State Immigration Policy: Beyond Population Growth*

Robert Nathenson
Department of Sociology
Johns Hopkins University
rnathenson@jhu.edu

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Extended Abstract

Background

In recent decades the immigrant population in the United States has continued to increase, reaching 38.5 million individuals in 2009, or 12.5% of the entire U.S. population, the highest percentage in nearly a century (MPI 2010). This increase is a pervasive trend across the nation, not limited to certain parts of the United States. This diffusion created a large number of new immigrant communities, changing the national dynamics of which states are considered immigrant- receivers and which are not (Portes & Rumabut 2006).

The Federal Government dictates the legal status of these immigrants as they enter the United States. While this authority is unquestioned, it is, however, uncertain as to where federal authority regulating immigrants' lives ends. In the absence of clear federal guidelines, states have exercised authority over much of immigrants' daily lives. As a point of fact, 200 immigrant related bills were passed and over 1,000 proposed in both 2007 and 2008 (NCSL 2007; 2008).

These state-based immigration laws have garnered a large amount of media attention in recent years. On September 18th an Arizona-based U.S. district court judge lifted the injunction on the component of Arizona's controversial immigration law, SB1070, that allows police authorities to check legality of residence when stopping an individual for a separate independent reason, commonly referred to as the "show me your papers" clause. Other laws have been just as contentious. For instance, Alabama's HB56 is often considered the most anti-immigrant law in the nation. However, numerous states have taken the opposite tact, passing pro-immigration laws. Maryland, Texas, California, New York, and Illinois, amongst others, have each passed their own version of the Dream Act, a law that encourages undocumented children to finish high school and attend college at in-state-tuition rates (NCSL 2011).

Research Questions

Why do some states pass anti-immigration laws while others pass pro-immigration laws? Can the increase of the foreign-born within a state explain a state's passage of immigration laws? What if the laws are decomposed into pro- and anti-immigrant? How do a state's cultural, historical, and political landscapes affect this relationship? This research examines the mechanisms behind the passing of a state's quantity and typology of immigrant-related legislation.

This paper is part of a broader research agenda that examines how place of destination matters for immigrants, specifically the educational and socio-emotional outcomes of immigrant children. While this paper seeks to explain the mechanisms behind state-based immigration policy, related research will examine the effect of pro- and anti-immigrant legislation upon child developmental outcomes.

Theory

The Modes of Incorporation framework emphasizes the key institutional and contextual factors within an environment that shape immigrant incorporation (Portes &

Rumbaut 1990). Specifically, the policies of the host government, the reception of the labor market, and the characteristics of the co-ethnic community, are all key components of the environmental context, shaping the structures and interactions of immigrants on a daily basis. While the labor market and co-ethnic community are allowed to vary across states, the policies of the host government are generally attributed to the federal level. The federal government may treat each distinct immigrant group in a different manner, e.g. Iraqi refugees and Mexican immigrants.

However, a federal level analysis of immigrant policy overlooks the variability between states. As discussed, states vary tremendously in their immigration policy. To elaborate, the state, not the federal government, regulates much of an immigrant's daily life. For example, the state decided how to implement the 1996 welfare reform act (PRWORA; Cho 2010). Further, the state decides which benefits undocumented immigrants are entitled to, such as public assistance for unemployment, aid to mothers, healthcare, and right to in-state tuition in postsecondary schooling. The state also exercises great authority over identification laws, controlling the difficulty of obtaining identification, e.g. a driver's license, and the ease in which immigrants may be stopped and asked for such identification. Harsh enough policy may even drive immigrant families out of the state, seeking a less hostile environment elsewhere. It is critical to acknowledge the impact of state-based immigration policy on the day-to-day lives of immigrant parents and children alike. I therefore expand upon the modes of incorporation framework by modeling governmental policy at the state level.

Hypotheses

This paper will examine the mechanisms behind state-based immigrant legislation. First, it explores the effect of a state's percent immigrant growth on its immigrant legislation. It does so in order to assess if there is a clear relationship across all fifty states – that as a state's percent immigrant rises so too do the number and intensity of anti-immigrant (or all immigrant-related) legislation. I expect to find that this relationship does not hold. The motivation behind immigrant-legislation is more complex than a linear trend tied to immigrant growth (H1). Indeed, there are other key factors that must be accounted for. Both a state's historical past and previous reception of immigrants or minorities groups should be included. Specifically, a state with an overtly racist past, such as being a slave state, having race riots, or a history of anti-Civil Rights Movement action, will be more likely to pass anti-immigrant legislation (H2). As well, the historical political leanings of a state will also influence the likelihood of passing anti-immigrant legislation (H3). For instance, both Minnesota and Wisconsin are generally considered to be socially liberal states and therefore are expected to pass pro- rather than anti-immigrant legislation even in the face of rising immigration.

Research Design

This research treats counts of pro- and anti- state-based immigrant laws as the dependent variables. A state is observed to either pass or not to pass anti-immigrant legislation in a given year, likewise for pro-immigrant legislation. The data will be analyzed as time-series with the anti-immigrant (or pro-) legislation, and the explanatory variables, immigrant percent growth and state legislature, varying over time. Time-constant variables include historical political party affiliation, region of country, slave state past, race riot past, baseline percent immigrant, and immigrant legislation at baseline. As the data is observational, the research examines how the predicted probability of passing one or more anti- (or pro-) immigrant laws is influenced by the explanatory variables.

Data

Immigrant population data will be obtained from summary files of the U.S 2000 and 2010 Censes as well as the American Community Survey. The Censes and American Community Survey contain information on number and percent immigrant, allowing for the calculation of year-on-year percent immigrant growth.

The data is derived from a pre-existing source of state-based immigrant-relevant legislation from the National Conference of State Legislatures (NCSL). The NCSL annually compiles a list of state-based immigrant-relevant legislation, doing so since 2005. A summary measure for each state for each year (2005-2011) will be created based upon the above classification. Sub-analyses will be run using a schema also originated at the National Conference of State Legislatures. The categories are:

a. Budgets
b. Education
c. Employment
d. Health
e. Human trafficking
f. ID/Licensing
g. Law enforcement
h. Miscellaneous
i. Omnibus/multi-issue
j. Public benefits
k. Voting
l. Resolutions

Analytic Strategies

Immigrant legislation data is recorded as count data. That is, the number of laws a state passes in a given year related to immigration must be greater or equal to zero, $[0,\infty]$. This violates the assumption of OLS regression that the dependent variable is unbounded $[-\infty,\infty]$. As such, standard OLS regression is not appropriate (Osgood 2000, Gardner, Mulvey, and Shaw 1995). Instead, the Poisson distribution is used. The Poisson distribution is defined by a single parameter, λ, which is both the mean and the variance of the distribution, a strict assumption that is often violated in real world data.

The distribution itself, $P(Y=y)=\dfrac{e^{-\lambda t}(\lambda t)^n}{n!}$, measures the number of events, n, that occur in a given sample space or time period, t. The modeling of counts over time is referred to as a Poisson process. This research models the number of immigrant-related laws passed by a state on a year-to-year basis as a Poisson process. The Poisson process with rate $\lambda>0$ is an appropriate technique if: (1) no events have occurred at time=0; (2) the independent increment assumption is valid; (3) the stationary increment assumption is not violated; and (4) the probability of the number of events occurring in a given time period is equal to the Poisson distribution with parameter λ, time t, and events n, i.e.

$$P[N(s+t)-N(s)=n]=\frac{e^{-\lambda t}(\lambda t)^n}{n!}$$

If the variance is substantially larger than the mean in the observed data even after covariates are included, a.k.a. "overdispersion," which violates the 4th assumption, the negative binomial distribution can be used as an alternative means to model the data. It accounts for overdispersion of the data with the parameter r.

The Negative Binomial distribution has two parameters, r and p, where r is the dispersion parameter and p is the probability that an immigrant related law is passed. Formally, the negative binomial distribution is written as:

$NB \sim (r,p) = P(Y=y) = \begin{pmatrix} y-1 \\ y-r \end{pmatrix}(1-p)^r p^{y-r}$, which is equivalent to

$\frac{\Gamma(y+r)}{y!\Gamma(r)}(1-p)^r p^{y-r}$. As r approaches infinity this simplifies to the Poisson distribution with the single parameter λ. The mean of the negative binomial distribution is the same as the Poisson distribution. That is, the expected number of immigration laws passed in a given year still has the same expected value under both distributions. The variance, however, contains the dispersion factor, r. Formally, $\text{var} = \lambda + \lambda^2 / r$. As r approaches infinity the variance converges to λ, the variance of the Poisson distribution. Therefore, the negative binomial distribution is a more general form of the Poisson distribution that allows for randomness in the variance of the rate.

I model state-based immigrant-related legislation in the 2005 to 2011 time period both as a Poisson process and as a negative binomial. This treats state-based immigrant legislation as the dependent variable. Model 1 details a Poisson distribution with time period, t, no covariates, and an error term. The fit of fixed effects versus random effects will be examined. To account for time periods in the count data model 2 moves the time period over to the RHS. Model 3 includes covariates where I_{it} represents the percent immigrant, I, in a particular state in a given year, P_{it} indicates the political party of the state legislature in a given year, R_i is the region of the country of the state, S_i is a vector of time-constant variables including whether the state is a former slave state or if it has a history of race riots, and O_i is a vector of time-constant variables related to baseline, including historical political party affiliation, percent immigrant at baseline, and immigrant legislation at baseline. Model 4 treats the data as coming from a negative binomial distribution instead.

$$PP: \log(\lambda_{it} / t) = \beta_0 + e_{it} \tag{1}$$

$$PP: \log(\lambda_{it}) = \log t + \beta_0 + e_{it} \tag{2}$$

$$PP: \log(\lambda_{it}) = \log t + \beta_0 + \beta_1 I_{it} + \beta_2 P_{it} + \beta_3 R_i + \beta_4 S_i + e_{it} \tag{3}$$

$$NB: \log(\lambda_{it}) = \log t + \beta_0 + \beta_1 I_{it} + \beta_2 P_{it} + \beta_3 R_i + \beta_4 S_i + \beta_5 O_i + e_{it} \tag{4}$$