Inclusive Institutions in the United States: An Investigation of Sanctuary Cities

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Abstract

Using county-level census data on economic indicators and Immigration and Customs Enforcement (ICE) data, this study exploits quasi-experimental variation in the time and space of policy implementation to isolate the effects of immigration policy on U.S. counties in settings 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 per capita income by 4.8 percent, county GDP by 4.1 percent, and total employment by 4 percent, while unemployment experiences a 6.7 percent decline. Meanwhile, the data show that punitive measures have no statistically significant effect on income and unemployment, but do have adverse effects on GDP, total employment, and a decline in the foreign-born population. An explanation of the results is provided by extending the Solow neoclassical growth model to include institutions.

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

Introduction

Sanctuary cities are in the spotlight, with increasing anti-immigrant rhetoric and more hostile policies towards immigrants. Opponents of policies that give partial protection to undocumented families allege that immigration comes at an economic cost by arguing that immigration drives down wages for native workers and strains taxpayers and the national budget through social services. "Sanctuary cities" refer to municipal jurisdictions that limit their cooperation with the federal government efforts to enforce immigration law. Given the high level of stress propelled by fear of deportation and possible family separations found among people who reside without authorization in the United States (Squires et al. 2017, Mewes et al. 2017, Martinez et al. 2018), sanctuary policies strive to provide some protection and stability to immigrant families. Many proponents of sanctuary policies argue that they preserve local resources for local priorities, rather than volunteering assistance in immigration enforcement (Graber et al. 2016). The justification for this approach is that people will be more willing to report crimes, participate in local civic affairs, and contribute to the economy as employees, employers, and consumers (Avila et al., 2018).

The objective of this study is to examine the effects of immigration policies on U.S. counties in settings where immigrants' families are persecuted via collaboration with Immigration and Customs Enforcement (ICE) compared to those counties that provide legal protections. To assess the impact of a county's openness to immigrants on the local economy, I use U.S. Census data on income, GDP, and employment combined with newly digitized information on county-level immigration policies. The econometric approach uses quasi-experimental variation in the adoption of policies that are both welcoming and

restricting to undocumented immigrants. The circumstances for analysis create a staggered difference in difference environment. The analysis also includes fixed effects, time effects, time trends, and nearest-neighbor matching.

I begin by estimating the impact of policies comparing sanctuary and ICE counties to neutral counties. Then, in separate regressions using only those counties that ever end up with a sanctuary city or ICE designation, I limit the sample to counties that ever chose to adopt either policy, thus using the variation in policy timing to address the possibility that sanctuary counties might be fundamentally different from non-sanctuary counties. 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 with counties that share a common border with opposing policies.

The evidence supports the hypothesis that providing protections to illegal immigrants increases economic activity. The estimates show increases in per capita income ranging from 1.7 to 5.1 percent, increases in GDP ranging from 2.3 to 10 percent, increases in total employment ranging from 2 to 9.1 percent, and declines in the unemployment rate ranging from 6.7 to 14 percentage points. The data further show that punitive measures have no statistically significant effect on income or unemployment, but adverse effects on GDP with a decline ranging from 1.9 to 7.9 percent, a total employment decline ranging from 1 to 6 percent, and a decline in the foreign-born population ranging from 1.6 to 3.4 percent. When dividing the data by education attainment, gender, and races, the results show a positive effect in sanctuary counties in almost all categories, but no significant effects in ICE counties.

This study contributes to a growing literature on the economics of migration. Despite its hot-button nature, evidence on the impact of immigration on the U.S. economy is mixed. The partial equilibrium narrative suggests that an upshift in the labor supply will increase total employment, decrease wages, and increase unemployment accordingly. In these cases, people cite Borjas (2013, 2015) or Camarota (1998, 2011), where Borjas' studies mostly find lower wages for high school dropouts than wages before the shock of migration. In other words, the arrival of immigrant workers directly competes for a finite number of American jobs; thus, native workers will make less income, relocate somewhere else, or leave the labor market altogether if wages drop below their reservation wage. However, other work contradicts those predictions in the U.S. context. For example, Card (1990, 2001) found no effect of an episode of increased Cuban immigration on the wages or employment rates of non-Cuban workers in the Miami labor market. Perhaps more surprisingly, Card (1990) identified no substantial effect on the wages of other Miami-based Cubans. Similar studies with similar outcomes are Dustmann et al. (2005, 2013), Lalonde and Topel (1991), and Cortes (2008).

The general equilibrium narratives suggest that as new immigrants increase diversity and consumption, supply work that natives are less willing to supply, and provide a renovated entrepreneurial spirit, immigrants provide inputs with positive effects on the economy. This evidence suggests that immigration to the United States is associated with economic development due to productivity growth (Peri, 2012, 2016; Model 2008). The findings of the current paper are consistent with this story. Another possibility is that 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).

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. The year 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. The data used for my analysis shows no statistically significant evidence of an increase in the foreign-born population after counties adopt sanctuary policies. However, there is evidence of a decline in the foreign-born population when countries adopt policies to criminalize undocumented immigrants.

This paper also contributes to the discussion around the mechanisms through which immigration could increase GDP per capita. Studies suggest that immigrants have an entrepreneurial spirit with less risk-aversion, given that immigrating is itself an inherently risky decision (Peroni 2016). Further evidence of immigration's impact on productivity stems from findings that indicate that U.S. immigrants are two to three times more likely than U.S. natives to start a company and create patents. As a result, immigrants have started

30 percent of American businesses, despite only making up about 15 percent of the population (Jaumotte et al. 2016). Immigrants are also more likely to hold jobs characterized by a poor condition or high risk than natives (Orrenius et al. 2009, Heitmueller 2005, Wooland 2006, Orrenius et al. 2009). In this way, the migrant advantage can be 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, their resilience, their resources, and their resourcefulness (Model 2008, Bencivenga et al. 1997). However, 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 diminish human capital (Squires et al. 2017, Mewes et al. 2017, Martinez et al. 2018, Yim et al. 2019, Garcini et al. 2019, Keinan 1987; Keinan et al. 1987, Arnsten 1998). Therefore, local immigration policies can play an essential role in ameliorating or exacerbating the consequences of risk in immigrants' human capital (Woodland et al. 2006).

Emerging work suggests that institutions play an essential role in conditioning the effects of immigration. Kemeny et al. (2017) presents evidence supporting the hypothesis that urban immigrant diversity's benefits should be broader in regions where institutions are inclusive. Therefore, taking advantage of immigrant diversity is to take advantage of their diverse human capital. The framework of institutional economics theory introduces the concept of transaction costs, to propose that institutions are a medium not only for reducing transaction costs but also for achieving increased efficiency in economic performance (Coase 1960; Williamson 1975; North 1990; Milgrom and Roberts 1992, David 2017). Similarly, sanctuary cities' purpose is to decrease the cost from fear of

deportation or the constant fear of criminalization, a separate cost from the production process that is socially and economically costly due to the loss of benefits from human capital and the subsequential decline of economic performance.

These pieces of evidence suggest that institutions play an essential role in decreasing uncertainties and risks in immigrant communities, and productivity improvements may be driven by reducing immigrant stress. The findings of this paper are consistent with this hypothesis. Hence, 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, 2000; Sokoloff, 2003; Acemoglu & Robinson, 2013).

The study begins with section 2 identifying the knowledge gap in the existing literature about migration economics. The theoretical model uses an extension of the Solow model to include institutions explaining the study's result. Section 3 describes the data, section 4 presents the empirical model, section 5 tests for the parallel pre-trend assumption, section 6 gives the results of this study, section 7 gives the discontinuity regression results, and section 8 concludes.

2. Theoretical Model

Despite the wealth of attention to the potential effects of immigration on labor markets in the U.S. context, consensus about immigration effects have yet to emerge. What are the features of the U.S. economy's dynamic nature that make the labor market robust to the short-term effect of immigration-related additions to the labor market? Alternatively, what

are the coordination mechanisms that allow newcomers to be productive for the economy? This section presents a modified growth model that integrates the idea that policies that support illegal immigrants can increase their productivity, whereas antagonistic policies may decrease it. Given that sanctuary cities reduce uncertainty and risk for immigrants' interactions in their new communities, optimize their human capital, and subsequentially increases economic efficiency.

There is considerable evidence that stress reduces economic productivity. Symptoms of depression, anxiety, and stress produce low attention, which in turn makes people less productive. High risk and uncertainty bring worry, chronic stress, depression, and high cortisol levels among immigrants (Squires et al. 2017, Mewes et al. 2017, Martinez et al. 2018, Yim et al. 2019, Garcini et al. 2019). Undocumented workers and their families contend with a level of risk that is hard to overstate. In everyday activities, undocumented immigrants carry the risk of losing all possessions, their children, their families, their livelihoods, or other household breadwinners. Vulnerability to deportation may motivate undocumented individuals to maintain vigilance while going grocery shopping, taking their kids to school, driving to work, or going to the hospital. Research shows a strong correlation between poverty and the body's production of the stress hormone cortisol (Banerjee and Duflo 2011). Cortisol is an indicator of stress, directly disrupts cognitive and decision-making abilities, and impairs human capital (Keinan 1987; Keinan et al. 1987, Arnsten 1998). As in an experiment for financial decisions, subjects with higher basal cortisol levels were more risk aversive (Van Honk et al. 2003). In sum, depression, stress, and uncertainty about the future restrict people's optimal contribution to society and inhibits their potential human capital.

The model presented here extends the Solow human-capital augmented growth model (Mankiw, Romer, and Weil 1992) by noting that social and institutional constraints may limit people's realization of their potential (North 1990). Furthermore, institutional constraints may impede the exchange of ideas necessary for innovation and sustained growth (Romer 1990, 2016). The usual human-capital augmented growth model emphasizes that human capital stock increases through physical investments in human capital. Hence, these investments are measurable and accessible to analyze since they are rival to consumption and excludable. The notation is standard: Y is output, K is capital, H is human capital, L is labor, and the A term reflects not just technology but resource endowments, climate, and institutions. Then the production function is

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

The growth rates of depreciation (δ) and productivity *(g)* are assumed to be constant across countries (in our case, counties). Output per effective unit of labor is given by $y = \frac{Y}{AL}$, h is the level of human capital per effective unit of labor, $h = \frac{H}{AL}$, and k is the level of the stock of capital per effective unit of labor, $k = \frac{K}{AL}$. The evolution of human capital in the economy is determined by equations (3a) and the evolution of the stock of capital is determined by equation (3b); where $S_h y(t)$ is the income invested in human capital and *S* is a constant fraction.

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

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

Hall and Jones (1999) extend this model to accommodate institutional differences, noting that physical capital and educational attainment can only partially explain productivity variation. They define a variable that captures the quality of institutions and

determines the economic environment within which individuals accumulate skills. Similarly, Eicher, Garcia, and Teksoz (EGT 2006) combined HJ and MRW models and allowed the elasticity of output with respect to input to depend on the quality of institutions *(I)* at every location *(i)*. They also allowed for the total factor productivity A to depend on institutions such that $A_i = Ae^{pI_i}$.

The concept of local policy towards illegal immigrants 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 exclude (g) and describe the total factor of productivity as $A_i = A(e^{pI_i})$. 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, the equation for income per capita includes the total factor productivity (A) that also depends on the quality of institutions, such that.

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

Human capital is therefore constrained and shaped by institutions' excludability function, represented by pI, as well as by investment in human capital ($ln(s_h)$). In the setting studied here, the institution of interest is policy towards illegal immigrants, represented both by the presence of sanctuary and by its opposite, direct collaboration with ICE. The next sections describe the data and estimation used to identify this relationship.

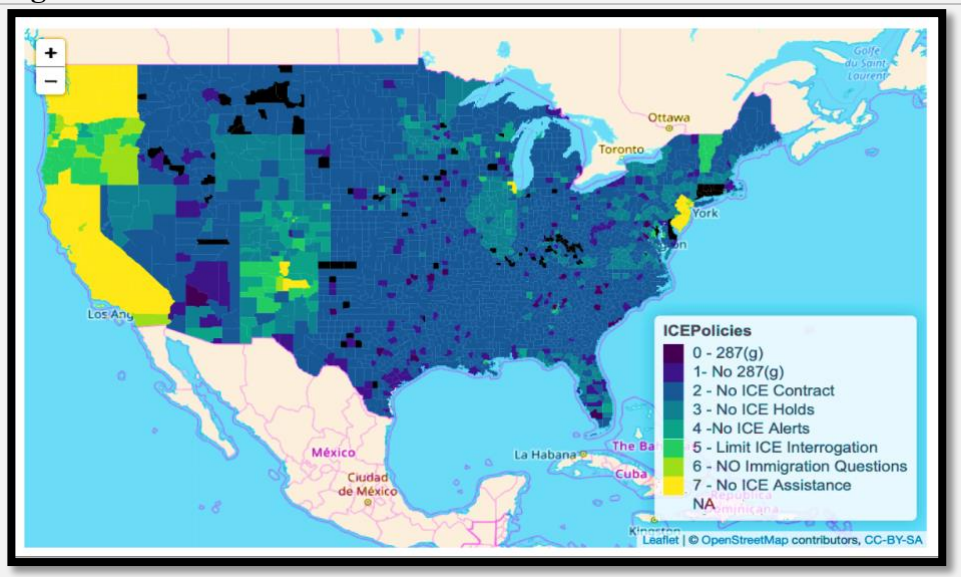
3 Data and Summary Statistics

The 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 helped 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. There have been jurisdictions that have called themselves sanctuary cities without related policies in place. 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 the 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 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

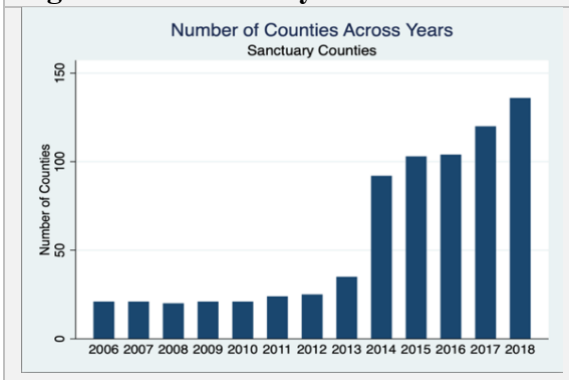
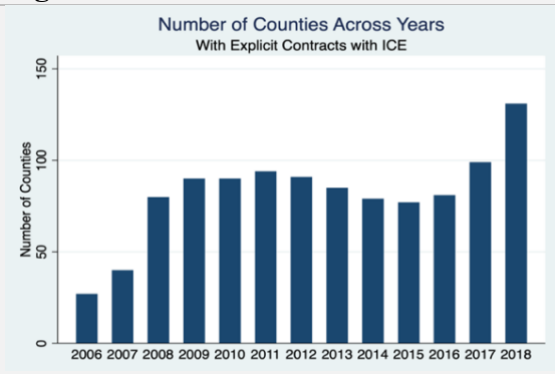


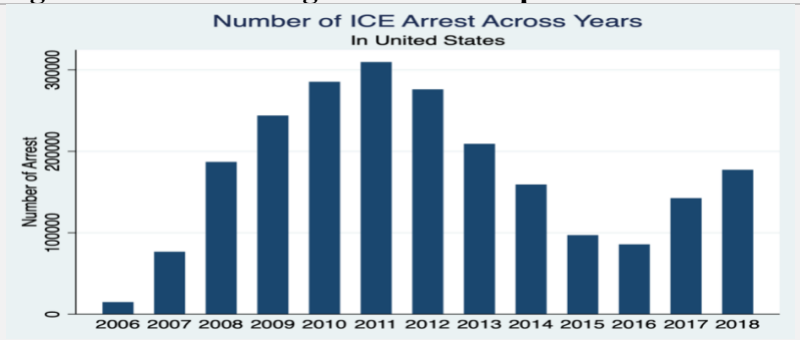
Fig. 3 ICE Counties



The number of sanctuary counties start increasing in 2013, and the number of immigration-related arrests starts declining the same year, shown in Figure 4. The same ICE data from Figure 4 shows that the most significant number of arrests happened from 2008 to 2013 and that arrests started to rise again in 2017. Data shows that the relative number of sanctuary counties was stable and low between 2006 and 2012. An increase in sanctuary cities (circa 2014) lagged several years behind an uptick in mass arrests and deportation that appeared to start in 2008. Figures 3 and 4 exhibit similar patterns across

the years. Changes in ICE arrests appear to coincide with changes to the number of counties with explicit contracts to coordinate with ICE.

Figure 4 Immigration Arrests per Year



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 immigrants' receptiveness. 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-level 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.

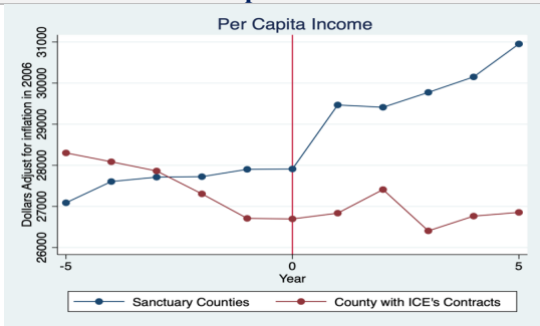
Additionally, sanctuary counties have a more diverse community with a higher rate of Latino-origin and foreign-born residents. However, all these indicators are also higher in ICE counties compared to NC Some features of ICE counties may be attractive to immigrants (despite the ICE status of these counties). More likely, the higher presence of immigrants in S.C. 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.

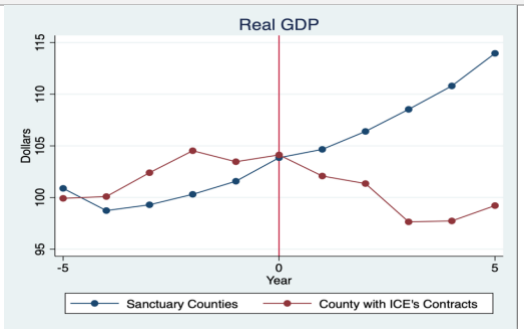
To visualize the difference between counties, I aligned the change in policies at a fixed period for all counties when a county became S.C. or ICE, as shown in Figure 5, describing the change in economic indicators over immigration policies' impact at the beginning of the fixed year zero. Sanctuary counties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

Figures 5

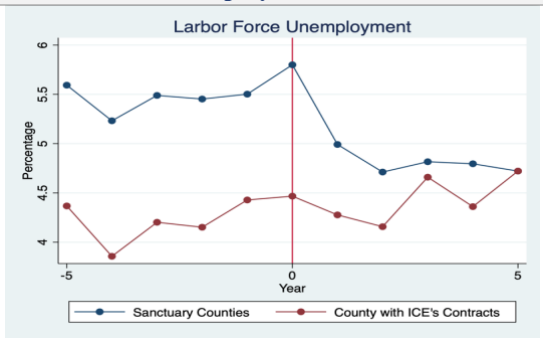
Per Capita Income



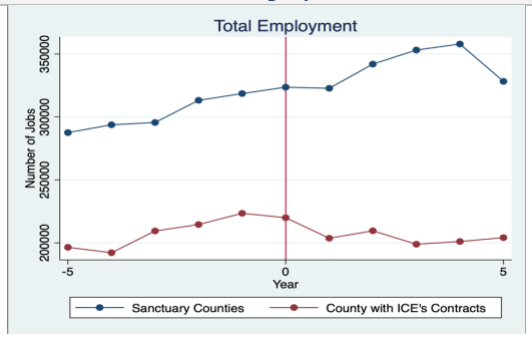
Real GDP



Unemployment Rate



Total Employment



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 when looking at the unemployment rate for women, white and Latino, and the average family income for white and Latino. 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.

4 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, 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, using only the variation in sanctuary designation timing, thus addressing 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. Then, I test for differential pre-trends between ever-sanctuary and never-sanctuary counties, as well as between early and late implementers, and economic attributes. Then, I repeat these processes with each economic indicator, and finally, using median family income among education levels and unemployment rates by gender, ethnic categories, rural, and urban areas. The first estimation that includes the full sample is:

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

For only sanctuary counties, we use:

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

And for only ice counties the estimation is:

$$EI_{it} = \alpha + \beta_2 ICEC_{it} + \gamma_i + \sum_{i=1}^{8} \varphi_i Reg_i * Y + Y + \theta' X_{it} + \epsilon_{it} \quad (3)$$

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 S.C. 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. It also includes eight economic region time trends (Reg*Y), 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, and ethnicities. As a robustness check, we will 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.

5. 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 equation is:

$$EI_{it} = \alpha + \sum_{t=1}^{7} \delta_t Y_t * Ever_{SC_i} + \sum_{t=1}^{7} \theta_t Y_t * Ever_{CEC_i} + X_{it}\Gamma + \gamma_i + \epsilon_{it} \qquad (4)$$

For only sanctuary counties,

$$EI_{it} = \alpha + \sum_{t=1}^{6} \delta_t Y_t * Ever_{SC_i} + X_{it}\Gamma + \gamma_i + \epsilon_{it} \quad (5)$$

For only ICE counties,

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

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 six years before the policy change and omits the first.

Table 2 **Natural Log of Per Capita Income**

	Ordinary Least Squares		Fixed Effects		Fixed Effects & Time-Varying Controls	
Pre-trend test between sanctuary, ICE and neutral counties - Equation 4						
Sanctuary County in 2007	0.0066	(0.04)	0.0039	(0.01)	0.0012	(0.01)
Sanctuary County in 2008	0.015	(0.04)	0.025**	(0.01)	0.015	(0.01)
Sanctuary County in 2009	-0.02	(0.04)	-0.0056	(0.01)	-0.0029	(0.01)
Sanctuary County in 2010	-0.018	(0.04)	-0.0025	(0.01)	0.0065	(0.01)
Sanctuary County in 2011	-0.029	(0.04)	-0.011	(0.01)	0.00032	(0.01)
Sanctuary County in 2012	-0.01	(0.04)	0.0063	(0.02)	0.011	(0.01)
Sanctuary County in 2013	-0.021	(0.04)	-0.0099	(0.02)	0.0091	(0.01)
ICE County in 2007	0.013	(0.03)	0.016	(0.01)	0.0084	(0.01)
ICE County in 2008	0.037	(0.04)	0.033*	(0.02)	0.030**	(0.01)
ICE County in 2009	0.023	(0.04)	0.0027	(0.03)	-0.0035	(0.02)
ICE County in 2010	0.024	(0.04)	-0.00019	(0.02)	-0.016	(0.02)
ICE County in 2011	0.04	(0.04)	0.012	(0.01)	-0.005	(0.01)
ICE County in 2012	0.041	(0.04)	0.019	(0.02)	0.011	(0.02)
ICE County in 2013	0.037	(0.04)	0.0048	(0.01)	-0.012	(0.01)
Observations	8371		8371		8360	
Adjusted R-squared	0.012		0.026		0.211	
Pre-trend test for sanctuary counties, using early adopter as counterfactual – Equation 5						
SC Early adopter on year 5	-0.019	(0.10)	-0.014	(0.03)	-0.029*	(0.02)
SC Early adopter on year 4	-0.029	(0.10)	0.02	(0.03)	0.0047	(0.03)
SC Early adopter on year 3	-0.1	(0.10)	-0.013	(0.03)	-0.036	(0.03)
SC Early adopter on year 2	-0.13	(0.11)	-0.037	(0.04)	-0.052	(0.04)
SC Early adopter on yea 1	-0.15	(0.11)	-0.018	(0.03)	-0.027	(0.03)
SC Early adopter on year zero	-0.13	(0.11)	0.0082	(0.05)	-0.016	(0.02)
Observations	1103		1103		1103	
Adjusted R-squared	0.035		0.013		0.128	
Pre-trend test for ICE counties, using late policy adopter as counterfactual – Equation 5						
ICE C. Early adopter on year 5	0.037	(0.07)	0.081**	(0.03)	0.099***	(0.03)
ICE C. Early adopter on year 4	-0.0026	(0.06)	0.0032	(0.04)	0.00077	(0.04)
ICE C. Early adopter on year 3	0.081	(0.08)	0.058*	(0.03)	0.077**	(0.04)
ICE C. Early adopter on year 2	0.065	(0.09)	0.008	(0.05)	0.015	(0.04)
ICE C. Early adopter on year 1	0.062	(0.07)	0.049	(0.05)	0.056	(0.04)
ICE C. Early adopter on year zero	0.073	(0.07)	0.015	(0.03)	0.036	(0.03)
Observations	738		738		735	
Adjusted R-squared	-0.007		0.018		0.206	

Ordinary Least Squares (OSL)	**Y**	**N**	**N**
Fixed Effects (FE)	**N**	**Y**	**Y**
Time Trends (RT)	**Y**	**Y**	**Y**
Time- Varying controls	**N**	**N**	**Y**
Standard errors in parentheses	*** p<0.10, ** p<0.05, *** p<0.01**		
All regressions contain robust standard errors clustered by state ID & year dummies time trend.			

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. It is supported because 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 estimated the same test for the labor unemployment rate, real GDP, and the total employment per county, shown in Tables 2.1-A, 2.2-A, and 2.3-A in the appendix. These results are also consistent except for the unemployment rate only when using late policy adopters as counterfactuals for sanctuary counties, and real GDP when comparing sanctuary to neutral counties. Both of them show a statistically significant change in at least three years out of seven.

6. Results

All tables start with a simple model containing fixed effects and varying covariates in the first column and progressively move to the fullest model containing fixed effects, regional time trends, time-varying covariates, and the nearest-neighbor matching estimator in the last column. 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 2.6 to 4.9 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**				
	Fixed Effects & Time Varying Covariates	**Ordinary Least Squares, Time Trends & Time Varying Covariates**	**Fixed Effects, Time Trends & Time Varying Covariates**	**Fixed Effects, & Time Varying Covariates & Matching**	**Fixed Effects, Time Trends, & Time Varying Covariates & Matching**
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					

Sanctuary County	0.047*	0.015	0.026*	0.049**	0.040**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ICE County	0.0094	-0.0031	-0.00093	0.029	0.026
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	10144	10144	10144	3836	3836
Adjusted R-squared	0.227	0.644	0.251	0.344	0.358
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	0.048**	0.0045	0.017*	0.051*	0.013
	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
Observations	1846	1846	1846	1326	1326
Adjusted R-squared	0.334	0.762	0.355	0.368	0.409
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	0.0076	-0.0051	-0.0061	0.0025	-0.0086
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1778	1778	1778	1751	1751
Adjusted R-squared	0.272	0.654	0.298	0.297	0.329
Ordinary Least Squares (OLS)	N	Y	N	N	N
Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y
Standard errors in parentheses	*** p<0.10, ** p<0.05, *** p<0.01**				
All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID					

When estimating the impacts using only those counties that ever end up with a sanctuary city designation using Equation 2, we obtain similar results with slightly more variation in magnitude, ranging from 1.7 to 5.1 percent increase in per capita income in Sanctuary counties. 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. The study argues that immigrants' human capital benefits ought to be larger in regions where institutions are inclusive. Similarly, this study finds that when using the percent foreign-born per county as the dependent variable, sanctuary policies in a county maintain their immigrant population while ICE policies drive them away. As shown in Table 4, the adoption of punitive measures against undocumented workers reduces the foreign-born population by up to 3.4 percent.

Table 4 Natural log of Foreign-Born Population

	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1				
Sanctuary County	-0.031	0.0013	0.00018	0.014
	(0.04)	(0.01)	(0.00)	(0.01)
ICE County	-0.041	-0.012	0.0063	0.0042
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	10147	10147	3836	3836
Adjusted R-squared	0.808	0.535	0.514	0.518
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	-0.032	0.0033	0.00062	0.0089
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	1846	1846	1326	1326
Adjusted R-squared	0.890	0.620	0.700	0.70
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3				
ICE County	-0.061	-0.016**	-0.019**	-0.034***
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	1778	1778	1751	1751
Adjusted R-squared	0.824	0.593	0.576	0.583
Ordinary Least Squares (OLS)	Y	N	N	N
Fixed Effects (FE)	N	Y	Y	Y
Time Trends (TT)	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01			

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 5-A shows the impacts of the policies on GDP. The results in most models are statistically significant for sanctuary counties with magnitudes ranging from 2.5 to 10 percent increase, but no significant evidence for decline or increase of GDP on ICE counties, using neutral counties as the control groups. When using late policy adopters as the control groups, I find similar results with higher variance for sanctuary cities, ranging from 2.3 to 13 percent increase in GDP in sanctuary counties. However, in this case, ICE counties show statistically significant declines of 1.3 and 1.5 percent.

As in previous economic indicators, total employment shows a statistically significant increase for sanctuary counties with both analytical approaches ranging from 7.9 to 9.1 percent increases. However, this time, total employment shows a statistically significant decline for ICE counties using both approaches, ranging from 1.9 to 4.9, as

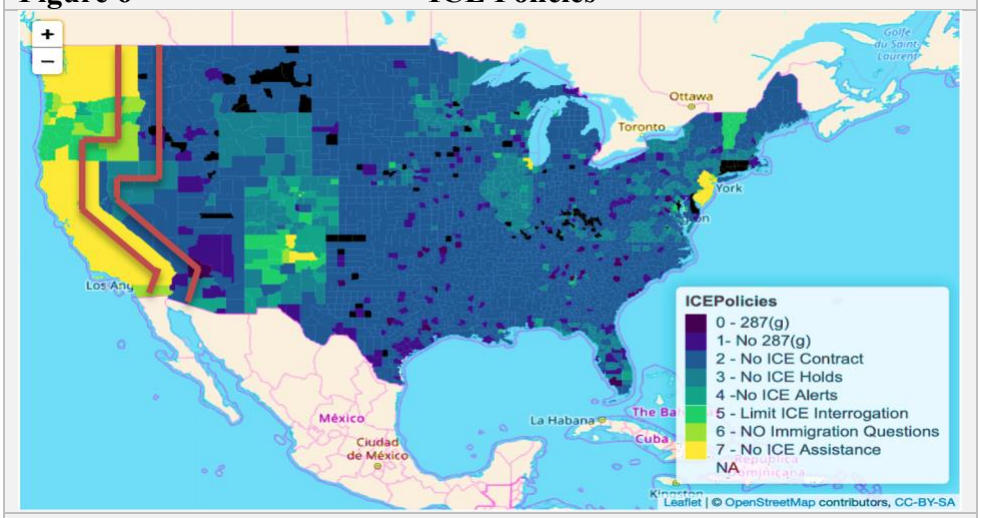
shown in Table 6-A. When looking at the natural log of labor force unemployment, Table 6.1-A in the appendix shows the impacts of immigration policies. All models' results are statistically significant, with magnitudes ranging from 8.8 to 15 percent declines in unemployment in sanctuary counties, but no significant effect on ICE counties. Also, by dividing the natural log of labor force unemployment by gender and race, I find statistically significant positive results for women, men, whites, and Latinos in sanctuary counties, but again no significant effect on ICE counties, shown in Table 6.2-A in the appendix.

Table 7-A shows income effects across different educational attainment levels using fixed effects, regional time trends, and time-varying covariates. Interestingly, I find positive and significant results at all educational attainment except at the college level in sanctuary counties. However, more interesting is that contrary to most of the literature, I obtain favorable outcomes for workers without a high school diploma. Similarly, punitive measurements in ICE counties show no significant effects. In other words, locations that human capital that immigrants provide.

Finally, I repeat all previous results dividing the data between rural and urban counties, thus further addressing the criticism that sanctuary counties might be fundamentally different from non-sanctuary counties. I do so for the natural log of the per capita income, GDP, total employment, and the labor force unemployment, shown in Tables 7.1-A, 7.2-A, and 7.3-A in the appendix. Again, results reinforce the previous effects by showing a highly significant economic increase in sanctuary counties, but no significant effect on ICE counties. That is also when estimating the impacts using only those counties that ever end up with a sanctuary city designation or with an ICE county designation.

7. Regression Discontinuity

Figure 6 **ICE Policies**



The ILRC policy classification in 2019

As a final robustness check and to reduce selection problems, we address, one last time, the criticism that sanctuary counties might be fundamentally different from non-sanctuary counties by using a geographical regression discontinuity analysis. Here we select only counties that share a border with other counties with distinct policies. When looking at the map, we find a clear contrast in immigration policies between the counties and California, Oregon, and Washington states that share borders with Arizona, Nevada, and Idaho. Here, the formers offer better protections to immigrants, represented by the lighter colors between the red lines in Picture 2. Hence, I trim the data to only those counties along the border. Table 8 presents results from Equation 1 using the natural log of per capita income, GDP, total employment, and the labor force unemployment as the dependent variable. The point estimates for sanctuary counties are favorable for the economy and statistically significant in most models. Per capita income results show a 5.9 percent increase, a 5.4 increase in GDP, an 8.4 increase in the total employment, and a 13 percent decrease in unemployment for sanctuary counties. On the contrary, ICE counties

show no significant effects for per capita income, a decline of GDP by 6.2 percent, a decline of 6.7 percent in total employment, and contradicting unemployment results. Congruently, it is consistent with our previews results, but it is crucial to indicate that this regression highly reduces our number of observations.

Table 8	Regression Discontinuity Model		
	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates
Treatment Effect of the natural log of Per Capita Income between sanctuary, ICE and neutral counties - Equation 1			
Sanctuary County	0.059**	0.19*	0.041
	(0.02)	(0.08)	(0.02)
ICE County	0.035	-0.0084	0.061
	(0.04)	(0.09)	(0.03)
Observations	169	169	169
Adjusted R-squared	0.342	0.649	0.466
Treatment Effect of the natural log of GDP between sanctuary, ICE and neutral counties - Equation 1			
Sanctuary County	0.42**	0.054**	0.089***
	(0.14)	(0.01)	(0.01)
ICE County	-0.19	-0.070***	-0.062**
	(0.16)	(0.01)	(0.01)
Observations	169	169	169
Adjusted R-squared	0.726	0.499	0.292
Treatment Effect of the natural log of total employment between sanctuary, ICE and neutral counties - Equation 1			
Sanctuary County	0.088**	0.084*	0.11***
	(0.02)	(0.03)	(0.01)
ICE County	-0.089***	-0.082***	-0.067***
	(0.01)	(0.01)	(0.01)
Observations	169	169	169
Adjusted R-squared	0.479	0.480	0.315
Treatment Effect of the natural log of Labor Force Unemployment between sanctuary, ICE and neutral counties - Equation 1			
Sanctuary County	-0.14**	-0.13*	-0.0066
	(0.05)	(0.05)	(0.08)
ICE County	0.11*	-0.098	-0.16**
	(0.05)	(0.06)	(0.04)
Observations	169	169	169
Adjusted R-squared	0.138	0.270	0.280
Ordinary Least Squares (OLS)	N	Y	N
Ordinary Least Squares (OLS)	N	Y	N
Time Trends (TT)	N	Y	Y
& Time Varying Covariates (TC)	Y	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01		
All regressions contain robust standard errors clustered by state ID & year dummies time trend.			

8 Conclusion

This study contributes to the literature on the economics of migration by finding further evidence that support for immigrations in the United States is associated with economic expansion due to productivity growth. However, the main differences with other studies are that I looked at the change in immigration policies by location, and the evidence

supports the hypothesis that providing protections to illegal immigrants increases efficiency in the economy. Conversely, punitive measures are detrimental to economic outcomes.

A possible mechanism for this result is that immigration policy that decreases uncertainty and risk for immigrants by decreasing the cost from fear of deportation or criminalization, optimize human capital, and allow for the subsequential increase of economic performance. Given that sanctuary cities constitute an example of an inclusive policy, characterizing sanctuary cities' economic features may have implications for more inclusion in other economic areas. Coase (1960) argues that uncertainty in human behavior is the reason for increased cost 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.

Presently, US policy makes it less appealing for immigrants than in the previous decades, according to the migration data. It is ironic then that local policies that welcome immigrants primarily occur in booming metro areas, and policies that restrict immigrants are in the communities that need immigrants the most. As data shows that U.S. population growth has fallen, as the last decade became the first time in this last century, the labor force population between 25 and 65 fell on a sustained basis. The country now adds around 900,000 fewer people each year than it did in the early 2000s. This is the case in 86 percent

of U.S. counties, and as the population shrinks, the proportion of people over 65 is increasing faster (Ozimek et al., 2019).

In sum, institutional inclusion creates the dynamic nature of the US 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 sectors that are no longer competitive and would otherwise be sent abroad. It also enables immigrants to take on the responsibilities of (and care for) a rapidly aging population.

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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 S.C., ICE, and NC, use the mean before and after 2013.

Table 1.1-A Descriptive statistics among sanctuary counties (SC), counties with explicit contracts with ICE (ICE) 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 - A **Natural Log of Labor Force Unemployment**

Pre-trend test between sanctuary, ICE and neutral counties - Equation 4

	Ordinary Least Squares		Fixed Effects		Fixed Effects & Time-Varying Controls	
Sanctuary County in 2007	0.048	(0.05)	0.046	(0.07)	0.039	(0.06)
Sanctuary County in 2008	-0.0028	(0.05)	-0.016	(0.03)	-0.019	(0.03)
Sanctuary County in 2009	-0.024	(0.05)	-0.04	(0.03)	-0.052	(0.03)
Sanctuary County in 2010	0.00027	(0.05)	-0.016	(0.05)	-0.047	(0.05)
Sanctuary County in 2011	0.067	(0.05)	0.052	(0.06)	0.0087	(0.05)
Sanctuary County in 2012	0.048	(0.05)	0.033	(0.09)	-0.011	(0.08)
Sanctuary County in 2013	0.049	(0.05)	0.045	(0.07)	-0.028	(0.08)
ICE County in 2007	-0.11*	(0.06)	-0.094*	(0.05)	-0.084	(0.06)
ICE County in 2008	-0.14**	(0.07)	-0.11*	(0.06)	-0.11**	(0.06)

ICE County in 2009	-0.039	(0.07)	0.015	(0.08)	0.02	(0.08)
ICE County in 2010	0.011	(0.07)	0.072	(0.06)	0.10*	(0.06)
ICE County in 2011	-0.053	(0.08)	-0.0056	(0.05)	0.026	(0.05)
ICE County in 2012	-0.073	(0.07)	-0.023	(0.07)	-0.017	(0.07)
ICE County in 2013	-0.034	(0.07)	0.013	(0.04)	0.042	(0.05)
Observations	8316		8316		8307	
Adjusted R-squared	0.032		0.005		0.055	
Pre-trend test for sanctuary counties, using late policy adopter as counterfactual – Equation 5						
SC Early adopter on year 5	0.22	(0.13)	0.22**	(0.09)	0.25***	(0.06)
SC Early adopter on year 4	0.12	(0.13)	0.11	(0.10)	0.14	(0.10)
SC Early adopter on year 3	0.20*	(0.12)	0.16	(0.09)	0.19*	(0.10)
SC Early adopter on year 2	0.25**	(0.11)	0.21**	(0.07)	0.23***	(0.06)
SC Early adopter on yea 1	0.18	(0.13)	0.13	(0.09)	0.14	(0.08)
SC Early adopter on year zero	0.33***	(0.12)	0.27***	(0.07)	0.30***	(0.04)
Observations	1099		1099		1099	
Adjusted R-squared	0.03		0.009		0.042	
Pre-trend test for ICE counties, using late policy adopter as counterfactual – Equation 6						
ICE C. Early adopter on year 5	0.088	(0.12)	0.11	(0.12)	0.15	(0.12)
ICE C. Early adopter on year 4	-0.064	(0.14)	-0.038	(0.07)	-0.049	(0.08)
ICE C. Early adopter on year 3	0.031	(0.14)	0.17	(0.17)	0.21	(0.16)
ICE C. Early adopter on year 2	-0.074	(0.16)	0.056	(0.16)	0.058	(0.18)
ICE C. Early adopter on year 1	0.022	(0.23)	0.073	(0.16)	0.089	(0.15)
ICE C. Early adopter on year zero	-0.013	(0.17)	0.043	(0.27)	0.07	(0.26)
Observations	738		738		735	
Adjusted R-squared	-0.009		0.003		0.06	
Ordinary Least Squares (OSL)	Y		N		N	
Fixed Effects (FE)	N		Y		Y	
Time Trends (RT)	Y		Y		Y	
Time- Varying controls	N		N		Y	
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01					
All regressions contain robust standard errors clustered by state ID & year dummies time trend.						

Table 2.2 - A

Natural Log of GDP

Pre-trend test between sanctuary, ICE and neutral counties - Equation 4						
	Ordinary Least Squares		Fixed Effects		Fixed Effects & Time-Varying Controls	
Sanctuary County in 2007	0.0036	(0.01)	0.0034	(0.01)	0.001	(0.01)
Sanctuary County in 2008	-0.0019	(0.01)	-0.0021	(0.01)	-0.0073	(0.01)
Sanctuary County in 2009	0.0089	(0.01)	0.0073	(0.01)	0.0021	(0.01)
Sanctuary County in 2010	-0.0098	(0.01)	-0.012	(0.02)	-0.021	(0.01)
Sanctuary County in 2011	-0.023**	(0.01)	-0.027	(0.02)	-0.037**	(0.02)
Sanctuary County in 2012	-0.026**	(0.01)	-0.03	(0.02)	-0.047**	(0.02)
Sanctuary County in 2013	-0.023**	(0.01)	-0.027	(0.02)	-0.046*	(0.02)
ICE County in 2007	0.002	(0.02)	0.0028	(0.01)	0.0025	(0.01)
ICE County in 2008	0.0027	(0.02)	0.0025	(0.01)	0.0023	(0.01)
ICE County in 2009	0.0079	(0.02)	0.012	(0.02)	0.012	(0.02)
ICE County in 2010	0.0017	(0.01)	0.0025	(0.01)	-0.0025	(0.01)
ICE County in 2011	-0.0049	(0.01)	-0.0057	(0.02)	-0.011	(0.01)
ICE County in 2012	-0.015	(0.01)	-0.015	(0.02)	-0.023	(0.01)
ICE County in 2013	-0.0085	(0.01)	-0.0092	(0.02)	-0.017	(0.01)
Observations	8231		8231		8220	
Adjusted R-squared	0.204		0.28		0.317	
Pre-trend test for sanctuary counties, using late policy adopter as counterfactual – Equation 5						
SC Early adopter on year 5	-0.0052	(0.04)	0.00037	(0.01)	-0.0064	(0.01)
SC Early adopter on year 4	-0.01	(0.03)	-0.0063	(0.01)	-0.017	(0.01)
SC Early adopter on year 3	0.0038	(0.03)	0.00041	(0.02)	-0.0092	(0.02)
SC Early adopter on year 2	0.003	(0.03)	-0.00035	(0.02)	-0.01	(0.02)
SC Early adopter on yea 1	0.012	(0.03)	-0.0045	(0.03)	-0.015	(0.03)
SC Early adopter on year zero	0.0097	(0.03)	-0.0071	(0.03)	-0.016	(0.03)
Observations	1103		1103		1103	
Adjusted R-squared	0.103		0.143		0.243	
Pre-trend test for ICE counties, using late policy adopter as counterfactual – Equation 6						
ICE C. Early adopter on year 5	-0.0094	(0.03)	-0.0075	(0.01)	-0.0068	(0.01)
ICE C. Early adopter on year 4	-0.015	(0.03)	-0.012	(0.02)	-0.0022	(0.02)
ICE C. Early adopter on year 3	-0.067*	(0.04)	-0.029	(0.03)	-0.026	(0.03)
ICE C. Early adopter on year 2	-0.015	(0.03)	-0.0029	(0.03)	-0.003	(0.03)
ICE C. Early adopter on year 1	-0.012	(0.03)	-0.0034	(0.04)	-0.0071	(0.04)
ICE C. Early adopter on year zero	-0.0063	(0.02)	0.0087	(0.04)	0.014	(0.04)
Observations	728		728		725	
Adjusted R-squared	0.19		0.261		0.318	
Ordinary Least Squares (OSL)	Y		N		N	
Fixed Effects (FE)	N		Y		Y	
Time Trends (RT)	Y		Y		Y	
Time- Varying controls	N		N		Y	
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01					
All regressions contain robust standard errors clustered by state ID & year dummies time trend.						

Table 2.3 - A	Natural Log of Total Employment					
Pre-trend test between sanctuary, ICE and neutral counties - Equation 4						
	Ordinary Least Squares		Fixed Effects		Fixed Effects & Time-Varying Controls	
Sanctuary County in 2007	0.035	(0.15)	-0.0012	(0.00)	-0.00087	(0.00)
Sanctuary County in 2008	-0.012	(0.15)	-0.0032	(0.01)	-0.0043	(0.01)
Sanctuary County in 2009	-0.021	(0.15)	-0.0025	(0.01)	0.000028	(0.01)
Sanctuary County in 2010	-0.01	(0.15)	-0.0071	(0.01)	-0.0055	(0.01)
Sanctuary County in 2011	-0.052	(0.15)	-0.013	(0.01)	-0.01	(0.01)
Sanctuary County in 2012	-0.037	(0.15)	-0.01	(0.01)	-0.012	(0.01)
Sanctuary County in 2013	-0.047	(0.16)	-0.0043	(0.02)	-0.004	(0.01)
ICE County in 2007	0.025	(0.14)	0.00026	(0.00)	-0.0012	(0.00)
ICE County in 2008	0.0088	(0.17)	0.0016	(0.01)	-0.0025	(0.01)
ICE County in 2009	-0.011	(0.17)	0.0041	(0.01)	-0.0014	(0.01)
ICE County in 2010	-0.056	(0.17)	0.005	(0.01)	-0.0021	(0.01)
ICE County in 2011	-0.045	(0.17)	0.0015	(0.01)	-0.0057	(0.01)
ICE County in 2012	-0.018	(0.17)	0.0063	(0.01)	-0.0034	(0.01)
ICE County in 2013	-0.0046	(0.16)	0.0091	(0.01)	-0.0014	(0.01)
Observations	8231		8231		8220	
Adjusted R-squared	0.065		0.409		0.478	
Pre-trend test for sanctuary counties, using late policy adopter as counterfactual – Equation 5						
SC Early adopter on year 5	0.046	(0.41)	-0.0033	(0.00)	-0.005	(0.00)
SC Early adopter on year 4	-0.1	(0.43)	-0.0074	(0.01)	-0.0098	(0.01)
SC Early adopter on year 3	-0.22	(0.42)	-0.014	(0.01)	-0.015	(0.01)
SC Early adopter on year 2	-0.22	(0.42)	-0.012	(0.01)	-0.012	(0.01)
SC Early adopter on yea 1	-0.46	(0.44)	-0.0083	(0.02)	-0.0085	(0.01)
SC Early adopter on year zero	-0.57	(0.45)	-0.0079	(0.02)	-0.0078	(0.01)
Observations	1103		1103		1103	
Adjusted R-squared	0.001		0.442		0.499	
Pre-trend test for ICE counties, using late policy adopter as counterfactual – Equation 6						
ICE C. Early adopter on year 5	0.026	(0.28)	0.0014	(0.01)	0.0028	(0.00)
ICE C. Early adopter on year 4	0.011	(0.33)	0.00093	(0.01)	0.0096	(0.01)
ICE C. Early adopter on year 3	-0.02	(0.40)	0.0033	(0.01)	0.0082	(0.01)
ICE C. Early adopter on year 2	-0.29	(0.32)	0.011	(0.02)	0.011	(0.02)
ICE C. Early adopter on year 1	-0.27	(0.39)	-0.0021	(0.03)	-0.0026	(0.03)
ICE C. Early adopter on year zero	-0.13	(0.38)	0.0077	(0.03)	0.013	(0.03)
Observations	728		728		725	
Adjusted R-squared	-0.002		0.518		0.631	
Ordinary Least Squares (OSL)	Y		N		N	
Fixed Effects (FE)	N		Y		Y	
Time Trends (RT)	Y		Y		Y	
Time- Varying controls	N		N		Y	
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01					
All regressions contain robust standard errors clustered by state ID & year dummies time trend.						

Table 4-A	Natural log of Foreign-Born Population			
	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1				
Sanctuary County	-0.031	0.0013	0.00018	0.014
	(0.04)	(0.01)	(0.00)	(0.01)
ICE County	-0.041	-0.012	0.0063	0.0042
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	10147	10147	3836	3836
Adjusted R-squared	0.808	0.535	0.514	0.518
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2				
Sanctuary County	-0.032	0.0033	0.00062	0.0089
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	1846	1846	1326	1326
Adjusted R-squared	0.890	0.620	0.700	0.70
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3				
ICE County	-0.061	-0.016**	-0.019**	-0.034***
	(0.04)	(0.01)	(0.01)	(0.01)
Observations	1778	1778	1751	1751

Adjusted R-squared	**0.824**	**0.593**	**0.576**	**0.583**
Ordinary Least Squares (OLS)	**Y**	**N**	**N**	**N**
Fixed Effects (FE)	**N**	**Y**	**Y**	**Y**
Time Trends (TT)	**Y**	**Y**	**N**	**Y**
& Time Varying Covariates (TC)	**Y**	**Y**	**Y**	**Y**
Nearest-Neighbor Matching(NM)	**N**	**N**	**Y**	**Y**
Standard errors in parentheses	*** p<0.10, ** p<0.05, *** p<0.01**			

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 5 **Natural Log(GDP)**

	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					
Sanctuary County	**0.10*****	**0.014**	**0.024****	**0.100*****	**0.025***
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**
ICE County	**0.025***	**-0.013*****	**-0.0087**	**0.016**	**-0.015**
	(0.01)	**(0.00)**	**(0.01)**	**(0.02)**	**(0.02)**
Observations	**9988**	**9988**	**9988**	**3524**	**3524**
Adjusted R-squared	**0.067**	**0.267**	**0.318**	**0.135**	**0.454**
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	**0.10*****	**0.023*****	**0.041*****	**0.13*****	**0.037*****
	(0.01)	**(0.01)**	**(0.00)**	**(0.02)**	**(0.01)**
Observations	**1846**	**1846**	**1846**	**1326**	**1326**
Adjusted R-squared	**0.314**	**0.401**	**0.461**	**0.366**	**0.554**
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	**0.022**	**-0.015*****	**-0.013**	**0.021**	**-0.013***
	(0.01)	**(0.00)**	**(0.01)**	**(0.02)**	**(0.01)**
Observations	**1752**	**1752**	**1752**	**1619**	**1619**
Adjusted R-squared	**0.017**	**0.355**	**0.392**	**0.014**	**0.458**
Ordinary Least Squares (OLS)	**N**	**Y**	**N**	**N**	**N**
Fixed Effects (FE)	**Y**	**N**	**Y**	**Y**	**Y**
Time Trends (TT)	**N**	**Y**	**Y**	**N**	**Y**
& Time Varying Covariates (TC)	**Y**	**Y**	**Y**	**Y**	**Y**
Nearest-Neighbor Matching(NM)	**N**	**N**	**N**	**Y**	**Y**
Standard errors in parentheses	*** p<0.10, ** p<0.05, *** p<0.01**				

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 6-A **Natural Log (Total Employment)**

	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					
Sanctuary County	**0.083*****	**-0.099**	**0.036*****	**0.079*****	**0.020****
	(0.01)	**(0.07)**	**(0.01)**	**(0.01)**	**(0.01)**
ICE County	**0.019***	**-0.084**	**-0.0098***	**-0.060***	**-0.049****
	(0.01)	**(0.07)**	**(0.00)**	**(0.03)**	**(0.02)**
Observations	**9988**	**9988**	**9988**	**3652**	**3652**
Adjusted R-squared	**0.095**	**0.592**	**0.407**	**0.159**	**0.495**
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	**0.083*****	**-0.23*****	**0.040*****	**0.091*****	**0.036*****
	(0.01)	**(0.06)**	**(0.00)**	**(0.01)**	**(0.01)**
Observations	**1846**	**1846**	**1846**	**1326**	**1326**
Adjusted R-squared	**0.393**	**0.567**	**0.533**	**0.425**	**0.617**
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	**0.016**	**-0.12***	**-0.017*****	**0.018**	**-0.019*****

	(0.01)	(0.06)	(0.01)	(0.01)	(0.01)
Observations	1752	1752	1752	1619	1619
Adjusted R-squared	0.024	0.585	0.518	0.032	0.582
Ordinary Least Squares (OLS)	N	Y	N	N	N
Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 6.1-A Natural log of Labor Force Unemployment

	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					
Sanctuary County	-0.14**	-0.067**	-0.089	-0.13**	-0.14*
	(0.07)	(0.03)	(0.06)	(0.06)	(0.07)
ICE County	-0.015	0.0027	-0.011	-0.027	-0.039
	(0.02)	(0.02)	(0.02)	(0.08)	(0.07)
Observations	10084	10084	10084	3581	3581
Adjusted R-squared	0.056	0.160	0.065	0.079	0.089
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	-0.13*	-0.25***	-0.037	-0.13**	-0.037
	(0.07)	(0.08)	(0.03)	(0.05)	(0.03)
Observations	1841	1841	1841	1271	1841
Adjusted R-squared	0.034	0.474	0.057	0.050	0.057
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	-0.0044	-0.083	-0.024	-0.021	-0.024
	(0.02)	(0.07)	(0.02)	(0.03)	(0.02)
Observations	1773	1773	1773	2569	1773
Adjusted R-squared	0.006	0.455	0.025	0.008	0.025
Ordinary Least Squares (OLS)	N	Y	N	N	N
Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 6.2-A 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	-0.093	-0.095*	-0.089*	-0.060	-0.087
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
ICE County	0.0019	-0.013	-0.0084	-0.064**	0.00091
	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
Observations	9405	9405	10086	4774	3611
Adjusted R-squared	0.047	0.052	0.051	0.065	0.081
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	-0.14**	-0.15**	-0.13*	-0.076	-0.15*
	(0.06)	(0.07)	(0.06)	(0.05)	(0.08)
Observations	1800	1800	1841	882	1308
Adjusted R-squared	0.058	0.071	0.057	0.064	0.074
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	-0.0091	-0.027	-0.016	-0.058	0.00082
	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)
Observations	1684	1684	1767	983	803

Adjusted R-squared	0.040	0.044	0.043	0.097	0.102
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

All regressions use fixed Effects & Time Varying Covariates. All contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 7-A 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	0.036*	0.026***	0.0095	0.026***	0.019*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
ICE County	0.016	0.0070	-0.0042	-0.0041	-0.0024
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	10090	10090	10090	10090	10090
Adjusted R-squared	0.053	0.092	0.088	0.121	0.093
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					
Sanctuary County	0.021	0.021*	0.0037	0.022***	0.024**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1846	1846	1846	1846	1846
Adjusted R-squared	0.118	0.119	0.102	0.145	0.160
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					
ICE County	0.011	0.0038	-0.0043	-0.0092	-0.0039
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1767	1767	1767	1767	1767
Adjusted R-squared	0.061	0.111	0.099	0.164	0.128
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

All regressions use fixed Effects, time trends & Time Varying Covariates. All contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 7.1 - A Natural log of Per Capita Income using Urban and Rural counties

	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					**Urban**
Sanctuary County	0.043*	0.040**	0.021	0.045*	0.0083
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
ICE County	0.0053	0.063**	0.0069	0.0089	-0.00043
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Observations	1468	1468	1468	854	854
Adjusted R-squared	0.411	0.774	0.423	0.451	0.483
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					**Rural**
Sanctuary County	0.049*	0.039**	0.048*	0.036*	0.030*
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
ICE County	-0.022	0.0015	0.0073	-0.0074	0.00052
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	8681	8681	8622	8622	8622
Adjusted R-squared	0.098	0.048	0.234	0.428	0.253
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					**Urban**
Sanctuary County	0.054*	0.025	0.0057	0.061**	-0.0093
	(0.03)	(0.05)	(0.01)	(0.02)	(0.02)
Observations	472	472	472	316	316
Adjusted R-squared	0.457	0.372	0.513	0.472	0.583
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					**Rural**
Sanctuary County	0.043*	0.030	0.018*	0.035	0.016
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Observations	1374	1374	1374	932	932

Adjusted R-squared	0.360	0.599	0.375	0.335	0.358
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					Urban
ICE County	0.0059	0.0099	0.0023	0.0040	0.0038
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
Observations	301	301	301	250	250
Adjusted R-squared	0.443	0.554	0.445	0.555	0.605
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					Rural
ICE County	0.0052	-0.0086	-0.0033	0.0047	0.0011
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Observations	1466	1466	1466	1736	1736
Adjusted R-squared	0.288	0.446	0.313	0.344	0.371
Ordinary Least Squares (OLS)	N	Y	N	N	N
Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y

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

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 7.2-A Natural log of GDP using Urban and Rural counties

	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					Urban
Sanctuary County	0.12***	0.016	0.036**	0.12***	0.037**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
ICE County	0.059***	0.0010	0.0073	0.043*	0.0046
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	1429	1429	1429	771	771
Adjusted R-squared	0.197	0.484	0.548	0.281	0.554
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					Rural
Sanctuary County	0.091***	0.0099	0.018	0.092***	0.023
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
ICE County	0.018	-0.016***	-0.012	-0.0035	-0.012
	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)
Observations	8559	8559	8559	2529	2529
Adjusted R-squared	0.065	0.250	0.293	0.105	0.439
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					Urban
Sanctuary County	0.12***	0.016**	0.032***	0.093**	0.020
	(0.02)	(0.01)	(0.01)	(0.04)	(0.01)
Observations	472	472	472	316	316
Adjusted R-squared	0.343	0.498	0.553	0.265	0.650
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					Rural
Sanctuary County	0.090***	0.025***	0.041***	0.093***	0.028***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	1374	1374	1374	932	932
Adjusted R-squared	0.320	0.411	0.477	0.368	0.598
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					Urban
ICE County	0.062**	-0.011	-0.0049	0.027	-0.0072
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Observations	249	249	249	161	161
Adjusted R-squared	0.160	0.656	0.659	0.326	0.772
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					Rural
ICE County	0.016	-0.017***	-0.014	0.00041	-0.023
	(0.02)	(0.00)	(0.01)	(0.02)	(0.01)
Observations	1464	1464	1464	1442	1442
Adjusted R-squared	0.022	0.330	0.363	0.033	0.414
Ordinary Least Squares (OLS)	N	Y	N	N	N

Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 7.3-A Natural log of Total Employment using Urban and Rural counties

	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					**Urban**
Sanctuary County	0.11***	0.090	0.044***	0.11***	0.040***
	(0.01)	(0.12)	(0.01)	(0.01)	(0.01)
ICE County	0.056***	0.12	0.0058	0.040*	-0.0031
	(0.01)	(0.17)	(0.01)	(0.02)	(0.00)
Observations	1429	1429	1429	849	849
Adjusted R-squared	0.239	0.344	0.664	0.316	0.737
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					**Rural**
Sanctuary County	0.071***	-0.16**	0.026***	0.073***	0.017
	(0.01)	(0.06)	(0.01)	(0.01)	(0.01)
ICE County	0.012	-0.074	-0.013**	-0.030*	-0.038**
	(0.01)	(0.07)	(0.01)	(0.02)	(0.02)
Observations	8559	8559	8559	2321	2321
Adjusted R-squared	0.119	0.563	0.387	0.115	0.508
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					**Urban**
Sanctuary County	0.11***	0.014	0.038***	0.065***	0.016
	(0.02)	(0.09)	(0.01)	(0.02)	(0.01)
Observations	472	472	472	316	316
Adjusted R-squared	0.501	0.519	0.738	0.434	0.752
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					**Rural**
Sanctuary County	0.071***	-0.21***	0.040***	0.076***	0.038***
	(0.01)	(0.07)	(0.00)	(0.01)	(0.01)
Observations	1374	1374	1374	932	932
Adjusted R-squared	0.401	0.534	0.492	0.449	0.616
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					**Urban**
ICE County	0.0061	0.031	0.0008	0.0039	0.0086
	-0.01	-0.02	-0.01	-0.01	-0.01
Observations	301	301	301	248	248
Adjusted R-squared	0.447	0.676	0.454	0.444	0.45
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					**Rural**
ICE County	0.0055	-0.0096	-0.0024	0.017***	0.012**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1477	1477	1477	1442	1442
Adjusted R-squared	0.304	0.627	0.320	0.343	0.365
Ordinary Least Squares (OLS)	N	Y	N	N	N
Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

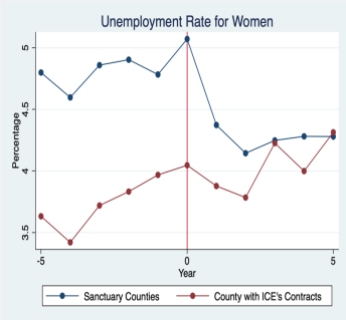
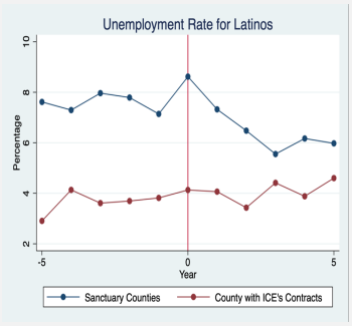
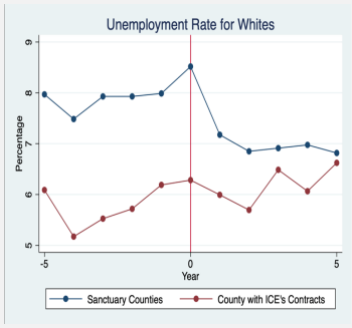
All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Table 7.4-A **Natural Log of the labor force unemployment Urban and Rural counties**

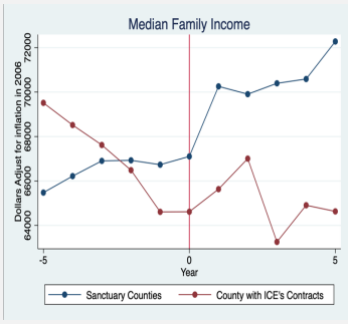
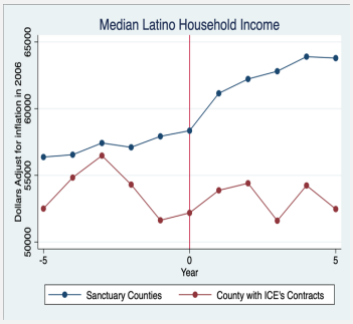
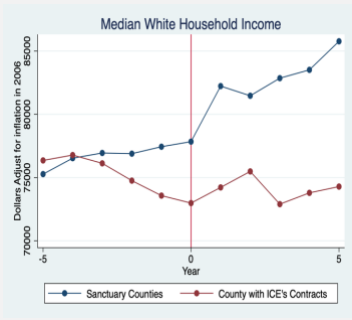
	Fixed Effects & Time Varying Covariates	Ordinary Least Squares, Time Trends & Time Varying Covariates	Fixed Effects, Time Trends & Time Varying Covariates	Fixed Effects, & Time Varying Covariates & Matching	Fixed Effects, Time Trends, & Time Varying Covariates & Matching
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					**Urban**
Sanctuary County	-0.11*	-0.10	-0.11*	-0.12	-0.046
	(0.06)	(0.08)	(0.06)	(0.07)	(0.07)
ICE County	0.038	0.11	0.017	0.066	0.073
	(0.05)	(0.07)	(0.05)	(0.09)	(0.09)
Observations	1468	1468	1468	790	790
Adjusted R-squared	0.108	0.093	0.116	0.093	0.121
Treatment Effect between sanctuary, ICE and neutral counties - Equation 1					**Rural**
Sanctuary County	-0.15**	-0.096***	-0.11	-0.15**	-0.14*
	(0.07)	(0.03)	(0.07)	(0.07)	(0.07)
ICE County	-0.032*	-0.00051	-0.021	-0.040	-0.046
	(0.02)	(0.02)	(0.02)	(0.05)	(0.06)
Observations	8564	8564	8564	2371	2371
Adjusted R-squared	0.057	0.119	0.065	0.058	0.066
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					**Urban**
Sanctuary County	-0.11	-0.019	-0.025	-0.067	0.065
	(0.07)	(0.05)	(0.05)	(0.07)	(0.07)
Observations	472	472	472	316	316
Adjusted R-squared	0.108	0.177	0.112	0.071	0.126
Treatment Effect for sanctuary counties, using late policy adopter as counterfactual – Equation 2					**Rural**
Sanctuary County	-0.12	-0.21***	-0.048	-0.12*	-0.048
	(0.07)	(0.07)	(0.05)	(0.06)	(0.05)
Observations	1369	1369	1369	1021	1369
Adjusted R-squared	0.040	0.451	0.057	0.028	0.057
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					**Urban**
ICE County	0.028	0.30	0.055	-0.0067	0.055
	(0.06)	(0.21)	(0.06)	(0.09)	(0.06)
Observations	301	301	301	639	301
Adjusted R-squared	0.077	0.429	0.112	0.056	0.112
Treatment Effect for ICE counties, using late policy adopter as counterfactual – Equation 3					**Rural**
ICE County	-0.033	-0.059	-0.038	-0.035	-0.038
	(0.02)	(0.06)	(0.02)	(0.03)	(0.02)
Observations	1460	1460	1460	2108	1460
Adjusted R-squared	0.010	0.462	0.028	0.020	0.028
Ordinary Least Squares (OLS)	N	Y	N	N	N
Fixed Effects (FE)	Y	N	Y	Y	Y
Time Trends (TT)	N	Y	Y	N	Y
& Time Varying Covariates (TC)	Y	Y	Y	Y	Y
Nearest-Neighbor Matching(NM)	N	N	N	Y	Y
Standard errors in parentheses	* p<0.10, ** p<0.05, *** p<0.01				

All regressions contain robust standard errors clustered by state ID & year dummies time trend. Nearest – neighbor matching in base on counties' economic attributes, education index, family income and Regional ID

Figures 5-A **Unemployment Rate**

Women	Latino	White
		

Median Household Income

Median Family	Latino	White
		

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