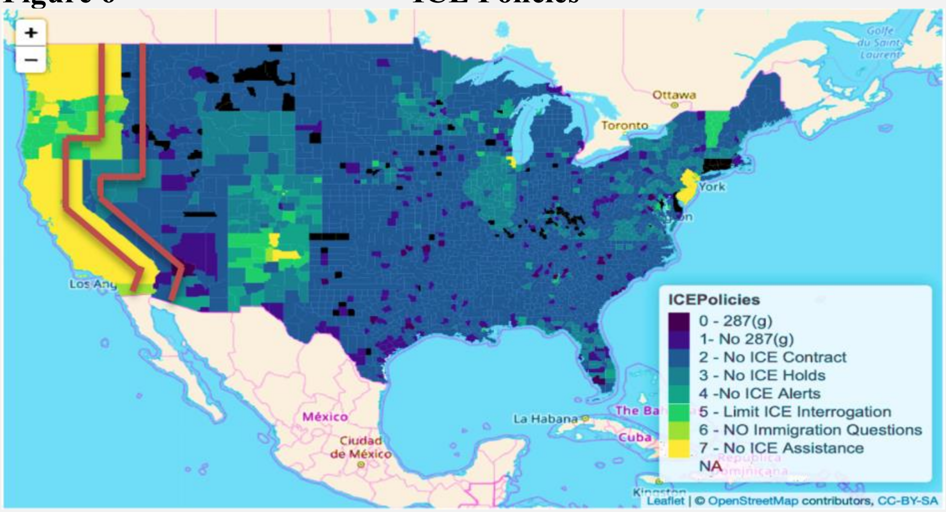
* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Then, by dividing the population among quintiles using average household income in Table 5.1, results show positive results on all quintiles in sanctuary counties ranging from 2 to 3.8 percent increase, but no effect on ICE counties. Finally, in Table 5.2, by dividing the labor force unemployment by gender and race, I find statistically significant positive results for women, men, whites, and Latinos in sanctuary counties. However, this time results show a positive effect on ICE counties only on the African American population.

6. Regression Discontinuity

The final robustness check applies a geographical regression discontinuity analysis. Here we select only counties that share a border with other counties with distinct policies. The map shows a clear contrast in immigration policies between bordering counties alone California, Oregon, and Washington that share borders with Arizona, Nevada, and Idaho. Here, the former offers better protections to immigrants, represented by the lighter colors between the red lines in Picture 2.

Figure 6 **ICE Policies**



The ILRC policy classification in 2019

After restricting the data to only those counties along the border, results are still consistent and robust. Table 6 gives the results using the natural log of per capita income, labor force unemployment, GDP, total employment, and the median wages as the dependent variables. Here, I only use the OLS and fixed effects model due to the decrease in observations to 169, using equation 1. Nonetheless, this strategy confirms initial results with favorable outcomes for sanctuary counties across all dependent variables, and adverse effects for ICE counties. In the regression discontinuity model the per capita income increases by 5.9 percent in sanctuary counties. In addition, the unemployment decreases 22 percent (only using OLS), the GDP increases by 6 percent, the total employment increase by 3.5 percent, and the median wage increases by 7 percent. In contrast, ICE counties obtain an 8.5 percent decline in GDP, a 7.2 percent decrease in total employment, a 3 percent increase in wages, and no significant results for per capita income, and unemployment.

Table 6	Regression Discontinuity Model	
	Ordinary Least Squares	Fixed Effects

Natural log of Per Capita Income				
Sanctuary County	0.19**	(0.08)	0.059**	(0.01)
ICE County	0.015	(0.06)	0.049	(0.03)
Observations	169		169	
Adjusted R-squared	0.694		0.426	
Natural Log Labor Force Unemployment				
Sanctuary County	-0.22***	(0.02)	-0.14	(0.19)
ICE County	0.035	(0.03)	0.046	(0.04)
Observations	169		169	
Adjusted R-squared	0.499		0.292	
Natural log of Real GDP				
Sanctuary County	0.065**	(0.02)	0.064*	(0.03)
ICE County	-0.089***	(0.00)	-0.085***	(0.01)
Observations	169		169	
Adjusted R-squared	0.528		0.553	
Natural log of Total Employment				
Sanctuary County	0.35	(0.29)	0.035*	(0.02)
ICE County	-0.18	(0.18)	-0.072***	(0.01)
Observations	169		169	
Adjusted R-squared	0.742		0.561	
Natural log Median Wages				
Sanctuary County	0.17*	(0.06)	0.073***	(0.01)
ICE County	0.009	(0.02)	0.032**	(0.01)
Observations	169		169	
Adjusted R-squared	0.553		0.415	

* p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, all regressions contain robust standard errors clustered by county ID, time trends & time varying covariates

7. Theoretical Model

The previous section shows positive effects of inclusive policies on economic outcomes with no evident increase in population. How do we make sense of this? One possible framing of these results extends the Solow human-capital augmented growth model (Mankiw, Romer, and Weil 1992) to include institutional constraints limit on people's realization of their potential human capital (North 1990). The usual human-capital augmented growth model emphasizes that human capital stock increases through physical investments in human capital. These investments are measurable and accessible to analyze since they are rival to consumption and excludable. The analysis here integrates Hall and Jones (1999) to accommodate institutional differences. Their framework claims that output per worker is driven by differences in institution and government policies, which they call social infrastructure. In their frame, higher social infrastructure improves inputs productivity and increases output per worker, in that order. Hence, I extent this frame to include immigration policies.

The notation is standard: Y is output, K is capital, H is human capital, L is labor, and the A term reflects knowledge and technology. Then the production function is

$$1)\qquad Y_i(t) = F(K, H, AL) = K^{\propto} H^{\beta} (AL)^{1-\alpha-\beta} \qquad (0 < \alpha < 1,\ 0 < \beta < 1)$$

The growth rates of depreciation (δ), population (n), and productivity *(g)* are assumed to be constant across countries (in our case, counties). After deriving for all market factors, the evolution of capital and human capital in the economy, in equations 2a and 2b, growth by physical investment S_k and S_h. The evolution of labor (L) is assumed to grow exogenously and constantly at rate n, in equation 3a. In equation 3b, the total factor productivity should be a function of human capital and assumed to grow by knowledge (g). The standard equations of motion are:

$$2)\quad a)\ \dot{h}(t) = S_h y(t) - (n+g+\delta)h(t) \qquad \&\quad b)\ \dot{k}(t) = S_k y(t) - (n+g+\delta)h(t)$$

$$3)\quad a)\ L(t) = L(0)e^{nt} \qquad\qquad \&\quad b)\ A(t) = A(0)e^{gt}$$

Following Eicher, Garcia, and Teksoz (EGT 2006), I allow the elasticity of output with respect to input to depend on the quality of institutions *(I)* at every location *(i)*. Total factor productivity A depends on institutions such that $A_i = Ae^{pI_i}$. Hence, local immigration policies can be represented by the combination of the MRW and EGT models which allow the total factor of productivity A to depend on not just the advancement of knowledge (g) but also institutions according to $A_i = A(e^{gt} + e^{pI_i})$. However, the advancement of knowledge is non-excludable and non-rival across counties in our case; therefore, we can simplified the model by excluding (g) and describe the total factor of productivity as $A_i = A(e^{pI_i})$. Then, under the assumptions that $\alpha + \beta < 1$, the model converges to a steady state. By substituting h and k at the steady state into the production function and taking logs, equation 4, for income per capita includes the total factor productivity (*A*) that depends on the quality of institutions, such that.

$$4)\ ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + pI + \frac{\beta}{1-\alpha-\beta} ln(s_h) + \frac{\alpha}{1-\alpha-\beta} ln(s_k) - \frac{\alpha+\beta}{1-\alpha-\beta}\ln(n+g+\delta)$$

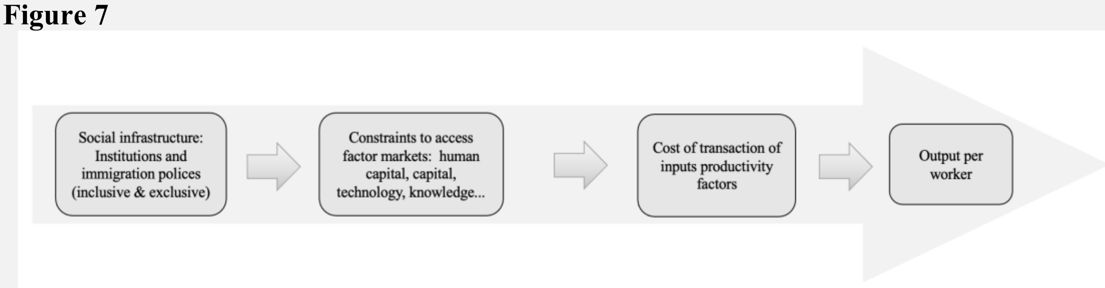
Thus, social infrastructure (institutions) affects input productivity, which affects output per worker. In addition, human capital is therefore constrained and shaped by institutions' excludability function, represented by pI, as well as by investment in human capital $ln(s_h)$.

However, why is that the case? Institutions (or policies) are the rules of the game, more specifically defined as "the humanly devised constraints that structure political, economic and social interactions" (North 1991). Hence, institutions constrain all access to factor markets such as capital, technology, knowledge, or human capital.

The case of undocumented workers and their families is fragile because they contend with a level of risk that is hard to overstate. In everydy activities, undocumented immigrants risk losing all possessions, their children, their families, their livelihoods, or the household breadwinners. Vulnerability to deportation may motivate undocumented individuals to maintain vigilance while grocery shopping, taking their kids to school, driving to work, or going to the hospital. There is considerable evidence that high risk and uncertainty brings chronic stress, and the high levels of cortisol produced in the body among immigrants due to stress reduce economic productivity and impair human capital (Squires et al. 2012, Mewes et al. 2017, Martinez et al. 2018, Yim et al. 2019, Garcini et al. 2019, Keinan 1987; Keinan et al. 1987, Arnsten 1998). In sum, depression, stress, and uncertainty about the future restrict people's optimal contribution to society and inhibit their potential human capital.

With restrictive local immigration policies, immigrant families experienced more economic insecurity, emotional stress, discrimination, racial profiling, detentions, and deportations (Androff et al., 2011; Ayon, 2014, 2015). Here, immigration policies play an essential role in ameliorating or exacerbating the consequences of risk in immigrants' human capital (Woodland et al., 2006). Hence, we can think of total factor productivity (A_i) in the Solow Model as the depression, stress, and uncertainty regulator for immigrants because they are (or not) allowed to live their life, work, and send their children to school without hesitations. Similarly, emerging work suggests that institutions play an essential role in constraining the effects of immigration, as Kemeny et al. (2017) present evidence supporting the hypothesis that urban immigrant diversity's benefits should be broader in regions where institutions are inclusive.

Figure 7



Finally, institutions regulate transaction cost of the total factor productivity by increasing or decreasing uncertainty, which in principle, determines whether human capital is fully optimized as it is represented by Ae^{pI_i} in the model. To sum, as describe in Figure 7, institutions decrease uncertainty and constrain human interaction (the access to factor markets), decrease transaction cost (the inputs of productivity factors), and increase efficiency in the economy (the output per worker) (Coase 1960; Williamson 1987; North 1990; Milgrom and Roberts 1992; Hall and Jones 1999; Acemoglu and Robinson 2008, 2013; David 2017). Analogously, sanctuary cities reduce uncertainty, constraints, and risk for immigrants' interaction in their communities, decrease the cost from fear of deportation or the constant fear of criminalization, and optimize their human capital. This cost is separate in the production process that is socially and economically costly due to the loss of benefits from human capital and the subsequential decline in the productivity factors.

8. Conclusion

This study contributes to the economics of migration literature and seeks to understand the mechanism through which inclusive policies affect society. Given that sanctuary cities constitute an example of inclusive policies, characterizing sanctuary cities' economic features may have implications for inclusive institutions more generally (Sokoloff et al. 2000; Sokoloff 2003; Acemoglu & Robinson, 2013). Coase (1960) argues that uncertainty in human behavior is the reason for increased costs resulting from market transactions. Hence, the decrease in uncertainty and risk increases coordination and market exchange, improves the information flow, decreases transaction costs in society, and increases productivity. In the process, it strengthens social trust and cooperation. In many ways, that is the purpose of sanctuary cities. Fear of deportation or a constant fear of criminalization, a separate cost from the production process, is socially and economically costly for people and all businesses.

On the other hand, institutional inclusion creates the dynamic nature of the U.S. economy, as it allows for an economic expansion due to the extension of fundamental freedoms to newcomers. Inclusive policies enable new immigrants to increase consumption, supply hard work, provide a renovated entrepreneurial spirit, create more jobs, invent new industries, and revive no longer competitive sectors and would otherwise be sent abroad.

The evidence supports the hypothesis that providing protections to undocumented immigrants increases economic activity. In addition, results support the hypothesis that immigration policies or institutions play an essential role in conditioning the effect of immigration. Clearly, sanctuary policies yield economic benefits for counties that adopt them. Future work should examine why some counties choose not to do so, and look at long term effect of such choices.

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Appendix

Table 2-A starts by exploring the differences in demographics that do not change significantly over time, such as the percentage of the rural population, ethnic composition of counties, and relative percentages of citizen and foreign-born populations. Then the table shows the differences in unemployment, average income by ethnicities, median earnings by school attainment, per capita income, percentage of working poor, and the Gini Index of Inequality. These comparisons between SC, ICE, and NC, use the mean before and after 2013.

Table 1: Descriptive statistics among sanctuary counties (SC), ICE counties, and neutral counties (NC).

	Mean Before 2013			Mean After 2013		
	SC	ICE	NC	SC	ICE	NC
Variable	Mean	Mean	Mean	Mean	Mean	Mean
Observations	994	958	3549	710	718	2,790
Total Mean Population	606652.90	363969.50	245357.40	625667.70	356486.50	232287.80
% Rural Population	0.74	0.83	0.89	0.74	0.81	0.89
% White Population	73.46	80.30	81.05	72.76	80.20	80.90

% Latin Population	21.57	15.32	11.02	22.54	15.73	14.36
% Citizen by Birth	85.45	91.35	94.09	85.37	91.42	93.98
% Foreign Born	14.55	8.65	5.91	14.63	8.58	6.02
% Unemployment	5.43	4.45	4.56	4.66	4.17	4.32
% Women Unemployed	4.79	4.00	4.06	4.17	3.85	3.96
% White Unemployed	7.77	6.14	6.47	6.70	5.82	6.18
% Latino Unemp.	7.22	4.04	2.30	6.35	3.84	2.15
% Black Unemp.	6.63	7.13	6.41	5.90	6.50	5.89
$ Med. Family Income	68582.80	65977.90	63575.23	72910.59	68377.13	65288.18
$ White Ave. Income	79853.49	74651.13	70469.21	85676.80	77561.83	72562.27
$ Latino Ave. Income	58211.46	53930.03	56108.42	63659.53	56254.11	57810.13
$ Black Ave. Income	26742.61	28631.59	21766.83	27799.75	27091.27	20197.11
$ Med. Earnings	36337.13	35193.91	34292.18	37980.18	36084.53	35216.59
$ Med. Ear. No High School	20529.61	20765.23	20391.03	21767.37	21222.81	21296.95
$ Med. Ear. High Sch.	28442.09	27939.58	27861.09	29451.17	28612.71	28402.48
$ Med. Ear. Some College	34474.61	33594.31	32919.90	35294.28	33848.65	33545.93
$ Med. Ear. College	48901.69	46877.18	45294.58	50968.28	47931.52	46308.68
$ Med. Ear. Grad	64876.84	59941.41	58358.18	67352.04	61574.88	59636.48
$ Per Capita Income	28773.84	27312.25	26105.04	30656.21	28141.94	26901.12
% Working Poor	13.81	12.62	13.45	14.02	12.97	13.87
Gini Index	0.45	0.44	0.44	0.46	0.45	0.44

Table 2.1 Pre-Trend Test using Natural Log of Labor Force Unemployment

	Ordinary Least Squares		Fixed Effects	
Sanctuary County in 2007	0.034	(0.06)	0.047	(0.07)
Sanctuary County in 2008	-0.016	(0.04)	0.0044	(0.03)
Sanctuary County in 2009	-0.031	(0.05)	-0.011	(0.04)
Sanctuary County in 2010	-0.0021	(0.07)	0.0071	(0.07)
Sanctuary County in 2011	0.058	(0.09)	0.074	(0.09)
Sanctuary County in 2012	0.046	(0.12)	0.064	(0.12)
Sanctuary County in 2013	0.052	(0.10)	0.055	(0.11)
ICE County in 2007	-0.11*	(0.06)	-0.093	(0.06)
ICE County in 2008	-0.13**	(0.06)	-0.14**	(0.06)
ICE County in 2009	-0.028	(0.08)	-0.0100	(0.07)
ICE County in 2010	0.038	(0.06)	0.075	(0.06)
ICE County in 2011	-0.032	(0.05)	-0.0014	(0.05)
ICE County in 2012	-0.065	(0.07)	-0.048	(0.06)
ICE County in 2013	-0.017	(0.04)	0.016	(0.05)
Observations	9296		9296	
Adjusted R-squared	0.112		0.068	
Pre-trend test for sanctuary counties, using early adopter as counterfactual				
Sanctuary County in 2007	-0.15	(0.16)	-0.19	(0.16)
Sanctuary County in 2008	-0.058	(0.15)	-0.079	(0.14)
Sanctuary County in 2009	-0.0050	(0.14)	-0.00029	(0.13)
Sanctuary County in 2010	-0.070	(0.14)	-0.025	(0.13)
Sanctuary County in 2011	-0.082	(0.11)	-0.035	(0.11)
Sanctuary County in 2012	-0.12	(0.15)	-0.10	(0.13)
Sanctuary County in 2013	0.064	(0.15)	0.087	(0.13)
Observations	1841		1841	
Adjusted R-squared	0.165		0.099	
Pre-trend test for ICE counties, using late policy adopter as counterfactual				
ICE County in 2007	-0.037	(0.08)	-0.0024	(0.07)
ICE County in 2008	0.070	(0.11)	0.10	(0.08)
ICE County in 2009	0.028	(0.10)	0.030	(0.08)
ICE County in 2010	-0.095	(0.11)	-0.080	(0.10)
ICE County in 2011	0.016	(0.10)	0.039	(0.08)
ICE County in 2012	0.056	(0.09)	0.076	(0.07)
ICE County in 2012	-0.066	(0.08)	-0.071	(0.07)
Observations	1773		1773	
Adjusted R-squared	0.078		0.067	

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01 All regressions contain robust standard errors clustered by county ID, time trends and time variant covariates.

Table 2.2 Pre-Trend Test using Natural Log of Real GDP

	Ordinary Least Squares		Fixed Effects	
Sanctuary County in 2007	0.0012	(0.01)	-0.00011	(0.01)
Sanctuary County in 2008	-0.0083	(0.01)	-0.0099	(0.01)
Sanctuary County in 2009	-0.0022	(0.02)	-0.0021	(0.02)
Sanctuary County in 2010	-0.027	(0.02)	-0.027	(0.02)
Sanctuary County in 2011	-0.043**	(0.02)	-0.044**	(0.02)
Sanctuary County in 2012	-0.051**	(0.02)	-0.054**	(0.02)
Sanctuary County in 2013	-0.053**	(0.03)	-0.055**	(0.02)
ICE County in 2007	0.0031	(0.01)	0.00096	(0.01)
ICE County in 2008	0.0059	(0.01)	-0.00088	(0.01)
ICE County in 2009	0.016	(0.02)	0.0089	(0.02)
ICE County in 2010	0.0052	(0.01)	-0.00078	(0.01)
ICE County in 2011	-0.0022	(0.01)	-0.010	(0.01)

ICE County in 2012	-0.014	(0.01)	-0.021	(0.01)
ICE County in 2013	-0.0093	(0.01)	-0.017	(0.01)
Observations	9206		9206	
Adjusted R-squared	0.303		0.360	
Pre-trend test for sanctuary counties, using early adopter as counterfactual				
Sanctuary County in 2007	0.025**	(0.01)	0.022*	(0.01)
Sanctuary County in 2008	0.041*	(0.02)	0.038*	(0.02)
Sanctuary County in 2009	0.038	(0.02)	0.035	(0.02)
Sanctuary County in 2010	0.047	(0.03)	0.043	(0.03)
Sanctuary County in 2011	0.039	(0.03)	0.031	(0.03)
Sanctuary County in 2012	0.043	(0.03)	0.038	(0.03)
Sanctuary County in 2013	0.040	(0.03)	0.029	(0.03)
Observations	1846		1846	
Adjusted R-squared	0.478		0.546	
Pre-trend test for ICE counties, using late policy adopter as counterfactual				
ICE County in 2007	0.024	(0.01)	0.027**	(0.01)
ICE County in 2008	0.023	(0.02)	0.029	(0.02)
ICE County in 2009	0.019	(0.02)	0.027	(0.02)
ICE County in 2010	0.019	(0.02)	0.026	(0.02)
ICE County in 2011	0.025	(0.02)	0.032*	(0.02)
ICE County in 2012	0.036*	(0.02)	0.043**	(0.02)
ICE County in 2012	0.038**	(0.02)	0.043**	(0.02)
Observations	1753		1753	
Adjusted R-squared	0.387		0.448	

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01 All regressions contain robust standard errors clustered by county ID, time trends and time variant covariates.

Table 2.3 Pre-Trend Test using Natural Log of Total Employment

	Ordinary Least Squares		Fixed Effects	
Sanctuary County in 2007	0.039	(0.02)	-0.0021	(0.00)
Sanctuary County in 2008	0.0029	(0.03)	-0.0044	(0.01)
Sanctuary County in 2009	0.052*	(0.03)	-0.0014	(0.01)
Sanctuary County in 2010	0.058*	(0.03)	-0.0077	(0.01)
Sanctuary County in 2011	0.034	(0.05)	-0.013	(0.02)
Sanctuary County in 2012	0.045	(0.05)	-0.014	(0.01)
Sanctuary County in 2013	0.026	(0.06)	-0.0074	(0.02)
ICE County in 2007	0.024	(0.03)	-0.0013	(0.00)
ICE County in 2008	0.030	(0.07)	-0.0044	(0.01)
ICE County in 2009	0.030	(0.08)	-0.0044	(0.01)
ICE County in 2010	-0.00092	(0.07)	-0.0020	(0.01)
ICE County in 2011	-0.012	(0.08)	-0.0052	(0.01)
ICE County in 2012	0.014	(0.07)	-0.0017	(0.01)
ICE County in 2013	0.026	(0.07)	0.000024	(0.01)
Observations	9206		9206	
Adjusted R-squared	0.570		0.517	
Pre-trend test for sanctuary counties, using early adopter as counterfactual				
Sanctuary County in 2007	-0.035	(0.11)	0.011*	(0.01)
Sanctuary County in 2008	-0.014	(0.12)	0.014	(0.01)
Sanctuary County in 2009	0.13	(0.14)	0.013	(0.02)
Sanctuary County in 2010	0.13	(0.14)	0.014	(0.02)
Sanctuary County in 2011	0.28***	(0.06)	0.0084	(0.02)
Sanctuary County in 2012	0.32***	(0.07)	0.011	(0.03)
Sanctuary County in 2013	0.44***	(0.09)	0.0068	(0.03)
Observations	1846		1846	
Adjusted R-squared	0.544		0.683	
Pre-trend test for ICE counties, using late policy adopter as counterfactual				
ICE County in 2007	-0.039	(0.07)	0.018***	(0.01)
ICE County in 2008	-0.078	(0.11)	0.029***	(0.01)
ICE County in 2009	-0.048	(0.11)	0.032***	(0.01)
ICE County in 2010	-0.054	(0.10)	0.027**	(0.01)
ICE County in 2011	-0.050	(0.11)	0.030**	(0.01)
ICE County in 2012	-0.053	(0.11)	0.028***	(0.01)
ICE County in 2012	-0.045	(0.11)	0.029***	(0.01)
Observations	1753		1753	
Adjusted R-squared	0.555		0.636	

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01 All regressions contain robust standard errors clustered by county ID, time trends and time variant covariates.

Table 3.1 Natural log of Labor Force Unemployment

	Ordinary Least Squares	Fixed Effects	Fixed Effects & Matching
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1			
Sanctuary County	-0.12***	-0.12***	-0.17***
	(0.04)	(0.03)	(0.04)
P- value from Randomization Inference	0.014	0.000	0.008
ICE County	0.0025	-0.00065	-0.00085

	(0.03)	(0.02)		(0.02)
P- value from Randomization Inference	0.51	0.324		0.569
Observations	10087	10087	3650	3406
Adjusted R-squared	0.105	0.058	0.073	0.067
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	-0.25**	-0.12***	-0.12***	
	(0.12)	(0.03)	(0.03)	
Observations	1841	1841	1841	
Adjusted R-squared	0.474	0.036	0.036	
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3				
ICE County	-0.083	-0.024	-0.024	
	(0.07)	(0.02)	(0.02)	
Observations	1773	1773	1773	
Adjusted R-squared	0.455	0.025	0.025	

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. All regressions contain robust standard errors clustered by county, time trends, and time variant covariant. Nearest – neighbor matching is based on counties' economic attributes, education index, family income, and region.

Table 4.1 Rural and Urban: Natural log of Labor Force Unemployment

	Equation 1		Equation 2	Equation 3
	Urban	Rural	Urban- Early vs Late Adopter	Rural - Early vs Late Adopter
Sanctuary County	-0.071	-0.13***	-0.052	-0.12***
	(0.04)	(0.03)	(0.05)	(0.03)
Observations	1292	7755	472	1369
Adjusted R-squared	0.057	0.021	0.062	0.050
ICE County	0.064*	-0.0059	0.081*	-0.016
	(0.04)	(0.02)	(0.05)	(0.03)
Observations	1286	8059	301	1472
Adjusted R-squared	0.052	0.014	0.052	0.009

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Table 3.2 Natural log of Real GDP

	Ordinary Least Squares	Fixed Effects	Fixed Effects & Matching	
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1				
Sanctuary County	0.029***	0.024**	-0.0061	
	(0.01)	(0.01)	(0.02)	
P- value from Randomization Inference	0.014	0.000	0.253	
ICE County	-0.012**	-0.0087	-0.0033	
	(0.00)	(0.01)	(0.01)	
P- value from Randomization Inference	0.51	0.324		0.569
Observations	9991	9991	3583	3395
Adjusted R-squared	0.264	0.318	0.477	0.388
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	0.022***	0.041***	0.057***	
	(0.01)	(0.00)	(0.01)	
Observations	1846	1846	1131	
Adjusted R-squared	0.400	0.461	0.571	
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3				
ICE County	-0.015***	-0.0016	-0.016	
	(0.00)	(0.01)	(0.01)	
Observations	1752	1752	1749	
Adjusted R-squared	0.355	0.446	0.403	

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. All regressions contain robust standard errors clustered by county, time trends, and time variant covariant. Nearest – neighbor matching is based on counties' economic attributes, education index, family income, and region.

Table 4.2 Rural and Urban: Natural log of Real GDP				
	Equation 1		Equation 2	Equation 3
	Urban	Rural	Urban- Early vs Late Adopter	Rural - Early vs Late Adopter
Sanctuary County	0.035**	0.019**	0.032*	0.041***
	(0.02)	(0.01)	(0.02)	(0.01)
Observations	1264	7697	472	1374
Adjusted R-squared	0.556	0.278	0.553	0.477
ICE County	0.0072	-0.014*	-0.012	-0.014*
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1247	8001	288	1465
Adjusted R-squared	0.501	0.271	0.669	0.363

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Table 3.3 Natural log of Natural Log of Total Employment				
	Ordinary Least Squares,	Fixed Effects	Fixed Effects & Matching	
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1				
Sanctuary County	0.23*	0.036***	0.023**	
	(0.12)	(0.01)	(0.01)	
P- value from Randomization Inference	0.014	0.000	0.008	
ICE County	-0.073	-0.0098*		-0.013**
	(0.09)	(0.01)		(0.01)
P- value from Randomization Inference	0.51	0.324		0.569
Observations	9991	9991	3583	3395
Adjusted R-squared	0.568	0.407	0.513	0.453
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	-0.19* Not past	0.040***	0.026*	
	(0.11) P-test	(0.01)	(0.01)	
Observations	1846	1846	1131	
Adjusted R-squared	0.545	0.533	0.700	
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3				
ICE County	-0.12*	-0.017*** Not past P-test	-0.020**	
	(0.06)	(0.01)	(0.01)	
Observations	1753	1753	1750	
Adjusted R-squared	0.558	0.518	0.489	

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. All regressions contain robust standard errors clustered by county, time trends, and time variant covariant. Nearest – neighbor matching is based on counties' economic attributes, education index, family income, and region.

Table 4.3 Rural and Urban: Natural Log of Total Employment				
	Equation 1		Equation 2	Equation 3
	Urban	Rural	Urban- Early vs Late Adopter	Rural - Early vs Late Adopter
Sanctuary County	0.045***	0.026***	0.038***	0.040***
	(0.01)	(0.01)	(0.01)	(0.00)
Observations	1264	7699	472	1374
Adjusted R-squared	0.663	0.367	0.738	0.493
ICE County	0.0070	-0.015**	-0.011	-0.018***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1247	8001	288	1465
Adjusted R-squared	0.591	0.367	0.733	0.493

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Table 3.4	Natural log of Median Wages			
Model	(1) Ordinary Least Squares,	(2) Fixed Effects	(3) Fixed Effects & Matching	
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1				
Sanctuary County	0.052**	0.024***	0.026***	
	(0.02)	(0.01)	(0.01)	
ICE County	0.0016	-0.00098		0.0013
	(0.02)	(0.00)		(0.00)
Observations	10147	10147	3705	3095
Adjusted R-squared	0.296	0.218	0.330	0.256
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	0.0045	0.017*	0.013	
	(0.02)	(0.01)	(0.02)	
Observations	1846	1846	1326	
Adjusted R-squared	0.762	0.355	0.409	
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3				
ICE County	-0.0051	-0.0061	-0.0086	
	(0.01)	(0.01)	(0.01)	
Observations	1778	1778	1751	
Adjusted R-squared	0.654	0.298	0.329	

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. All regressions contain robust standard errors clustered by county, time trends, and time variant covariant. Nearest – neighbor matching is based on counties' economic attributes, education index, family income, and region.

Table 4.4 Rural and Urban:	Natural Log of Wages			
	Equation 1		Equation 2	Equation 3
	Urban	Rural	Urban- Early vs Late Adopter	Rural - Early vs Late Adopter
Sanctuary County	0.022**	0.023***	0.0043	0.014
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1292	7811	472	1374
Adjusted R-squared	0.381	0.214	0.468	0.311
ICE County	0.0024	-0.0018	0.0037	-0.0021
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1286	8118	301	1478
Adjusted R-squared	0.340	0.219	0.416	0.270

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Table 3.5	Natural log of Foreign-Born Population		
	Ordinary Least Squares	Fixed Effects	Fixed Effects & Matching
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1			
Sanctuary County	-0.14	-0.0021	0.0091
	(0.08)	(0.01)	(0.01)
ICE County	0.051	-0.013	-0.013
	(0.07)	(0.01)	(0.01)
Observations	10158	10158	3064
Adjusted R-squared	0.513	0.052	0.052
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2			
Sanctuary County	-0.070	0.010	0.0051
	(0.08)	(0.01)	(0.01)
Observations	1846	1846	1079
Adjusted R-squared	0.554	0.031	0.059
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3			
ICE County	0.044	-0.014	- 0.042**
	(0.07)	(0.01)	(0.02)
Observations	1786	1786	2108

Adjusted R-squared	0.437	0.052	0.065

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. All regressions contain robust standard errors clustered by county, time trends, and time variant covariant. Nearest – neighbor matching is based on counties' economic attributes, education index, family income, and region.

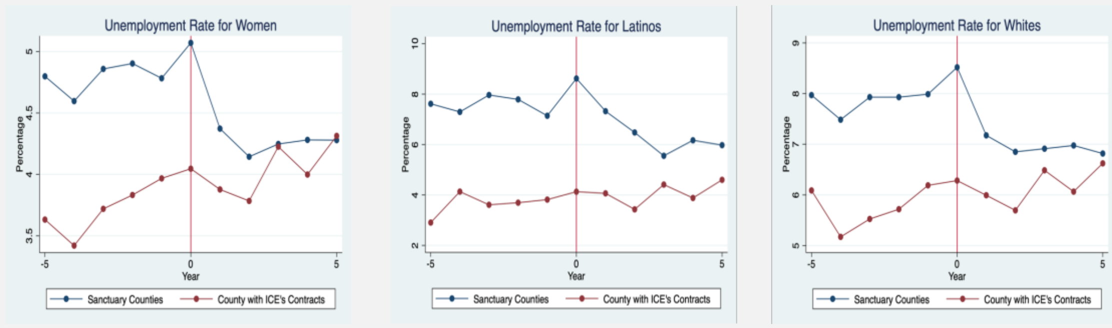
Table 5.1	Natural log of Average Household Income by Quintile				
	Lowest Q	Second Q	Third Q	Fourth Q	Highest Q
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1					
Sanctuary County	0.020**	0.028***	0.032***	0.033***	0.038***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ICE County	-0.0030	0.0015	0.00068	-0.0017	-0.0028
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	10150	10150	10150	10150	10150
Adjusted R-squared	0.068	0.181	0.236	0.281	0.227
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	0.011	0.021**	0.024**	0.025***	0.030***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1846	1846	1846	1846	1846
Adjusted R-squared	0.073	0.224	0.307	0.359	0.337
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	-0.0063	-0.0024	-0.0023	-0.0069	-0.0082
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1779	1779	1779	1779	1779
Adjusted R-squared	0.096	0.226	0.286	0.340	0.274

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

Table 5.2	Natural log of Labor Force Unemployment by Gender and Race				
	Women	Men	White	Black	Latino
Treatment Effect between sanctuary, ICE, and neutral counties - Equation 1					
Sanctuary County	-0.12***	-0.12***	-0.12***	-0.063	-0.11***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
ICE County	0.013	0.0010	0.0058	-0.052*	0.018
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Observations	9442	9442	10143	4793	3611
Adjusted R-squared	0.040	0.042	0.040	0.050	0.071
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	-0.14***	-0.16***	-0.14***	-0.088***	-0.17***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Observations	1800	1800	1841	882	1308
Adjusted R-squared	0.054	0.061	0.048	0.036	0.062
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	0.0058	-0.0081	-0.0011	-0.051*	0.030
	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)
Observations	1694	1694	1779	983	803
Adjusted R-squared	0.037	0.034	0.032	0.076	0.095

* p<0.10, ** p<0.05, *** p<0.0, Standard errors in parentheses, all regression use FE, Time Trends, and Time Variant Covariant, Robust Standard errors clustered by county ID.

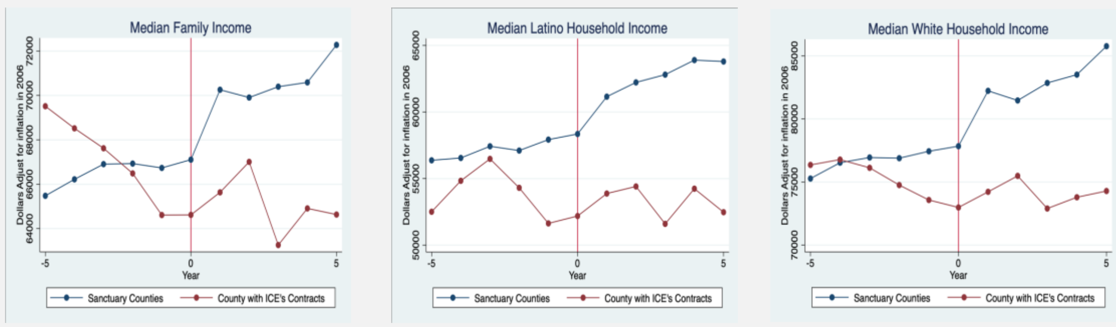
Figures 5	Unemployment Rate	
Women	Latino	White



Median Family

Median Household Income
Latino

White



All event graphs show 5 years before and after the adoption of the immigration policy for SC and ICE counties.