Writing Sample - Excerpts from MA Thesis*

Moving To Inclusion: The Migration Effects of Sanctuary City Policies

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1 Introduction

Immigration has long been a heated topic in US politics, but sanctuary city policies have especially been in the hot seat since 2014, starting with Donald Trump's presidential campaign. However, the elusive nature of data on undocumented immigration and the complexity of sub-national policies have made these studies of immigration policies' effects difficult. In this paper, I extend the typical residential segregation model used in other contexts to study the migration effect of sanctuary city policies in three steps. First, I apply a Probit model to estimate the effect of sanctuary city policies on individual migration decisions. Then, I take individual cities as agents and model their choices of becoming or staying sanctuary within a discrete choice framework. Lastly, I look at the dynamic effect of sanctuary city policies using fixed-effect models with and without matching as an event history analysis.

1.2 Sub-National Immigration Laws

Because of the complexity of immigration enforcement, the Department of Homeland Security [DHS] has historically relied on local-level law enforcement through laws like *287(g)*, *Secure Communities*, etc. These laws generally require local law enforcement to report, arrest, or further detain undocumented immigrants. After 2011, DHS changed the compliance to this cooperation from optional to mandatory. Backlashes and non-cooperation followed these changes by some local authorities. The media then refered to these non-cooperative local authorities as sanctuary cities. This non-cooperative nature also means that sanctuary city policies are not necessarily announced by the city. In fact, many cities became sanctuary because the county sheriff announces that they will not hold any individuals solely for immigration purposes. However, when the city, including such sanctuary counties, does not disagree with these decisions, these cities become de facto sanctuary and are considered sanctuary by ICE.

1.3 Immigration Enforcement

The federal-level immigration enforcement is administered by two agencies: *Customs and Border Protection* [CBP] and *Immigration and Customs Enforcement* [ICE][1]. ICE handles immigration enforcement within the country and outside of the 100-mile border zone. The typical

*This sample only has select paragraphs from my thesis. Click here for full paper

[1]See full paper for description of DHS enforcement

immigration raids reported by the media are conducted by ICE and sometimes in cooperation with local law enforcement. Under *287(g)* and *Secure Communities*, non-sanctuary law enforcement would notify ICE if an arrested individual is an undocumented immigrant.

Contrary to standard rhetoric, the unlawful presence of an immigrant in the United States is not criminal unless the individual was previously removed from the country and then returned without permission (ACLU). This distinction means that most immigration proceedings are held in civil courts and not criminal courts; hence undocumented immigrants are not entitled to a public defense attorney in most cases. The flip side of this non-criminal nature is that if the local authorities do not criminalize immigration offenses, they could restrict local law enforcement's ability to cooperate with ICE, thus enabling the most common form of sanctuary city policies.

2 Background: Sanctuary City Policies

Although there is no concrete legal definition, sanctuary city policies, in general, are policies that protect non-criminal undocumented immigrants. These policies can be regulations such as requiring local law enforcement not to honor an ICE detainer request, requiring local law enforcement to not take enforcement actions solely based on an individual's immigration status, or refusing to inform ICE the detention of undocumented individuals. In 2014, California and Connecticut enacted their own *Trust Acts* and became the only two states with state-level sanctuary policy. Within these two states, there were still city-level sanctuary policies, and there were also counties that refuse to follow the state-level sanctuary policy.

3 Diversity, Migration, and Immigration Politics

Currently, there are few quantitative studies about sanctuary city policies. Wang (2017) looked at the effect of sanctuary city policy and found an increase in labor force participation and median household income and a decrease in crime, poverty, and unemployment. We can infer some information from *Moving To Opportunity* [MTO] and work on the Schelling (1969; 1971) framework such as Caetano & Maheshri (2017). From MTO, we know that migration decisions can be highly restricted by poverty (Aliprantis 2014; Bergman et al. 2020), which could suppress the revelation of preferences. Within the Schelling framework, I assume that different racial groups have preferences for different social and private amenities such as schooling, housing, diversity, opportunities, etc. This information enables us to more generally form a hypothesis on what contributes to migration decisions and how to correctly estimate the effect of sanctuary city policy on migration decisions.

Given the complicated immigration-law enforcement structure, the effect of Sanctuary city policies needs to be thought of on three fronts: (1) Direct effects, (2) Indirect effects, and (3) Dynamic effects. Direct effects can be observed immediately as people react to the ideological stance through migration and voting. Indirect effects can be observed through the changes in other city characteristics and how those characteristics affect migration. Dynamic effects can be observed at both the individual-level and the city-level. The individual-level dynamic effect changes how sanctuary cities are valued based on the scarcity of sanctuary cities. The city-level dynamic effect combines all the effects described above and can only be observed as a net effect. To examine these effects using the above framework, I need to explore several possible channels of influence on migration decisions.

3.1 Private Amenities

Private amenities include amenities such as income, opportunities, education, housing, consumption, etc. In terms of the labor market, Albert (2017) showed that undocumented immigrants are in a separate labor market from the labor market of documented immigrants and the natives. Hence sanctuary city policies can only affect one's expectations of job prospects and not their actual job prospects with undocumented immigrants in the labor market. They further pointed out that documented immigrants diminish the job prospects of natives. Therefore, sanctuary city policies will have complicated effects on the job market for natives depending on how it attracts or deters documented immigrants.

In terms of education, people who move between cities just for education are almost negligible; otherwise, residential sorting for high-quality education would be observed at the city-level, and not by school districts. In terms of housing, the cost of renting or owning takes up part of one's income and leaves the rest for consumption. This implies an implicit substitution in housing and consumption that, on a large scale, could be captured in income.

3.2 Social Amenities

Social amenities per Caetano & Maheshri (2017) are aggregated characteristics in a place. In the case of sanctuary city policies, the social amenities presumed to matter for people's migration decisions are the wealth, employment opportunities, diversity, and ideological leaning of a city. How groups of people value these social amenities are also presumed to be different. For example, documented immigrants can prefer not to live in a sanctuary city due to toxic ties (Del Real 2019) and the belief of increased immigration policing from ICE (New York Times 2020). On the other hand, the ideological meaning of sanctuary city policies can be attractive

to both documented and undocumented immigrants.

4 Data

I used data from the American Community Survey [ACS] data provided by Integrated Public Use Microdata Series [IPUMS] for the population and economic measure. An important note is that while ACS is surveyed mostly by self-reporting, it has over 2 million samples yearly, providing a more accurate picture of the national population than the Current Population Survey [CPS]. I also collected data from the Department of Homeland Security Immigration and Customs Enforcement [DHS ICE] regarding sanctuary city status in 2017 and immigration removal from 2000-2018. To utilize the political leaning of cities, I gathered county-level 2000-2016 presidential election data from the MIT Election Data and Science Lab. Since presidential elections are four years apart, I impute voting data of non-election year to be the same as the nearest year of election. The overlapping year is imputed to be the mean of the two elections.

5 The 3-step estimation

5.1 Step 1: Individual Migration Decisions (Methodology)

Following Caetano & Maheshri (2017), I separate the contributing factors of migration decisions into three parts: private amenities, social amenities, and unmeasurable amenities. Private amenities include housing quality, schooling [teacher] quality, cost of living, etc. Since identifying some of these factors in a hedonic model would require rich administrative data, I assume these preferences are fixed and monotonic. Social amenities are emergence that is only measurable at a group level, such as diversity and political ideology in an area. An example of an unmeasurable amenity is an emotional value attached to a place that could induce a strong preference over the value of the other two amenities in either direction.

If one chooses to migrate from city c to c', it must be that the expected utility of moving is higher than the expected utility of staying. Thus I can estimate the probability of the migration decision using a hedonic utility form that is rather agnostic. Formally, let $S_{i,c}$ be the vector of social amenities, Ψ be the price vector associated with the vector of private amenities $X_{i,c}$, and $U_{i,c}$ be the random variable representing the idiosyncratic unmeasurable amenity, I can estimate the probability of choosing to migrate in a two-period model using information only from period-1:

$$Pr\{\beta S_{i,c'} + \Psi X_{i,c'} - U_{i,c'} > \beta S_{i,c} + \Psi X_{i,c} + U_{i,c}\} \tag{1}$$

where i represents individuals, c and c' represent the origin city and destination city, respectively. I can thus estimate the amenities that make one marginally more likely to migrate and observe the role sanctuary city policies play in individuals' migration decisions. To do that, I think of sanctuary city policies as an element in $S_{i,c}$ and rewrite the probability of moving as:

$$Pr\{\beta_{Sanctuary}(Sanctuary_{c'} - Sanctuary_c) + \beta(S_{i,c'} - S_{i,c}) + \Psi(X_{i,c'} - X_{i,c}) > (U_{i,c} - U_{i,c'})\} \quad (2)$$

Note that an implicit assumption in this two-period model is that private consumption and savings are both included in $X_{i,c}$, meaning that a better job or job opportunity is accounted for in this model. In addition, agents make migration decision based on period-1 information from both cities as well as what they can foresee for themselves in period-2. To estimate this probability, I assume that the unmeasurable amenities $U_{i,c}$ is distributed normally, hence the difference between the unmeasurable is distributed normally with: $(U_{i,c} - U_{i,c'}) \sim N(\mu, \sigma^2)$. With the assumed distribution of the RHS of equation (2), I can estimate this general probability with the Probit model.

Since sanctuary city policy is an immigration-related policy, it is intuitive to assume that the diversity of a city should be included in the measurable social amenities $S_{i,c}$. Traditionally, economic literature has used dissimilarity index [DI], a composite measure using only binary information[2], to measure the segregation of a city. However, DI cannot show a complete picture in this case due to race being more than just binary. In this paper, I propose and use a new measure of diversity called **Diversity Score [DS]**. DS is calculated as:[3]

$$DS_{city} = 100 \times (1 - \sum_{race} (\frac{Population_{race,city}}{Population_{city}})^2) \quad (3)$$

There are a couple of advantages of using DS as a measure of diversity. First of all, DS is a continuous measure between 0 and 100, where the magnitude of the measure is comparable across groups with different compositions. When a city has 100% one race, the DS of the city is 0. If a city has two races, with a 99:1 ratio, the DS of the city is 2. If a city has two races, with a 1:1 ratio, the DS of the city is 50. If a city has three races distributed equally, then the DS of the city is 67.7. This means that both the addition of a new race and of new people in a minority race will increase the diversity of a place. In addition, the extreme values of diversity are comparable under this measure.

In addition to sanctuary city policies and diversity, I include the following factors for social

[2]Example of DI for income segregation: $DI = \frac{1}{2} \sum_{n=1}^{N} \mid \frac{\#LowIncome_n}{\sum_{n=1}^{N} \#LowIncome_n} - \frac{\#NotLowIncome_n}{\sum_{n=1}^{N} \#NotLowIncome_n} \mid$

[3]I want to thank Professor Kevin Murphy of the University of Chicago; for this measure is a modified version of a measured we used in Price Theory I to measure political monopoly.

and private amenities:

1. Social Amenities (period-1 city amenities): City %Non-citizens, City Population, City Median Household Income, City Unemployment rate, and City Median Cost of Housing.

2. Private Amenities (period-2 personal private amenities): Unemployment, Education Attainment, Wealth, Household Income, Costs of Housing, Age, and Sex.

To conduct the individual-level analysis, I need to be conscious of the value of sanctuary city policies to the marginal mover. The first sanctuary city policy was enacted in 2008, and the next landmark year of sanctuary city policies is 2013, where the policy received more attention as a result of the DACA discussion. Hence, I split up the individual stage of estimation into two eras: 2008-2012 and 2013-2018. This choice of the eras is also partially due to the introduction of sanctuary states in 2014 by California and Connecticut.

5.2 Step 1: Individual Migration Decisions (Results)

5.2.3 Overall Individual-level effect

Overall, we see that individuals reflect their preferences over sanctuary city policies through migration decisions. The direct effect, as described in section 3, is that people on the margins are induced to move to their preferred type of sanctuary status. We learned that individuals with higher income and own housing are less likely to move, but income has no effect on one's preference of sanctuary status. Also, individuals of higher education attainment are more likely to move, to move to sanctuary, and to move across sanctuary types. We also see that the marginal movers are different in nature between the two eras. Movers from the first era exhibit preferences through being induced to move while movers in the second era exhibit preferences while moving.

For the indirect and dynamic effects, we can expect sanctuary cities to become younger and more educated, which can imply future economic productivity. We would also expect the population growth of sanctuary cities to be slightly higher over time as more people choose to move in than to move out, and higher population attracts more to move in. Also, we know that employment in period-2 has a significant effect on moving though %non-Citizen, a proxy of job competition per Albert (2017), induces one to stay. Hence we could expect decreased unemployment and slightly decreased population since lower unemployment rate seems to be an attractive factor for migration.

5.3 Step 2: Choosing to be sanctuary (Methodology)

In this step, I view each city as an agent who, at each year, chooses to either be sanctuary or otherwise. This allows for a discrete choice framework where cities make these policy decisions based on their anticipated political, economic, and population effects. The discrete choice framework here follows the last section but with different control variables that are informed by theory.

Like equation (1), this general probability can be written as:

$$Pr\{\Omega_{sanc}X_{c,1} + U_{c,1,sanc} > \Omega_{non-sanc}X_{c,1} + U_{c,1,non-sanc}\} \tag{4}$$

where c represents the city, 1 represents period-1, the subscripts $_{sanc}$ represents the sanctuary status of a city, $\Omega_{sanc/non-sanc}$ represents the transformation vector mapping the characteristics to cities' utility for a policy decision.

The vector X should include characteristics linked to the first-step [section 5.2], presidential voting outcomes that better captures ideological leaning, and sanctuary states. In this step, I included Log(Median Household Income), %Moved from within US, Median Age of the city, % Population with less than high school education, Diversity Score, % Hispanic, Cost of owning housing as a percent of income. Since the majority of sanctuary cities are democrat-majority, I control for political leaning using % voted for Democratic president in the nearest election, and the change in % voted for Democratic president in the nearest election compared to 4 years ago.

I also created **Democratic Leaning [DL]** as a measure between -1 and 1 that is positive if the majority of voters voted for a Democratic president and negative if the majority voted for a Republican president. The magnitude of this measure is the proportion that voted for the majority party's candidate. For example, a very moderate city that voted for 45% democrat and 40% republican would have a DL of 0.45. And a very moderate city that voted for 40% democrat and 45% republican would have a DL of -0.45. In some estimations, I replaced the *% of Democratic votes* with *DL* and the *change in %* with the *change in DL*. DL is supposed to be a sanity check for just controlling for democratic votes.

With this model, I should be able to stay rather agnostic but also efficient in choosing characteristics for estimation. However, without failure, cities that chose to become sanctuary never became non-sanctuary. Hence, to ensure robustness, I estimate this two-period hedonic model with four different sub-samples and interpret the results collectively. The sub-samples include (1) Full sample (2) Sample of cities that are not sanctuary in period-1 [excluding cities that are already sanctuary] (3) Samples that all eventually become sanctuary and (4) Cities with over 1,000,000 population in 2010.

Another reason to use an agnostic hedonic model rather than a structural model in this step is that it is tricky to determine the mechanisms/information set that agents [cities] use to make the decision on sanctuary city policy. One possible mechanism is that cites make the decisions based on the expected gains informed by other already-sanctuary cities. Another possible mechanism is that certain levels in a unique combination of factors induce sanctuary city policy. In addition, these mechanisms can be intertwined and hence difficult to parse out.

In each scenario, the hedonic model described above can help us understand the underlying mechanisms. Moreover, my estimation results from the individual-level give insights on the population cities can expect to attract with the policy. For example, individuals with higher levels of education are more likely to move to a sanctuary city; a city can thus anticipate that and choose to become sanctuary to attract highly educated people and potential high-income earners.

5.4 Step 2: Choosing to be sanctuary (Results)

Results from the Probit estimations are posted in Tables 6, 7, 8, and 9 in the order of the sub-samples listed above. Across the four Tables, two consistently significant predictors of choosing to be sanctuary for cities outside of CA and CT are the % of Democratic votes and the change in DL. The similarly positive coefficients between % Democratic votes and DL are intuitive while the negative coefficient for Δ DL is not. Considering the coefficient of Δ % Democratic Votes are small and insignificant, the negative coefficient of Δ DL should be interpreted as the effect of a decrease in non-Democratic votes in Republican cities over the past four years. From the individual-level estimation, we know that individuals present strong preferences over sanctuary status. In other words, decreasingly less Republican cities are less likely to enact sanctuary city policies in order to attract more non-democratic voters. The dual of this is that if a city was attracting and preserving its democratic base without the policy, they did not have the political need for sanctuary city policies.

Outside of political leaning influences, the factors that I believed would be significant turned out to be significant as well. As discussed in section 5.2, cities that are less wealthy, have fewer in-migration, and less educated are more likely to become sanctuary to attract highly-educated in-migration as those are trade-offs individuals are willing to make for living in a sanctuary city. We also see that cities inside CA and CT with higher % Hispanic population are more likely to become sanctuary. As discussed in section 5.2, the diversity of a city can be seen as a trade-off for marginal movers. Hence, even if cities with higher diversity could be more likely to become sanctuary, cities with higher diversity would also have less need to become sanctuary for growth. This contradiction can then plausibly lead to our results that the Diversity Score of

a city does not seem to have much effect regardless of states.

5.5 Step 3: Dynamic Effects (Methodology)

In this final step, I conduct an event history analysis on sanctuary city policies. I utilize a city-year fixed-effect model on the panel of cities to tease out the dynamic effect on population growth, in-migration, and diversity. The fixed effect model is estimated as the following:

$$\begin{aligned} Y_{c,t+1} = \beta_{sanc}\{[&\text{Becoming sanctuary Year}_{c,t} + \text{First full sanctuary year}_{c,t} \\ &+ 1^{+} \text{ Sanctuary Year}_{c,t}] \times \mathbb{1}\{\text{CA or CT}_c\}\} \\ &+ \gamma X_{c,t} + \alpha_c + \theta_t + u_{c,t} \end{aligned} \tag{5}$$

where β_{sanc} is a vector with estimates of the short- and long- term effects of sanctuary city policies inside and outside of CA and CT on next-year outcome Y. $X_{c,t}$ is a vector of controls that include income, diversity, unemployment rate, $\%$ owned housing, poverty rate with city-year fixed-effects. In addition to the straight forward fixed effects, I conduct fixed-effect estimation using sub-samples of: (1) Cities that eventually become sanctuary (2) Top 30 largest sanctuary and non-sanctuary cities[4], and (3) Cities matched using **income, population size, and diversity score** in 2005 and 2006 since the first sanctuary policy was enacted in 2008. Also, I made similar estimations at the CPUMA level with both city-level and CPUMA level fixed-effects over the samples listed above.

The outcomes of interests are (1) Population growth, (2) Diversity, and (3) In-migration. I separated population growth into non-Hispanic and Hispanic population growth and captured them using the first difference in Log(Population) between years t+1 and t. For Diversity Score and In-migration, the outcomes are future [t+1] Diversity Score and In-migration, captured by % Moved from within US.

5.6 Step 3: Dynamic Effects (Results)

In Table 10, we see that sanctuary city policies have a positive effect on non-Hispanic population growth in the full sample but have little to null effect on Hispanic population growth in cities outside of CA and CT. Both effects are negative but small and insignificant in cities in CA and CT. Moreover, sanctuary city policies seem to have a positive and significant effect on city diversity and long-term in-migration in cities outside of CA and CT. However, the effects are in the opposite direction for cities inside CA and CT, with the effects on Diversity being between negative and inconclusive. Notably, the negative effects on in-migration in cities in CA and CT

[4]There are 30 total sanctuary cities by 2017

are both short- and long-term. On average, after a city in CA or CT becomes sanctuary, its in-migration decreased by around 1.5 to 2.5 percentage points.

Combining the results from in-migration and growth, one possible interpretation is that for sanctuary cities in CA and CT, fewer people are moving in, but fewer people are moving out, leading to no significant difference in population growth. For cities outside of CA and CT, the small increase in growth is only short-term, while the increase in in-migration is long-term. This is likely due to the self-sorting of people into and out of sanctuary cities at different times with different value-added to the sanctuary status.

6 Concluding Remarks

Sanctuary city policies will continue to be a heated topic for political discussions in the US for the foreseeable future. Yet, at the time of writing this paper [2020], both presidential candidates have supplied minimal empirical evidence for their position on immigration policies. This paper provides analyses and evidence that the immigration issue is as political as any other issue, and the effect of immigration laws extends beyond race and ethnicity. I conclude that people in the US show a strong preference for sanctuary city policies. At its start, individuals' preferences for sanctuary statuses are strong enough to induce inter-city migration. After many cities became sanctuary, the preferences exhibited not through induced migration but through the preference of cities' statuses upon migration. I also showed that sanctuary statuses are a type of social amenities for which individuals can make trade-offs in amenities like diversity, job opportunities, cities' income levels, etc.

In the hedonic model of cities' choices, I discovered that cities lacking in the trade-offs found in the individual step are more likely to become sanctuary. This potentially simplifies the framework for future research on local policy decisions and provides a way to model city decisions not through aggregating individual decisions but through an agent-based framework. The differences between cities in CA and CT and cities outside of CA and CT imply that policy studies need to be cautious about localized differences at the policy-city level. If the estimations in this paper were done without separating CA and CT, the effects would likely be canceled out and show very little of the true effect.

One element this paper lacks is the effect of the policy on crime and how crime affects migration. While exploring this aspect, I realized that the only way to properly do so is through the proprietary data set National Crime Victimization Survey. Future researchers should look into incorporating that data, instead of crime reporting, and go through these three steps of analysis to have an encompassing study of sanctuary city policies.