Stanford
Center for International
Development

Working Paper No. 331

Immigration, Legal Status, and Public Aid Magnets

by

Anita Alves Pena*

June 2007

Stanford University
579 Serra Mall @ Galvez, Landau Economics Building, Room 153
Stanford, CA 94305-6015

* Stanford University and SCID

Immigration, Legal Status, and Public Aid Magnets

Anita Alves Pena[†]

June 2007

Abstract

Legal and illegal immigrants are concentrated in U.S. border states. This paper asks to what extent geographic clustering is attributable to differences in state-provided public aid. California has been shown to have a disproportionate number of legal immigrant welfare users, but little evidence exists concerning illegal persons. Illegal immigrants may collect welfare benefits on behalf of legal children or by using false documents, and legal status verification is often unnecessary for education or public medical services. Evidence from a nationally-representative farmworker survey featuring direct legal status data does not support welfare migration for any immigrant group. Conversely, U.S. Census data on immigrants in industries with lower illegal concentrations are consistent with a welfare migration story, even after the 1996 federal welfare reform. Additional analysis of the locational choices of farmworkers reveals that personal and social networks are primary determinants of state choice and border enforcement is a deterrent; however, welfare benefit levels and education program values are uncorrelated with settlement patterns.

Keywords: immigration, welfare magnets, self-selection, legal status

JEL codes: I38, O15

[†]Email: aalves@stanford.edu. Address: Stanford University, Department of Economics, 579 Serra Mall, Stanford, CA 94305-6072.

I thank Michael J. Boskin, John B. Shoven, Aprajit Mahajan, Christina Gathmann, Giacomo De Giorgi, Nicholas C. Hope, Seema Jayachandran, and the public economics, labor, and development groups at Stanford, especially Colleen Flaherty, Gopi Shah Goda, and Kevin Mumford whose support has been a blessing. I thank seminar participants at Stanford University, Economic Research Service of the U.S. Department of Agriculture, Analysis Group–Denver, Colorado State University, California State University East Bay, CNA Corporation, the U.S. Government Accountability Office, IDA, and Towson University for helpful comments. I am indebted to Daniel J. Carroll of the Office of Policy Development and Research, Employment and Training Administration at the Department of Labor for permission to use the NAWS data and to Susan Gabbard and her staff at Aguirre International for resources and hospitality. I acknowledge Christina Gathmann and Gordon H. Hanson for sharing unpublished sector-level border patrol data and Lorin Kusmin of USDA for providing necessary inputs to calculate state-level rural unemployment rates. The views expressed in this paper are mine and do not necessarily represent those of the U.S. Department of Labor, JBS International, or anyone mentioned above.

1 Introduction

Public aid and education participation imposes direct costs on state governments. States are concerned therefore about attracting a disproportionate number of program participants. Recent state legislation suggests that some states consider illegal immigrants to be a liability on this dimension. In 2006 alone, state legislatures considered 570 bills related to illegal and legal immigration, many of which focused on restricting access to welfare, education, and medical service. Camarota (2004) estimates that illegal immigrant households used $2.5 billion in Medicaid benefits, $2.2 billion in uninsured medical treatment, $1.9 billion in food assistance programs (Food Stamp Program (FSP), Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), and subsidized school lunches), $1.6 billion in prison and court related expenses, and $1.4 billion in federal aid to schools in 2002. It may be surprising that these expenditures occurred well after the 1996 passage of the Personal Responsibility and Work Opportunity Reconciliation Act that strengthened immigrant eligibility requirements for means-tested benefits.

Migrants are said to engage in welfare migration if they respond to public aid differentials across locations, and states are "welfare magnets" if they attract disproportionate numbers of these migrants. Studies have demonstrated the presence of welfare migration and Tiebout-style "voting with one's feet" within low-income native and legal immigrant populations.[1] Little evidence exists concerning whether these mechanisms also operate within the illegal immigrant population.

The hypothesis of welfare migration among illegal persons may seem irrelevant given that extensive eligibility requirements for many U.S. welfare programs exclude those without documents. Empirical evidence shows that public aid participation rates among illegal immigrants are significant. Illegal immigrants may collect benefits on behalf of legal children or by using false documents, and public medical services and education programs often are not subject to legal status verification. In the sample of agricultural workers used in this paper, 13.8 percent of illegal immigrants between 1989 and 2004 report using some form of public aid. This compares with 23.1 percent of U.S. born citizens, 39.4 percent of naturalized citizens, 34.5 percent of Green Card holders, and 15.8 percent of immigrants with other work authorizations (e.g. those with special agricultural work permits). Figure 1 shows aggregate welfare participation rates for agricultural workers in the sample over time, and Table 1 documents participation rates across U.S. regions by legal status. Public aid is defined to include Aid for Families with Dependent Children (AFDC)/Temporary Aid for Needy Families (TANF), FSP, General Assistance, low-income housing, government health clinic services, Medicaid, and WIC. Compared with the national average within legal status group, Southern Plains (TX, OK) and Pacific Coast (WA, OR) residents have higher participation rates than those elsewhere. More

[1] The Tiebout (1956) conjecture is that people locate in the jurisdiction that best satisfies their tastes for local public goods such as desirable school districts. This leads to efficient scale and allocation in equilibrium.

Table 1: Welfare Program Participation, by Legal Status and Location (percentage)

	Native	Illegal	Nat. Citizen	Green Card	Other Author.
California	33.13	13.12	32.40	33.10	15.21
Southern Plains	41.41	23.17	54.72	48.84	24.55
Florida	30.24	11.46	23.62	39.38	19.51
Mountain III	19.45	7.24	41.12	16.23	6.84
Appalachia I, II	17.84	5.59	30.41	19.56	13.41
Cornbelt Northern Plains	13.90	17.39	37.02	29.91	19.01
Delta Southeast	34.83	6.46	49.93	30.71	4.38
Lake	21.28	17.65	50.43	50.84	9.13
Mountain I, II	24.37	22.02	18.56	44.03	36.92
Northeast I	12.19	19.48	50.88	20.58	10.60
Northeast II	24.38	10.35	43.41	26.79	11.03
Pacific	31.09	26.58	52.39	38.26	25.50
United States	23.12	13.81	39.43	34.52	15.84

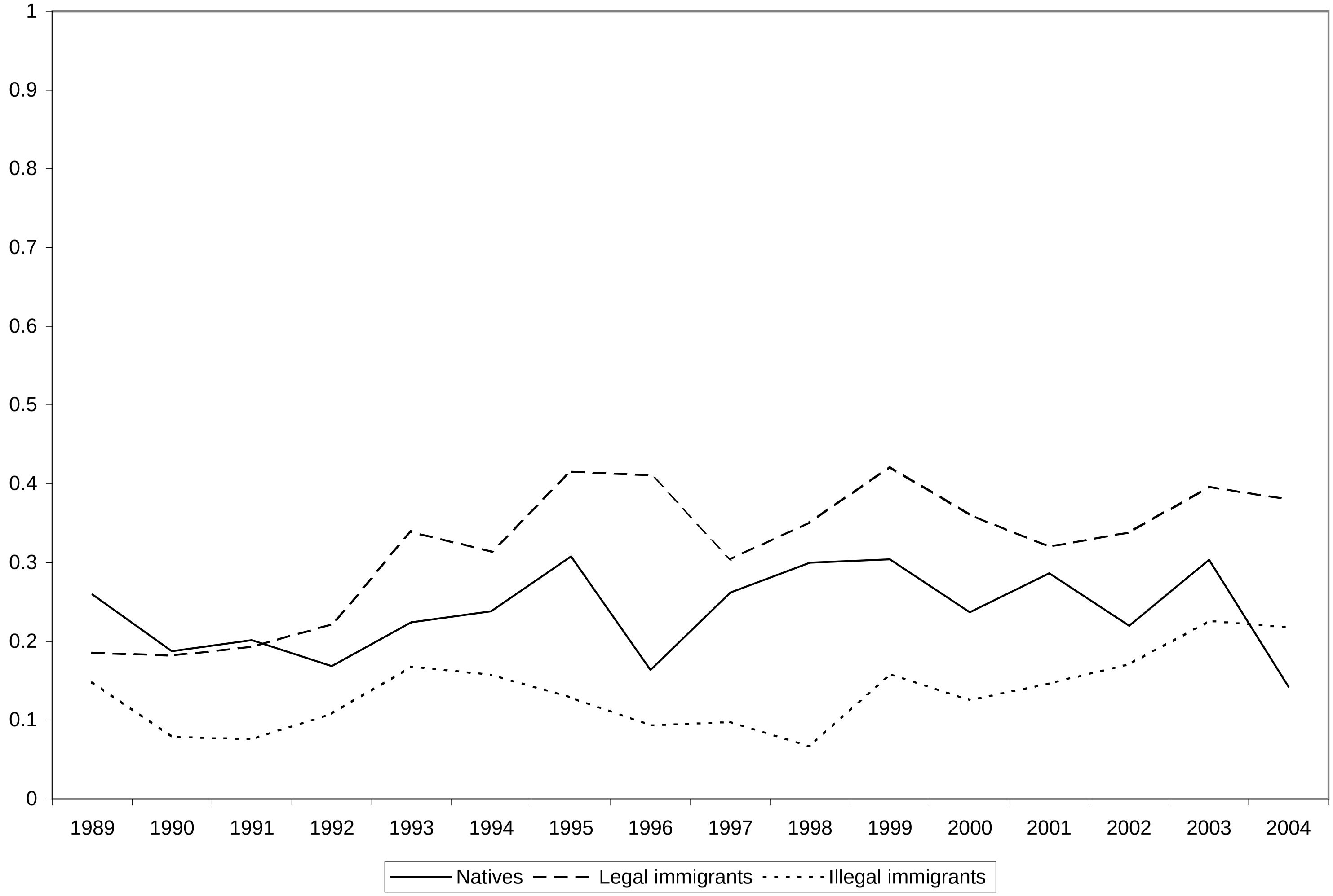
Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Note: Regions are defined in Table 3.

than 41 percent of U.S. born Southern Plains workers, for example, reveal that they (or their families) participate in welfare programs compared with the national average of 23 percent. Likewise, 23 percent of illegal Southern Plains workers report welfare participation compared with an average of less than 14 percent.

California, known for welfare generosity, is usually suspected to be a welfare magnet for immigrants. Using 1980 and 1990 U.S. Census data, Borjas (1999) finds support for this claim: immigrant welfare participants are more likely to reside in California than are U.S. born persons and immigrants who do not use welfare. Different states, however, may be magnets for different benefit programs, and welfare migration may exist to different degrees across legal status groups. Immigrants may respond not only to generosity differences across potential locations, but also to differences in availability. A contribution of this paper is to consider the possibility of welfare migration (1) by members of refined legal status groups: illegal immigrants, naturalized citizens, Green Card holders, immigrants with other work authorization, and U.S. born citizens; (2) based not only on traditional welfare, but also on food aid, medical service, and education programs; and (3) to each of four immigrant destinations: California, Arizona, Texas, and Florida. Documenting the existence (or absence) of welfare migration for different groups and public aid programs to different destinations contributes to a better understanding of the effect of state and local public finance on the locational distribution of migrants.

The data used in this paper represent a necessary compromise in order to learn more about illegal populations present in the United States. Primary data come from the National Agricultural Workers Survey (NAWS), a nationally-representative dataset conducted by the U.S. Department of Labor. The sample design of the NAWS, unlike traditional micro-level data sources, specifically accounts for migratory behavior. The NAWS asks questions relating to public aid and education participation and, most importantly,

Figure 1: Welfare Participation Rates of U.S. Farmworkers, by Legal Status



Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.

direct questions relating to legal status. Due to data restrictions, previous studies of welfare migration by immigrants have only considered legal permanent residents and naturalized citizens. The NAWS affords the opportunity to extend this area of research to illegal immigrants and to those with other work authorization.

Results using the NAWS data do not support welfare-induced migration for any legal status group in agriculture, and highly educated migrants are found to locate in border states more so than those with fewer years of education. Consistent with Borjas (1999), results using the full population U.S. Census, however, do suggest welfare-induced migration by noncitizens, but do not support welfare migration by those in seasonal industries with large concentrations of illegal immigrants such as agriculture. The empirical analysis therefore contributes to the literature by confirming previous results regarding welfare migration by legal immigrants, extending these results to the post-PRWORA period, and challenging notions of welfare migration by illegal immigrants and those in seasonal occupations.

The rest of this paper is organized as follows. Section 2 presents motivation and context from state-level program characteristics and policy initiatives relating to immigration and the welfare state. Section 3 illustrates how the Borjas-Roy self-selection model can be extended to both a multiregion setup and one that distinguishes persons based on legal status. Section 4 reviews relevant academic literature and controversy regarding appropriate data sources for immigrant welfare migration studies. Section 5 introduces the NAWS in more detail and presents empirical evidence of the extent of geographic clustering of public aid and education participants in the NAWS and in the U.S. Census respectively. Participants are compared with nonparticipants both within and across legal status groups unconditionally and conditional on socioeconomic controls. Section 6 considers self-selection to border states independent of participation behavior. Using conditional logistic regression, Section 7 examines the effects of state specific labor market and public policy attributes, including public aid benefit and education values, on migration decisions. Section 8 concludes.

2 State Institutional and Legislative Background

Evidence of geographic clustering of immigrants is well-documented. Official statistics on residential choices of legal immigrants—naturalized citizens and legal permanent residents—reveal concentrations of individuals in California, New York, Florida, and Texas. Estimates of the illegal immigrant population also show patterns consistent with purposeful locational clustering, particularly in border states. This paper addresses to what extent geographic clustering in the border states—defined here to include California, Arizona, Texas, and Florida—is due to welfare migration.

California has traditionally offered more generous benefits than other U.S. states and therefore is the usual candidate for a welfare magnet in the literature. In 2003, the maximum monthly TANF benefit for a family of four in California was \$809 compared with \$418 in Arizona, \$364 in Florida, and \$241 in Texas. These patterns have been evident over time, and persist after cost of living adjustments are made. Figure 2 presents maximum monthly AFDC/TANF benefit levels and FSP values for a family of four. Values of these variables for other family structures are parallel shifts up or down of these curves for each state. Figure 3 presents welfare data for a family of four in real terms.[2] In addition to its higher absolute benefits, California uses state funds to provide cash welfare, FSP, Medicaid, and Supplemental Security Income (SSI) to post-1996 immigrants otherwise ineligible due to the five-year residency requirement introduced in PRWORA. Texas, Florida, and Arizona do not use state funds to supplement federal benefits.[3]

Different states, however, may be magnets for different programs. California, for example, may not be a likely candidate for medical program-induced migration. Medicaid payments per person served in 2002 in California were \$2,541. This is compared with \$3,767 in Texas, \$3,672 in Florida, and \$3,281 in Arizona that year. In terms of eligibility, 47 states allow self-declaration of legal status for Medicaid, and 27 do not have quality control procedures in place to verify responses. Of the border states, Texas is the only state to require legal status documentation.[4] Therefore, despite Texas' higher payments per person served, eligibility restrictions work against the hypothesis that it is a welfare magnet on the dimension of medical care.

Texas, however, may be a likely candidate for education-induced migration. Texas is generous in migrant-focused education programs such as Migrant Head Start.[5] Texas offers 74 Migrant Head Start programs. This number corresponds to 6.2 percent of the Head Start programs in that state and 15.6 percent of Migrant Head Start programs in the nation. Florida offers 47 migrant programs out of 782 Head Start programs (6.0 percent), California offers 112 out of 2,286 (4.9 percent), and Arizona offers nine migrant programs out of its 295 Head Start programs (3.1 percent).

Given that provision of welfare, medical, and education programs is costly, several states have taken action to dissuade the use of these programs by illegal immigrants. Despite the previous descriptive evidence of Texas being generous in terms of migrant education, the state has not always been generous to illegal immigrants. A distinctive court case, originating in Texas, pointed out that "free" public education is not really free and that illegal immigration can impose significant fiscal costs at state and local levels. In September 1978, in *Doe v. Plyler*, Judge William Wayne Justice of the Texas Eastern District Court ruled that a 1975 section of the Texas Education Code which denied public education to illegal immigrant children,

[2]The series is deflated by a state-level cost of living index from Berry, Fording, and Hanson (2003). Values are in year 2000 dollars based on the median cost of living state in 2000. The two middle states in terms of cost of living that year, South Dakota and Delaware, were averaged to construct the base.

[3]Kaushal (2005).

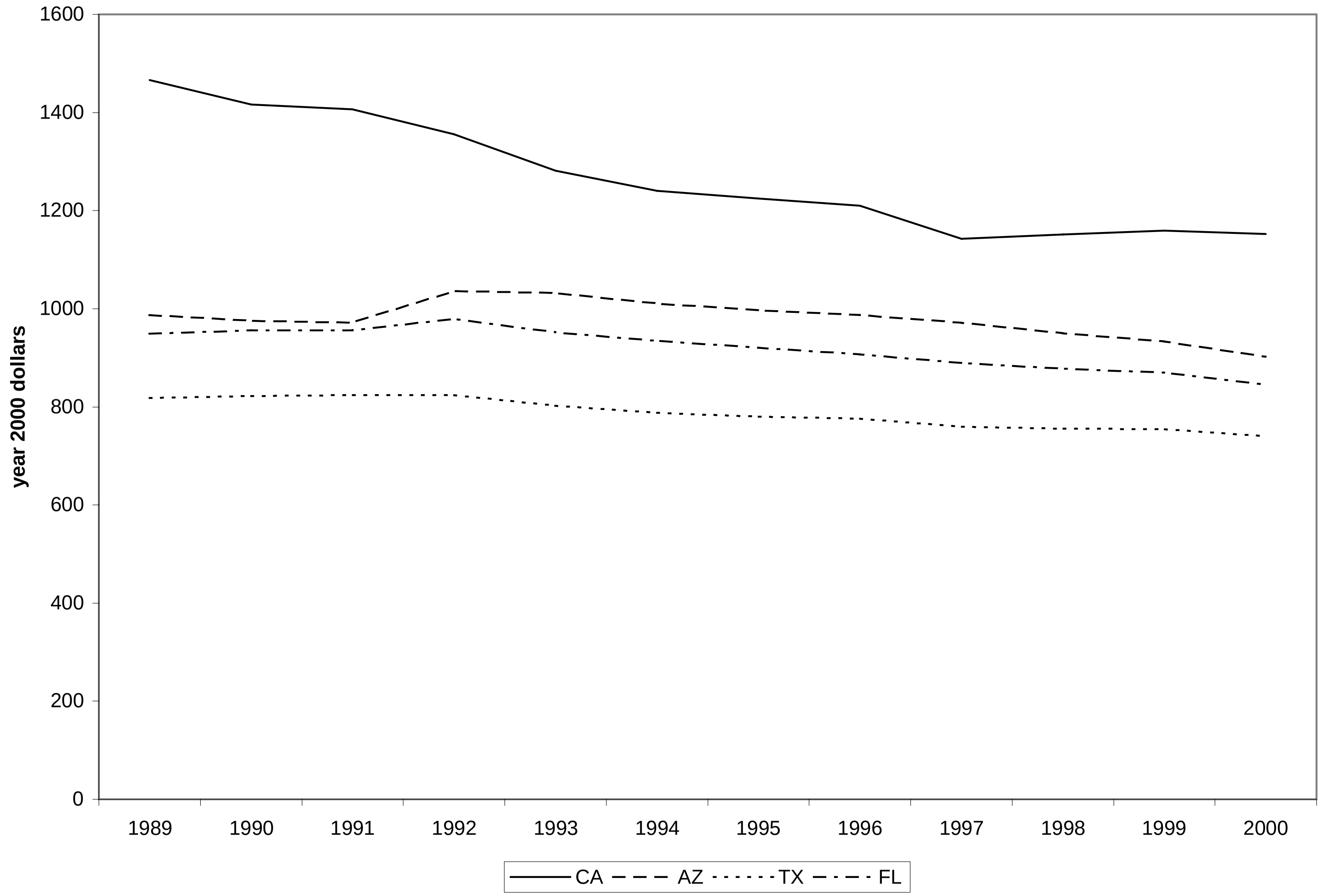
[4]Levinson (2005). Medicaid directors in California and Florida report that documentation is required in some but not all cases. Arizona reports allowing self-declaration in all cases.

[5]Migrant Head Start, under the umbrella of Head Start, provides education, nutrition, health, disability services, parental involvement, and social services to migrant children and their parents.

Figure 2: (Nominal) Maximum Monthly AFDC/TANF plus FSP for Family of Four

Source: U.S. House of Representatives Committee of Ways and Means, *Green Book*, and author's calculations

Figure 3: (Real) Maximum Monthly AFDC/TANF plus FSP for Family of Four



Source: U.S. House of Representatives Committee of Ways and Means, *Green Book*, and author's calculations
Note: Deflated using the CPI2000 from Berry, Fording, and Hanson (2003)

was unconstitutional.[6] In October 1980, the Fifth Circuit Court in New Orleans upheld this verdict, and in *Texas v. Certain Named and Unnamed Undocumented Alien Children* in June 1982, the U.S. Supreme Court did the same.

Another well-publicized state position elevated questions regarding illegal immigrant use of publicly-funded programs to national interest. California's Proposition 187 in 1994 proposed an almost complete restriction of public aid and services including public education, health care, and welfare to illegal residents of the state. The original proposition consisted of five parts.[7] First, it barred illegal immigrants from California's public education system at all levels (kindergarten through university) and required schools to verify legal status of students and their parents. Second, it required all publicly-paid, non-emergency health care service providers to verify legal status before treatment in order to be reimbursed by the state. Third, it required welfare benefit offices to verify legal status before benefit transfers. Fourth, it required a broad classification of service providers to report suspected illegal immigrants to the state's attorney general and to the INS. This was to apply not only to employees of schools, hospitals, and welfare offices, but also to state and local police who would be required to determine legal status of those under arrest. Finally, Proposition 187 declared production, distribution, and use of false documents to be a state felony. Proposition 187 passed by a margin of 59 to 41 percent in November 1994. In November 1995, Proposition 187 was ruled unconstitutional in federal court on grounds that it exceeded state authority on immigration policy.

Doe v. Plyler and California Proposition 187 are only two examples of state-level responses to illegal immigration. Table 2 presents specific state legislations in 2006 relating to public benefits. Of particular interest, and reminiscent of California Proposition 187, is Colorado HB 1023. Colorado HB 1023, signed July 31, 2006, bars illegal immigrants from participating in a number of public aid programs, including retirement, welfare, health, disability, public or assisted housing, postsecondary education, food assistance, and unemployment insurance. State courts also continue to face questions regarding the constitutionality of public aid entitlements to illegal immigrants. An August 2006 Arizona Supreme Court case brought by the State Compensation Fund questions a 1925 Arizona law deeming illegal immigrants eligible for disability pay.[8] At the time of this writing, the matter is unresolved.

3 Theoretical Model

A theoretical model illustrating how the existence of various welfare programs and educational opportunities may differently influence locational choices of U.S. born citizens, legal immigrants, and illegal immigrants

[6] Flores (1984).
[7] Martin (1996).
[8] Davenport (2006).

Table 2: State Legislation on Immigrant Public Benefit Use, 2006

Arizona	HB 2448/SB 2738	Requires U.S. citizenship or legal immigrant status to receive health benefits; illegal immigrants can receive emergency medical services only
Arizona	SB 1137	Limits eligibility for state's Comprehensive Care for the Elderly program to citizens and legal immigrants
California	SB 1534	Authorizes cities, counties, and hospitals to provide health care and other aid to persons who would be eligible if not for PRWORA immigration requirements
California	SB 1569	Extends eligibility for state and local public benefits, Medi-Cal, and refugee cash assistance and employment services to immigrant victims of trafficking, domestic violence, and other serious crimes; implementation by July 1, 2008
Colorado	HB 1002	Mandates that illegal immigrants receive services including investigation, identification, testing, preventive care, and treatment of epidemic or communicable disease, including TB, HIV, AIDS, and venereal diseases
Colorado	HB 1023	Restricts public benefits from those who are not U.S. citizens or legal permanent residents; restricted benefits include retirement, welfare, health, disability, public or assisted housing, postsecondary education, food assistance, unemployment; all Colorado residents, regardless of legal status, can receive emergency medical services, immunizations, and treatments for communicable diseases, other services necessary for life and safety, prenatal care, and short-term emergency relief; if caught using false documents to receive benefits, offender faces up to a year and a half in jail and $5,000 fine
Hawaii	HB 2966	Amends public housing rules and regulations to restrict down payment and mortgage loans to "qualified applicants" defined as citizens or legal immigrants
Maine	HB 1242/LD 1734	Defines a person "legally domiciled" in the state as one who has a resident visa; allows noncitizens who have resident visas and who are living in Maine to be eligible for Medicare coverage
Maryland	HB 89	Requires Governor to support the Maryland Medical Assistance Program for health care services for specified legal immigrant children under 18 and pregnant women in the annual budget beginning in FY 2008; pregnant legal immigrant women who entered the country after August 22, 1996 and who meet eligibility guidelines for federal and state medical assistance programs qualify
Nebraska	LB 239	Allows illegal immigrant students to qualify for in-state tuition
Rhode Island	HB 7120	Requires that no new noncitizen child be enrolled in Rhode Island Medicaid program after December 31, 2006
Virginia	SB 542	Establishes eligibility for in-state tuition for those with a visa or classified as a political refugee; students with temporary or student visas are ineligible
Wyoming	SB 85	Provides scholarships to Wyoming students to attend community colleges and the University of Wyoming; noncitizen students and students whose parents claimed foreign residency during the student's high school years are ineligible

Source: National Conference of State Legislatures.

is developed in this section. The model builds on that of Borjas, Bronars, and Trejo (1992) and Borjas (1999). Borjas, Bronars, and Trejo (1992) present a multiregion extension of the Roy model, which they apply to internal U.S. migrants. Their model predicts that regions paying high returns to skills attract higher skilled workers while lower return regions attract lower skilled persons. Thus, workers self-select to the state that gives them their highest expected earnings. Borjas (1999) extends the model to immigrants and to welfare participation. His extension predicts that foreign-born welfare recipients will cluster in locations offering the highest welfare benefits more than natives will, and he confirms this prediction with U.S. Census data. This paper extends the model to distinguish immigrants by legal status. While regions with high returns to skills again attract higher skilled workers and likewise lower return regions attract those with lower skills, specific skill-level cutoffs depend on the differing migration cost and public aid benefit schedules faced by each legal status group. Specifically, when expected migration costs are allowed to vary across origin country/destination state pairs, it is theoretically ambiguous which legal status group will cluster to the greatest extent. The model therefore serves to characterize a variety of potential equilibria but, unlike Borjas (1999), is agnostic concerning which one will emerge in the data.

Consider a country consisting of s=1,...,S mutually-exclusive states. The expected net benefits from making a migration to state s (V_s) is:

$$V_s = w_s + B_s(w_s) - C_{os} \tag{1}$$

where w_s is a worker's expected wage earnings in state s, $B_s(w_s)$ is his or her expected cash and time-equivalent value of public aid programs in state s (broadly-defined to include welfare, education, medical, and any other aid and allowed to be a function of earnings), and C_{os} is his or her expected cash and time-equivalent migration cost from an origin o to destination s, where $C_{ss} = 0$ corresponds to a stay-at-home option for native residents of a state.[9] Thus, earnings, public aid program benefits, and migration costs are defined as individual-level expected values. Subscripts indicating that these are individual-level quantities are suppressed for simplicity. Because the variables are expected values, they represent the interaction between the probability of having access to welfare, the choice to participate, and state-level generosity.[10]

[9]The assumption that benefits and costs are cash and time-equivalent allows ready comparison to earnings. For example, if earnings are expressed as hourly wages, benefits and costs are hourly dollar equivalents.

[10]Borjas (1999) introduces welfare programs as a minimum guaranteed income and considers the case where welfare recipients and workers are mutually exclusive. Lower skilled persons opt into welfare when the minimum guarantee exceeds expected wage earnings. Because many low income immigrants receive both wage earnings and supplemental public aid and because aid is not guaranteed for immigrants, a more general case is considered here. Migration costs as in Borjas (1999) are assumed to be a fixed percentage of income for simplicity. It is possible to extend the model to allow costs to vary with wages, and thus with skill levels.

Utility-maximizing (or income-maximizing) agents prefer to locate in state s if:[11]

$$V_s > V_{s'} \ \forall s' \neq s \tag{2}$$

Assuming the initial distribution of skills is equal across regions, the log earnings distribution in each state s (and analogously for each country of origin o) is written:

$$w_s = \mu_s + \nu_s \tag{3}$$

where μ_s is the mean log earnings in state s and ν_s is a mean zero random variable with variance σ_s^2 measuring person-specific deviations from mean income in state s. Differences in earnings across regions are thought to be attributable to differing state-level endowments of factors of production and varying socioeconomic and technological conditions.

An assumption that earnings are perfectly correlated across regions (i.e. that the skill measure ν determines each individual's earnings in each state) allows further characterization of equilibrium sorting. The wage earnings equation is rewritten:

$$w_s = \mu_s + \eta_s \nu \tag{4}$$

where η_s is the rate of return to skills in s, and ν is a single-dimensional measure of relative ability, assumed perfectly transferable nationally and internationally and across regions.

Sorting conditions are found by combining equations 1, 2, and 4. These conditions depend on the functional form assigned to $B_s(w_s)$. In the simplest case, if benefits are independent of wages ($B_s(w_s) = B_s$), region s is preferred to region s' when:

$$\nu < \frac{\mu_s - \mu_{s'} + (B_s - B_{s'}) - (C_{os} - C_{os'})}{\eta_{s'} - \eta_s}$$

In this case, expected benefits and costs, which are allowed to differ based on legal status, shift the wage-skills curve and result in variation in the economic opportunities available to each group in each state.

This benefit formula simplification, however, may be unrealistic. Many public aid programs phase out as earnings increase. Therefore, benefits might be better thought of as decreasing functions of earnings ($\frac{\partial B_s(w_s)}{\partial w_s} < 0$). Under an assumption that $B_s(w_s) = a + bw_s$ and $B_{s'}(w_{s'}) = c + dw_{s'}$ where $a, c \geq 0$; $b, d < 0$;

[11] Risk-neutrality is implicitly assumed.

and $B_s, B_{s'} \geq 0$; the sorting condition in which region s is preferred to region s' is:

$$\nu < \frac{(1+d)\mu_s - (1+b)\mu_{s'} + (c-a) - (C_{os} - C_{os'})}{(1+b)\eta_{s'} - (1+d)\eta_s}$$

Ordering locations based on economic opportunities as opposed to locational proximity (i.e. such that $\eta_1 < \eta_2 < ... < \eta_{s'} < ... < \eta_S$), the necessary condition for some agents to locate in region s is:

$$\begin{aligned} &\frac{(1+d)\mu_{s-1} - (1+b)\mu_s + (c-a) - (C_{o,s-1} - C_{os})}{(1+b)\eta_s - (1+d)\eta_{s-1}} \\ < &\frac{(1+d)\mu_s - (1+b)\mu_{s+1} + (c-a) - (C_{os} - C_{o,s+1})}{(1+b)\eta_{s+1} - (1+d)\eta_s} \end{aligned} \tag{5}$$

If equation 5 holds for all states $s = 2, ..., S-1$, then sorting conditions are such that the individual: locates in region 1 if

$$\nu < \frac{(1+d)\mu_1 - (1+b)\mu_2 + (c-a) - (C_{o1} - C_{o2})}{(1+b)\eta_2 - (1+d)\eta_1} \tag{6}$$

locates in region s if

$$\begin{aligned} \nu > &\frac{(1+d)\mu_{s-1} - (1+b)\mu_s + (c-a) - (C_{o,s-1} - C_{os})}{(1+b)\eta_s - (1+d)\eta_{s-1}} \\ \text{and } \nu < &\frac{(1+d)\mu_s - (1+b)\mu_{s+1} + (c-a) - (C_{os} - C_{o,s+1})}{(1+b)\eta_{s+1} - (1+d)\eta_s} \end{aligned} \tag{7}$$

locates in region S if

$$\nu > \frac{(1+d)\mu_{S-1} - (1+b)\mu_S + (c-a) - (C_{o,S-1} - C_{oS})}{(1+b)\eta_S - (1+d)\eta_{S-1}} \tag{8}$$

The equations can be thought of as marginality conditions describing individual sorting. The descriptive result generated by the model parallels that of Borjas, Bronars, and Trejo (1992): the least skilled workers choose the region with the lowest return to skills (equation 6) while higher skilled workers locate in higher return areas (equations 7 and 8). Public aid benefits and costs affect the skill distribution cutoff points corresponding to different locational choices and therefore have implications for equilibrium sorting.

Until this point, the primary difference between immigrants and natives in the model lies in the values assigned to expected migration costs and public aid benefits for each group. Legal immigrants may be argued to face the same wage-skills relationship as natives. However, the earnings of illegal immigrants are likely distributed differently:

$$w_s^I = \mu_s^I + \eta_s^I \nu \tag{9}$$

Whether illegal immigrants face a lower or higher wage-skills curve than do legal immigrants and U.S.

born citizens is theoretically ambiguous. Illegal immigrants may have less bargaining power (all else equal) in negotiating wage contracts with employers who face penalties if caught with illegal members in their workforces. This difference could result in lower wages for any given skill level. However, illegal immigrants, unlike their legal immigrant or U.S. born counterparts who are more likely to pay taxes, may consider gross wages, as opposed to net wages when deciding whether to migrate. The case where the wage-skills curve of illegal immigrants is lower than that of legal immigrants and natives is considered in what follows.[12] The model, however, can be used to examine alternative assumptions.

Expected values of migration costs and public aid benefits may also differ by legal status. Illegal immigrants may face higher migration costs and lower expected benefits than do legal immigrants and natives. Illegal immigrants may employ "coyotes"—border smugglers—or take longer routes to their destination to elude border patrol for example.[13] As discussed earlier, illegal immigrants may have fewer opportunities to receive supplemental sources of income from public aid programs, lower propensities to participate than those in other legal status groups, and lower benefit levels if they do participate.

Skill-level cutoffs are defined analogously to those for the legal immigrant and U.S. born populations. If illegal immigrants can collect benefits equal to $B^I_s(w^I_s) = a^I + b^I w^I_s$ in state s and $B^I_{s'}(w^I_{s'}) = c^I + d^I w^I_{s'}$ in state s' and if they face costs equal to C^I_{os} and $C^I_{os'}$ in these two states respectively, then illegal immigrants prefer region s over region s' when:

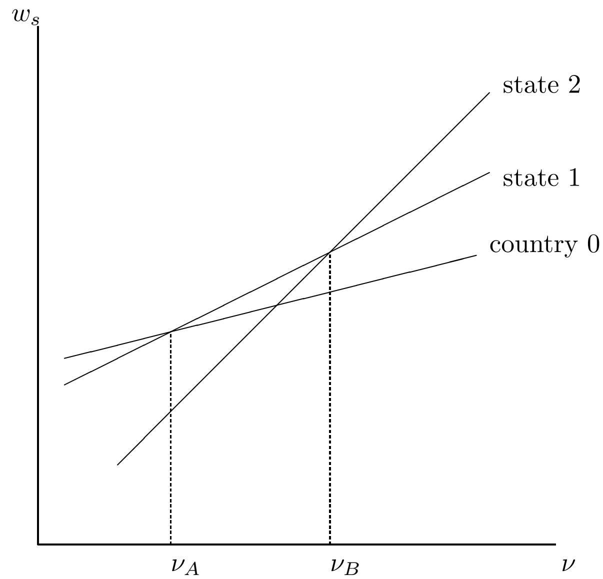
$$\nu < \frac{(1 + d^I)\mu^I_s - (1 + b^I)\mu^I_{s'} + (c^I - a^I) - (C^I_{os} - C^I_{os'})}{(1 + b^I)\eta^I_{s'} - (1 + d^I)\eta^I_s}$$

Sorting rules similar to equations 6 to 8 easily follow and the result is analogous: regions paying high returns to skills attract higher skilled illegal immigrant workers and lower return regions attract lower skilled illegal immigrants. Differences exist, however, between the specific skill-level cutoff points for illegal and legal persons.

Consider the case of two potential migration destinations (states 1 and 2) and one origin (country 0). Figure 4 illustrates the wage-skills curves of these locations under the assumption that the return to skills in the origin country is lower than the return to skills in each of the destination states. Chiquiar and Hanson (2005) using Mexican and U.S. Census data and Orrenius and Zavodny (2005) using Mexican Migration Project data consider self-selection among Mexican immigrants. Both studies find that immigrants are selected from the intermediate or high end of the Mexican education distribution. Given the majority of recent U.S. immigrants are from Mexico and assuming education is a valid proxy for skills, the assumption of returns to skills $\eta_2 > \eta_1 > \eta_0$ is adopted in the figure.

[12] There is a three to five percent wage differential between legal and illegal NAWS workers.
[13] See Gathmann (2004).

Figure 4: Wage-skills Curves of Two Destination States and One Origin Country



In the absence of welfare programs and migration costs, immigrants with skills below ν_A stay in the origin country and natives with skills in this range optimally geographically sort to state 1. Both immigrants and natives with skills between ν_A and ν_B on the other hand locate in state 1, and those with skills above above ν_B sort to state 2.[14]

Sorting is affected by the presence of migration costs. Borjas (1999) models migration costs as upward shifts of the curves associated with an individual's origin state or country. This approach, however, disallows the possibility that the migration costs faced by an individual to various locations are different. Alternately, migration costs can be thought of as shifts down of the wage-skills curves for each of the potential destination. This latter treatment is adopted in this paper. This difference between the specification of migration costs in Borjas (1999) and the more flexible specification here results in a difference in prediction. While Borjas predicts that immigrants will cluster to a greater extent than natives will, this prediction breaks down when costs are allowed to vary. The model allows for a spectrum of outcomes regarding the relative magnitudes of the effects of welfare programs on locational choice across legal status groups.

For U.S. born citizens, migration costs only apply to states other than their birth states ($C_{s,s-1} > 0$ but $C_{ss} = 0$). For immigrants, costs are applicable to all potential destinations. Figure 5 presents the addition of costs to state 1. The country curve is suppressed for simplicity, as is a cost-adjustment for state 2. When expected migration costs are positive, those with skills below $\nu_{B'}$ migrate to state 1 and those with

[14]This assumes that natives remain in their birth country. It is also possible that the lowest skilled natives realize an employment opportunity in the other country, but this paper restricts attention to inflows. Also note that if the rate of return to skills η_s does not vary across states, then migrants at any given skill level are indifferent regarding where to locate unless locations offer different costs and benefits.

Figure 5: Migration Costs to State 1

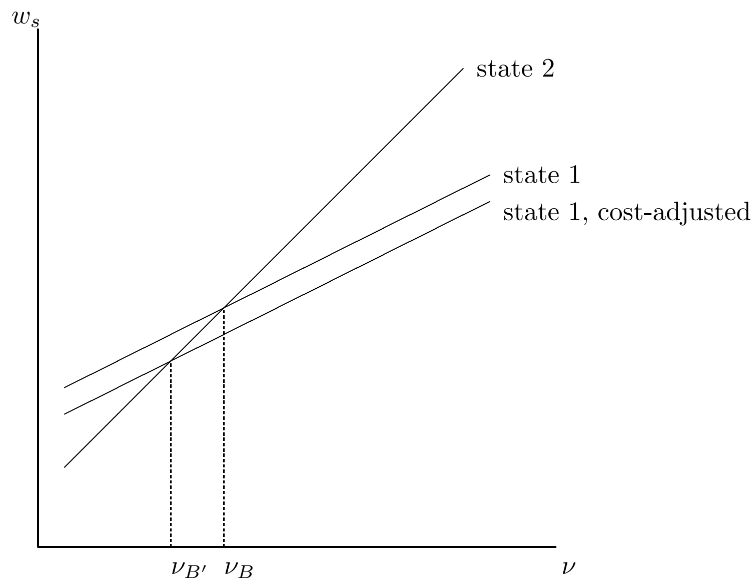


Figure 6: Migration Costs plus Public Aid in State 1

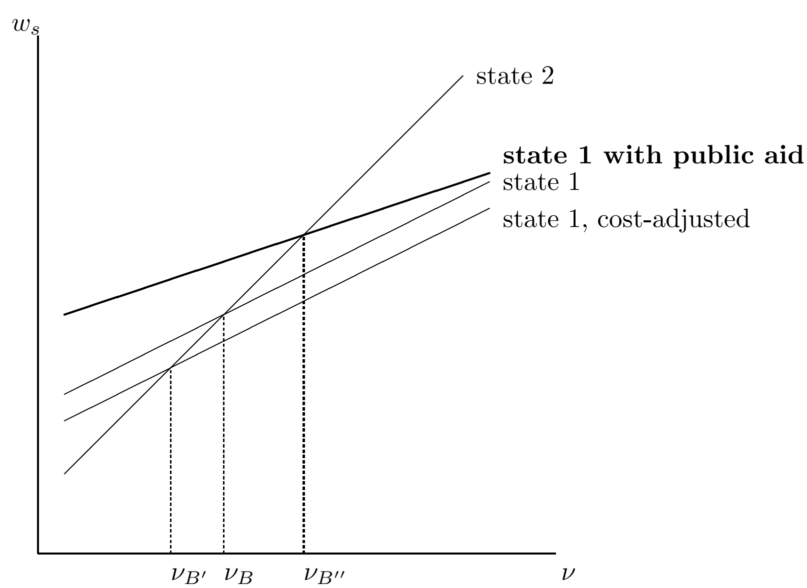
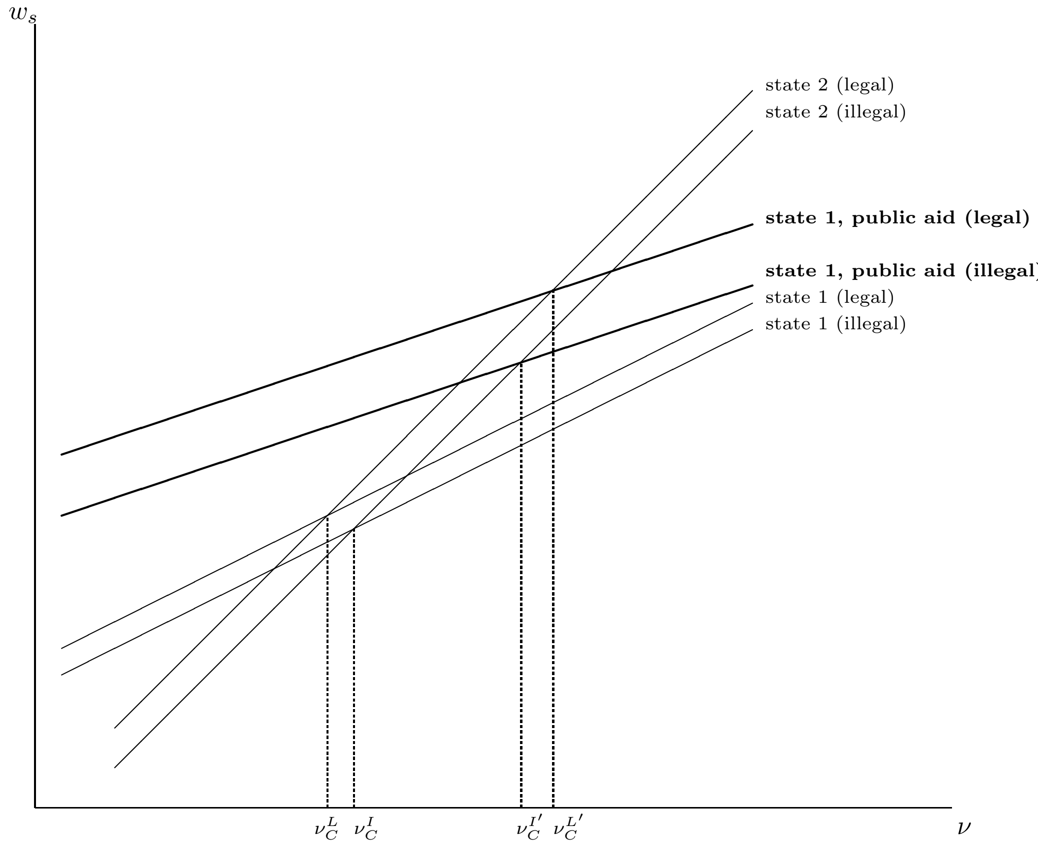


Figure 7: Illegal versus Legal Immigrants, Public Aid in State 1



skills above $\nu_{B'}$ sort to state 2. Asymmetrical migration costs therefore alter the locational distribution of migrants.

Figure 6 introduces public aid benefits in state 1. If public aid is assumed to be a decreasing function of earnings, public aid constitutes a non-parallel upward shift of the wage-skills curve. Those who do not expect to participate in aid programs locate based on $\nu_{B'}$, and those who do expect to participate (or who value the option) sort based on $\nu_{B''}$. Specifically, those with skills below $\nu_{B''}$ locate in state 1, and those with skills above this point locate in state 2. The after-benefit wage-skills curve as drawn is cost-adjusted. In this example, benefits are so generous in state 1 that they more than compensate for migration costs for those within the skill parameters in the figure. In the absence of migration costs, the after-benefit wage-skills curve would be higher and the difference between the skill-level cutoff points with and without welfare programs would be larger.

Illegal immigrants are distinguished from legal immigrants in Figure 7. As drawn, illegal immigrants face lower wage-skills curves in each destination state than do their legal counterparts. Within a state, illegal and legal immigrants have different program participation values. Both illegal and legal immigrants who place positive value on public aid cluster in the generous state. Specifically, the presence of positive expected benefits induces illegal immigrants to sort based on $\nu_C^{I'}$ instead of ν_C^I. Likewise, legal immigrants sort based on $\nu_C^{L'}$ instead of ν_C^L. The difference between the skill-level cutoff points associated with choosing one state over another in the presence and absence of welfare programs is larger in the figure for legal immigrants than for illegal immigrants.[15] The magnitudes of these differences for legal and illegal immigrants depend on relative program generosities.

Individual states offer competing welfare packages. Adding benefits in both states is straightforward. Sorting conditions adjust in favor of more migration to the state offering higher benefits. In case of equal benefits across states, sorting is equivalent to that when public aid programs do not exist.

4 Literature on Immigrant Welfare Migration

The literature concerning legal immigrant welfare migration is characterized by debates over appropriate data sources and econometric methods. Buckley (1996), Borjas (1999), and Dodson (2001) present evidence supportive of legal immigrant welfare migration. Zavodny (1999) and Kaushal (2005) present counterarguments.

Buckley (1996) uses INS admissions data from 1985-1991. He regresses the annual number of legal permanent residents in a state divided by its population on a measure of state-specific welfare levels (total AFDC monthly payments times a cost of living deflator divided by total recipients) and other state-level socioeconomic regressors. He considers separate regressions for each INS admission category identifiable in his data. These admission categories are based on (1) presence of immediate relatives in the U.S., (2) presence of remote relatives, (3) refugee or asylee status, and (4) employment or skill-based admission. Consistent with a welfare migration story, Buckley finds a strongly positive, significant relationship between legal immigration flows and AFDC levels. His result holds across admission categories; however, he finds refugees and asylees more responsive and employment category immigrants less responsive to welfare generosity than those gaining admission for family reasons. Specifically, he finds a one percent increase in average monthly AFDC payments is associated with a 0.6 to 1.2 percent increase in immigration the following year.

Zavodny (1999) challenges Buckley's conclusions using INS legalization data from 1989-1994 supplemented with data on refugees from the Office of Refugee Resettlement. She regresses the log number of persons immigrating to a state in a given year on state-level variables including real combined AFDC and FSP benefits for a family of three. Unlike Buckley, she controls for state fixed effects and for country-specific immigrant stock. With these new controls, she finds welfare levels only to have a significant positive effect on the location choices of refugees and asylees. She concludes that welfare is not an important determinant

[15] The model itself can support the opposite result under alternative assumptions.

of locational choice overall.

Dodson (2001) presents new evidence in favor of immigrant welfare migration. He uses INS data from 1991 and regresses the number of immigrants by admission category from a given country who locate in a given state on maximum combined AFDC and FSP benefit for a family of three using Tobit regression to account for censoring.[16] His added disaggregation of the dependent variable and revised econometric method yield a highly significant, positive relationship between immigration levels and welfare generosity. The welfare migration effects that he calculates are larger than those in Buckley (1996). A one percent increase in the maximum combined AFDC and FSP benefits for a family of three in Dodson's study is associated with a 8.8 percent increase in the number of immigrants in the immediate relative admission category choosing that state. For other family-sponsored immigrants, a one percent increase in maximum benefits is associated with a 31.7 percent increase. For employment based admissions, this increase is 40.6 percent.[17]

Using 1995-6 and 1998-9 INS data, Kaushal (2005) offers an additional challenge to the previous literature. She creates a state-level policy dummy variable for whether or not new immigrants are eligible for means-tested programs and uses the proportion of newly arrived immigrants in a given year who locate in a given state as her dependent variable. She concludes that means-tested programs have "at best a weak effect on the location choices of newly arrived immigrants."

As discussed in Section 3, Borjas (1999) presents a model of whether welfare generous states induce those immigrants at the margin (who may have stayed home or located elsewhere in absence of welfare) to make locational decisions based on social safety net availability. Borjas uses the 1980 and 1990 Census to test his theory.[18] He examines whether the interstate dispersion of public service benefits influences the locational distribution of legal immigrants relative to the distribution of U.S. born citizens. In this framework, he finds evidence of welfare-induced migration complementary to Buckley and Dodson. Additionally, he demonstrates that immigrant program participation rates are more sensitive to benefit level changes than native participation rates are, collaborating his story.

5 Empirical Evidence of Locational Clustering

The empirical literature on immigration and the welfare state primarily has used two data sources: INS cross-tabular administrative record data or the U.S. Census. As INS data is primarily available in "count" form,

[16] Immigrant stock is nonnegative.

[17] For refugees and asylees, this number is higher. A one percent increase in benefits is correlated with a 151.0 percent increase of immigrants to a state. This complements Zavodny's result for this subpopulation.

[18] Kaushal (2005) is critical of the use of Census data for the purpose of studying immigrant welfare migration. She stresses that welfare eligibility rules distinguish between illegal and legal immigrants and that these subgroups cannot be cleanly separated in traditional surveys.

Table 3: NAWS Agricultural Regions

Region	**States**
California	CA
Southern Plains	TX, OK
Florida	FL
Mountain III	AZ, NM
Appalachia I, II	NC, VA, KY, TN, WV
Cornbelt Northern Plains	IL, IN, OH, IA, MO, KS, NE, ND, SD
Delta Southeast	AR, LA, MS, AL, GA, SC
Lake	MI, MN, WI
Mountain I, II	ID, MT, WY, CO, NV, UT
Northeast I	CT, ME, MA, NH, NY, RI, VT
Northeast II	DE, MD, NJ, PA
Pacific	OR, WA

authors using it generally do not control for individual demographic characteristics important to locational decision-making. In addition, these researchers only consider legal permanent residents and are unable to characterize broader groups of immigrants, such as naturalized citizens and illegal immigrants. On the other hand, authors who use Census data are unable to fully control for legal status and may under-represent certain immigrant groups. This paper addresses these limitations by using the underused but representative survey of illegal and legal, immigrant and native, U.S. agricultural workers.

5.1 The National Agricultural Workers Survey

Primary data come from the National Agricultural Workers Survey (NAWS), a nationally-representative dataset of employed farmworkers conducted by the U.S. Department of Labor. Advantages of the NAWS include that its sample design, unlike traditional micro-level data sources, specifically accounts for migratory behavior, and that it contains direct information relating to the legal status of its respondents. NAWS workers are employed by growers and farm labor contractors in crop agriculture, where crops are defined as nursery products, cash grains, field crops, fruits, vegetables, silage, and animal fodder. NAWS has sampled from work sites three times per year (fall, winter/spring, summer) since fall of 1988. This dissertation uses the NAWS sample covering 1989 through 2004.[19] Of the 42,821 workers in the sample, 17,572 answer that they are of illegal immigration status. U.S. born workers total 8,292. In addition, 1,846 naturalized citizens, 10,717 Green Cards holders, and 3,689 individuals with other work authorization are identifiable. Mexican workers total 28,249 (66 percent), and 15,823 (56 percent) of Mexican workers are illegal. The NAWS is nationally and regionally representative of agricultural workers (with sampling weights) within the 12 spatial divisions defined in Table 3.

Table 4 shows key demographic and employment variables by legal status after pooling the cross-sectional

[19]Due to confidentiality restrictions, the full NAWS dataset can only be accessed on site at the Department of Labor or at the offices of its contractor, the Aguirre division of JBS International. Data were accessed at the Aguirre office in Burlingame, California for this project.

Table 4: Means of Key Demographic and Employment Variables, by Legal Status

	Native	**Illegal**	**Nat. Citizen**	**Green Card**	**Other Author.**
Female (%)	36.70	15.52	18.47	23.19	13.67
Age (yrs)	32.41	27.58	38.73	38.08	31.46
Married, spouse in U.S. (%)	42.34	18.42	46.38	56.67	33.55
Married, spouse anywhere (%)	44.73	46.28	61.02	76.17	63.67
Children in U.S. (#)	0.75	0.37	1.07	1.35	0.93
None (%)	64.72	83.08	58.17	48.14	65.86
One (%)	12.57	6.45	9.24	12.08	10.12
More than one (%)	22.72	10.46	32.59	39.78	24.02
Children anywhere (#)	0.79	0.93	1.23	1.74	1.01
Education (yrs)	10.70	6.22	7.53	5.89	5.51
U.S. farmwork experience (yrs)	13.46	4.12	16.46	15.49	9.53
Hourly wage ($1982-4)	4.02	3.70	4.07	4.10	4.06
Speaks English (%)	94.86	7.31	42.53	22.54	16.31
Reads English (%)	93.11	5.65	34.84	18.19	11.73
Has work network (%)	56.61	77.84	61.71	59.73	62.34
Paid below min wage (%)	7.62	12.74	7.27	6.64	7.48
Hispanic (%)	35.95	98.59	94.95	96.56	98.27
in California (%)	7.08	33.76	24.73	51.39	35.01
in Southern Plains (TX, OK) (%)	9.76	2.76	6.52	7.71	5.43
in Florida (%)	3.08	7.87	13.02	5.01	8.20
in Arizona or New Mexico (%)	0.87	1.66	1.83	4.24	3.21
from Mexico (%)		93.73	51.20	94.72	94.87
Observations	5664	16514	1598	9622	2547

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.

data. Immigrants working in agriculture are more likely to be male than are U.S. born citizens. Legal immigrants are older on average than natives, and illegal immigrants are younger. Immigrants have fewer years of education and are less likely to report English language ability. Illegal immigrants report fewer years of U.S. experience than do legal immigrants.[20] In terms of locational distributions across U.S. regions, immigrants are more likely to reside in California, Florida, or the Arizona/New Mexico region than are their native counterparts. The opposite is true of Southern Plains (TX, OK) farmworkers.[21]

In some sense, the data represent a compromise in order to say anything about the often transparent population of illegal immigrants. Although the agricultural industry is a major player in the overall labor market for illegal workers, using the NAWS for a study of migration, specifically illegal migration, has its limitations. Because NAWS is a survey only of farmworkers, those employed in other sectors of the economy and the unemployed are excluded. An additional consideration is that since the survey relies on end-point sampling within the destination country, data are only representative of successful border crossers. Thirdly, workers are observed only once, and it is uncertain to what extent observed locations correspond to points of entry.

Welfare participation rates by region are presented in Table 1. California and Florida represent their own regions. Texas is grouped with Oklahoma, and Arizona with New Mexico. These four regions, representing the border states and key U.S. agricultural players, are compared with an inclusive "other" category

[20]The experience variable is calculated as survey year minus reported first year of U.S. farmwork.

[21]Unfortunately, the NAWS does not survey workers in agriculture-related occupations such as livestock. This may account for the low percentages of Southern Plains respondents.

comprising workers from the remaining eight regions.

One previous paper using the NAWS is directly related to this one. Moretti and Perloff (2000) examine farmworkers' welfare program and private charity take-up decisions. The authors find that illegal immigrant families are more likely to use public medical assistance and less likely to use other public aid programs when compared with legal immigrants and U.S. born citizens. In addition, they show a positive correlation between public aid participation and U.S. born children in households headed by illegal immigrants. Although they do not consider geographic clustering, their paper has implications for this study. If welfare migration does exist, it may be stronger along the dimension of medical service or among those with certain family structures.

5.2 Locational Clustering of Public Aid Participants in the NAWS

As documented in Table 1, participation rates vary both across legal status and across states. Table 5 examines geographic clustering of NAWS households that have received aid in California, Texas, Florida, Arizona and other states. In the absence of welfare clustering, roughly equal percentages of welfare participants and nonparticipants would be expected to reside in each state. For example, if 30 percent of U.S. welfare participants live in California, then 30 percent of nonparticipants should also live there. Likewise, equal percentages of participants and nonparticipants in each legal status/state category are expected. The difference between the percentage of participant households living in state s and the percentage of nonparticipant households in state s is an unconditional estimate of the "welfare clustering gap" associated with that location. Table 5 presents percentages of NAWS households who participated and who did not participate in public aid programs in the last two years by legal status and region of residence. A two sample t-test of the equality of means between participant and nonparticipant percentages is an unconditional test for evidence of a welfare clustering gap.

The California panel of Table 5 shows that almost 30 percent of the U.S. farmworkers who received some form of aid lived in California while just over 29 percent of those who did not receive aid resided there. The difference is not statistically significant, discrediting the existence of overall welfare clustering in California in the raw data. The significant differences that do appear in the California panel of Table 5 correspond to U.S. born workers, naturalized citizens, and Green Card holders. The data suggests a positive welfare clustering gap for the U.S. born population in California. Of the full sample of native farmworkers who use aid anywhere in the country, 7.26 percent live in California, but only 4.41 percent of native farmworkers who do not use aid live there. Higher percentages of nonparticipating households than participating ones are observed among naturalized citizens and Green Card holders in California, indicating the absence of a

Table 5: Geographic Clustering of Welfare Recipients (percentage of households)

	have used welfare	have not used welfare	t-test equality	p-value
California migrants				
Full sample	29.98	29.40	-0.73	0.47
Natives	7.26	4.41	-3.10	0.00
Naturalized citizens	19.30	26.21	2.60	0.01
Green Card	48.91	52.11	1.93	0.05
Other work authorization	34.13	35.82	0.54	0.59
Illegal immigrants	31.10	33.02	1.24	0.21
Southern Plains (Texas, OK) migrants				
Full sample	9.37	4.18	-9.48	0.00
Natives	12.71	5.41	-5.98	0.00
Naturalized citizens	8.43	4.54	-2.05	0.04
Green Card	10.51	5.81	-4.17	0.00
Other work authorization	9.83	5.69	-2.38	0.02
Illegal immigrants	4.88	2.60	-3.28	0.00
Florida migrants				
Full sample	6.34	6.84	1.04	0.30
Natives	4.35	3.02	-2.52	0.01
Naturalized citizens	7.66	16.13	4.49	0.00
Green Card	6.45	5.23	-1.02	0.31
Other work authorization	10.54	8.19	-1.30	0.20
Illegal immigrants	6.90	8.54	2.39	0.02
Mountain III (Arizona, NM) migrants				
Full sample	1.32	2.36	6.78	0.00
Natives	0.53	0.66	0.64	0.52
Naturalized citizens	1.76	1.64	-0.18	0.86
Green Card	1.97	5.36	8.35	0.00
Other work authorization	1.59	4.08	4.56	0.00
Illegal immigrants	0.88	1.81	3.94	0.00
Other U.S. Region migrants				
Full sample	53.00	57.22	4.36	0.00
Natives	75.14	86.50	7.20	0.00
Naturalized citizens	62.86	51.48	-3.21	0.00
Green Card	32.16	31.49	-0.41	0.68
Other work authorization	43.92	46.23	0.60	0.55
Illegal immigrants	56.24	54.03	-1.25	0.21

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.

welfare clustering gap for these legal status groups in the raw data.[22]

For the Southern Plains, all subgroups display significant differences between participants and nonparticipants. Participants are unconditionally more likely to be observed in the Southern Plains than are nonparticipants. This is true across legal status groups. Also notable is the Arizona/New Mexico category, for which patterns are largely opposite of those for the Southern Plains. Florida presents an intermediate case.

The statistics presented in Table 5 do not control for socioeconomic characteristics, and therefore might reflect differences in the distributions of characteristics associated with participation across state instead of behavioral clustering. To further describe the participation data, an empirical test for the existence of a welfare clustering gap using multivariate regression analysis is developed.

5.3 Empirical Test of the Existence of a Welfare Clustering Gap

The probability of locating in state s (P_s) is assumed to be an increasing function of expected net benefits and is defined:

$$P_s = \Pr(U_s > U_{s'}, \forall s' \in S, s \neq s') \tag{10}$$

where

$$U_s = V_s + \epsilon_s \tag{11}$$

Utility from migrating to s (U_s) comprises two components, a systematic utility term (V_s) and a random error term (ϵ_s). As in the theoretical section, migrants select the location offering the highest value.

Borjas (1999) develops a descriptive linear probability model in which the probability of residing in California, his welfare magnet candidate, is regressed on a welfare participation indicator, an immigrant indicator, their interaction, and socioeconomic controls. His regression is of the form:

$$CA_i = X_i'\gamma + \alpha_1 Immigrant_i + \alpha_2 B_i + \alpha_3 (Immigrant_i \times B_i) + \epsilon_i \tag{12}$$

CA_i is a dummy variable corresponding to one if the survey respondent was observed in California. X_i is a vector of socioeconomic characteristics including gender, age, presence of spouse, number of children, years of education, and years of U.S. farm experience. B_i indicates if individual i (or i's family) is a public aid participant. The coefficient α_3 is an estimator of the welfare clustering gap in California. The welfare

[22] The welfare clustering gap definition in this section is the presence of a *positive* difference between the percentage of participant households locating in state s and the percentage of non-participant households locating there. Higher percentages of residents drawn from the non-participant distribution than from the participant distribution is evidence against the existence of a welfare clustering gap for that state.

Table 6: Borjas' Welfare Clustering Gap Hypothesis Test

Dependent variable: Probability of California	(1)	(2)	(3)	(4)
	CA	CA	CA	CA
immigrant	0.327***	0.362***	0.267***	0.261***
	(0.006)	(0.009)	(0.025)	(0.025)
used public aid	0.026***	0.003	0.018*	0.018*
	(0.009)	(0.010)	(0.010)	(0.010)
immigrant*used public aid	-0.026*	-0.063***	-0.041***	-0.040***
	(0.013)	(0.014)	(0.014)	(0.014)
includes socioeconomic characteristics?	no	yes	yes	yes
includes origin fixed effects?	no	no	yes	yes
includes work network controls?	no	no	no	yes
Observations	42619	40273	37238	36408

$***p < 0.01, **p < 0.05, *p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Linear probability model. Robust standard errors in parentheses.

clustering gap measures the difference between public aid participants and non-participants for immigrants relative to the estimate of this difference for the U.S. born population. The regression does not claim a causal relationship. Instead, it describes the equilibrium relationship between state choice and program participation.

Borjas runs this regression on Census data separately for 1980 and 1990. He finds that the coefficient α_3 is significant in the positive direction and argues that this is consistent with a welfare migration story in which immigrants who are welfare participants are more likely to be observed in high-benefit California than elsewhere in the country, even after controlling for differences in socioeconomic characteristics.

Table 6 shows results from this regression on the NAWS sample in the presence and absence of socioeconomic characteristic controls, place of origin fixed effects, and a variable indicating the presence of individual work networks.[23] The result is notably different in that the coefficient α_3 is significant in the negative direction across specifications.

The following probit regression extends Borjas' empirical model to allow for multiple treatment groups by legal status. Each immigrant legal status group is compared with a U.S. born control group. Consider:

$$\Pr(S_i) = \Phi[X_i'\lambda + \beta_1 I_i + \beta_2 N_i + \beta_3 G_i + \beta_4 O_i + \beta_5 B_i \tag{13}$$
$$+\beta_6(I_i \times B_i) + \beta_7(N_i \times B_i) + \beta_8(G_i \times B_i) + \beta_9(O_i \times B_i)]$$

Here, S_i is a binary variable for whether or not individual i is observed in state s. I_i is a dummy variable indicating whether or not a migrant farmworker is of illegal status. N_i, G_i, and O_i are binary variables for naturalized citizen, Green Card, and other work authorization respectively. B_i is defined as above. The coefficients β_6 through β_9 are estimators of the clustering gaps in state s between public aid participants and non-participants for each legal status group relative to the estimate of this gap for the native population.

[23]The work network variable equals one if the worker was referred to his or her job by a relative, friend, or fellow worker.

Table 7: Welfare Clustering Gap Hypothesis Test Revised

Dependent variable: Probability of State s	(1) CA	(2) TX	(3) FL	(4) AZ	(5) Other
naturalized citizen	0.446***	-0.021***	0.066**	-0.001	-0.324***
	(0.041)	(0.003)	(0.027)	(0.003)	(0.038)
Green Card	0.512***	-0.029***	0.034**	0.004	-0.396***
	(0.030)	(0.004)	(0.016)	(0.004)	(0.030)
other work author.	0.384***	-0.022***	0.066***	0.008	-0.257***
	(0.041)	(0.002)	(0.025)	(0.007)	(0.040)
illegal	0.350***	-0.062***	0.049***	0.002	-0.269***
	(0.026)	(0.010)	(0.013)	(0.003)	(0.033)
used public aid	0.073***	0.031***	0.013*	-0.001	-0.159***
	(0.024)	(0.007)	(0.007)	(0.002)	(0.023)
naturalized*used public aid	-0.078**	-0.014***	-0.030***	0.002	0.219***
	(0.034)	(0.005)	(0.004)	(0.005)	(0.036)
Green Card*used public aid	-0.072***	-0.012***	0.002	-0.003**	0.145***
	(0.023)	(0.004)	(0.011)	(0.001)	(0.026)
other author.*used public aid	-0.085**	0.001	-0.004	-0.003**	0.117**
	(0.035)	(0.011)	(0.012)	(0.001)	(0.054)
illegal*used public aid	-0.122***	-0.011***	-0.019***	-0.003***	0.230***
	(0.018)	(0.004)	(0.005)	(0.001)	(0.022)
Observations	35967	34884	35967	35898	35967

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Probit marginal effects. Robust standard errors in parentheses.

The characteristics in X_i control for demographic factors associated with program eligibility (e.g. family structure) and for systematic differences in the averages of these factors across legal status groups.[24] National or regional origin effects are included in reported specifications. Previous papers (e.g. Zavodny (1999), Borjas (1999), Dodson (2001)) use immigrant country of origin to control for linguistic and cultural networks. The NAWS allows for the opportunity to refine this to the state level within the country of origin. Due to low sample sizes from sending countries other than Mexico, state-level origin controls only are used in the case of Mexico. National-level origin controls are used for those from countries besides Mexico. Survey year and season fixed effects are included in all regressions.

Table 7 presents estimates of the clustering gaps between welfare participants and nonparticipants for the four immigrant legal status groups relative to natives in separate regressions for California, Texas, Florida, Arizona, and other U.S. states.[25] Negative coefficients on legal status/participation interactions indicate that there no evidence of welfare clustering relative to the U.S. born population. Using similar methodology, Borjas (1999) finds strong positive welfare clustering in California by legal immigrants relative to natives. As evident in Column (1) of Table 7, no such results are found for any legal status group in California for this analysis using the NAWS.[26] Instead, naturalized citizens who use public aid are 7.8 percent *less* likely to

[24]Income, which may be associated with eligibility for aid programs, is not explicitly accounted for in this framework. Given that the sample comprises farm laborers who are low income irrespective of legal status group, this is less of a concern than it would be for higher income persons who are excluded from participating. Borjas (1999) discusses a second issue surrounding income. Higher relative benefits cover larger ranges of the distribution of reservation incomes than do lower benefits, and the estimation method may integrate over different distributions even for members of various legal status groups who are observationally equivalent. In the theoretical model of Section 3, public aid is assumed to be a supplement to income, as opposed to a replacement of income, thus minimizing this concern.

[25]From this point forward, "Texas" refers to the "Southern Plains" and "Arizona" to Arizona/New Mexico.

[26]It should be noted again that all NAWS respondents are employed (at least part-time) by definition. Robustness analysis

be observed in California than naturalized citizens who do not; Green Card holders using aid are 7.2 percent *less* likely to live in California than Green Card holders who do not; those with other work authorization who use aid are 8.5 percent *less* likely to live in California than their nonparticipating counterparts; and illegal immigrants who use aid are 12.2 percent *less* likely to locate in California than are nonparticipating illegal immigrants.[27] The results are inconsistent with the hypothesis that California is a welfare magnet for agricultural workers.

Redefining the dependent variable using the other border states, Table 7 also presents results for Texas, Florida, and Arizona region regressions as well as for the nonborder states. As in the California case, immigrant clustering gap coefficients are negative for the border states, and many are significantly different from zero. Illegal immigrant workers who use public aid are 1.1 percent less likely to live in Texas, 1.9 percent less likely to live in Florida, and 0.3 percent less likely to live in Arizona than are illegal immigrants who do not use aid. Although statistically significant, these magnitudes are less economically significant than those associated with California.

Positive estimates of welfare clustering gaps are evident in the other states category. This result is consistent with at least two stories. Either border states repel immigrant welfare users across legal status categories and the positive welfare clustering result for other regions is mechanical, or welfare-induced migration does exist to non-border regions and the negative coefficients on the interaction terms in the border state regressions are a mechanical result. Although these interpretations cannot be disentangled in this framework, in both cases, evidence is inconsistent with welfare migration to the border states. Welfare migration does not explain geographic clustering of illegal and legal agricultural workers in California, Texas, Florida, and Arizona.

5.3.1 Family Structure Considerations

Moretti and Perloff (2000) find that illegal NAWS workers with U.S. born children are more likely to use welfare than are illegal workers without U.S. born children, suggesting that there may be differences in welfare clustering across family structures. Table 8 retests the clustering gap hypothesis after restricting the sample to those workers with U.S. born children. Of children reported by NAWS farmworkers, 45.2 percent are native.

As shown in Table 8, many of the clustering gap estimates lose significance for this subpopulation indicating that immigrant welfare participants with U.S. born children are more similar to their native counterparts

using employed and unemployed Census respondents is presented later in this section.

[27] Ai and Norton (2003) argue that in nonlinear differences-in-differences models in which the change in an outcome over time is measured for a treatment relative to a control group, the magnitude and statistical significance of interaction variable may be miscalculated by statistical software. The empirical framework here differs in that observations on individuals are not repeated, and outcomes are not measured over time.

Table 8: Farmworkers with U.S. Born Children Clustering Gap Test

Dependent variable: Probability of State s	(1) CA	(2) TX	(3) FL	(4) AZ	(5) Other
naturalized citizen	0.432***	-0.022***	0.040	-0.000	-0.236***
	(0.088)	(0.003)	(0.042)	(0.009)	(0.086)
Green Card	0.493***	-0.024***	0.009	0.004	-0.327***
	(0.062)	(0.008)	(0.022)	(0.010)	(0.068)
other work author.	0.313***	-0.020***	0.019	0.005	-0.118
	(0.093)	(0.004)	(0.029)	(0.013)	(0.093)
illegal	0.333***	-0.042***	0.029	0.000	-0.220***
	(0.053)	(0.015)	(0.020)	(0.008)	(0.070)
used public aid	0.083**	0.018*	0.011	-0.005	-0.130***
	(0.041)	(0.010)	(0.014)	(0.003)	(0.043)
naturalized*used public aid	-0.059	-0.000	-0.031***	0.001	0.186***
	(0.067)	(0.018)	(0.007)	(0.010)	(0.071)
Green Card*used public aid	-0.072*	-0.012*	0.011	-0.002	0.114**
	(0.041)	(0.006)	(0.025)	(0.004)	(0.050)
other author.*used public aid	-0.053	0.023	0.017	0.003	0.002
	(0.079)	(0.034)	(0.030)	(0.012)	(0.108)
illegal*used public aid	-0.118***	-0.008	-0.019*	-0.002	0.205***
	(0.030)	(0.008)	(0.010)	(0.004)	(0.042)
Observations	9308	8514	9067	8636	9319

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Probit marginal effects. Robust standard errors in parentheses.

than are those without U.S. born children. The coefficients on the interaction terms between participation and legal status for the three legal immigrant groups relative to natives are not significantly different from zero in most cases, but illegal immigrant households with U.S. born children who use welfare are still almost 12 percent less likely to live in California than are their native counterparts, suggesting that the California results are not driven by systematic family structure differences across states.

5.3.2 California Proposition 187 and PRWORA

The strong negative clustering gap coefficients in the California regression deserve additional consideration. As mentioned, California was the stage for multiple immigration and public aid related policy changes throughout the NAWS sample period. Table 9 considers welfare clustering gaps for California in three periods. The first period, 1989 to 1994, predates California Proposition 187, which eliminated welfare, education, and medical service eligibility for illegal immigrants. The second period, 1995 to 1996, corresponds to the period between the enactment of Proposition 187 and PRWORA.[28] The third, 1997 to 2004, is subsequent to federal welfare reform. The coefficients corresponding to the clustering gap for illegal immigrants over natives reflect these policy changes. Referring to the interaction term, before Proposition 187, illegal households in agriculture who used aid programs were 5.6 percent less likely to reside in California than were illegal households who did not use aid. In the Proposition 187 period, illegal participants were 16.3 percent less likely than their nonparticipating counterparts to be observed in California, and in the post-1996 welfare

[28]Since Proposition 187 was in effect from November 1994 until November 1995, the 1995 to 1996 data are pooled for this exercise. This is appropriate given that the survey question asks if the respondent or his or her family participated in public aid programs within the last two years.

Table 9: California Clustering Gap Test

Dependent variable: Probability of California	**1989-1994**	**1995-1996**	**1997-2004**
	(1)	(2)	(3)
	CA	CA	CA
naturalized citizen	0.579***	0.350**	0.394***
	(0.078)	(0.143)	(0.053)
Green Card	0.609***	0.582***	0.433***
	(0.053)	(0.068)	(0.042)
other work author.	0.475***	0.162	0.195**
	(0.065)	(0.116)	(0.084)
illegal	0.347***	0.366***	0.325***
	(0.050)	(0.065)	(0.036)
used public aid	0.049*	0.121**	0.060
	(0.028)	(0.061)	(0.038)
naturalized*used public aid	-0.064*	-0.027	-0.087*
	(0.036)	(0.136)	(0.052)
Green Card*used public aid	-0.062***	-0.086*	-0.074*
	(0.022)	(0.052)	(0.039)
other author.*used public aid	-0.030	-0.142**	-0.097
	(0.039)	(0.068)	(0.084)
illegal*used public aid	-0.056**	-0.163***	-0.141***
	(0.026)	(0.037)	(0.030)
Observations	8376	4127	23463

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-1994, 1995-1996, and 1997-2004. Probit marginal effects. Robust standard errors in parentheses.

reform period, this number is 14.1 percent. While illegal immigrants who use public aid were less likely to be in California than nonparticipants and natives before 1994, decreased participation by illegal farmworkers is observed during the Proposition 187 period. Results for regressions considering the pre- and post-1996 federal welfare reform periods for alternate destination states are similar and are not reported.

5.3.3 Food, Medical, and Insurance Programs

Camarota (2004) finds that due to individual program eligibility restrictions, illegal immigrants are more likely to use food assistance and medical programs than cash-transfers. Table 10 presents estimates of clustering gaps associated with specific aid programs, and the results parallel those for the full sample. Food aid consisting of FSP and WIC is presented in the top panel. The second panel presents results corresponding to a medical assistance category comprising Medicaid and public health center services. The third presents Social Security and disability insurance.

Even with these revised definitions, there is little evidence supporting welfare clustering in border states for agricultural workers. The difference in propensity to choose California between illegal immigrants who use aid and those who do not is strongest for medical care programs. Illegal immigrants who use medical services are 12.1 percent less likely to locate in California than illegal immigrants who do not. Illegal immigrants who use social insurance programs or food aid are 10.7 and 8.4 percent less likely respectively to live in California than are their nonparticipating counterparts. The negative significant welfare clustering gap estimates for the Texas and Florida regressions in Table 7 appear primarily driven by food aid participation, while that

Table 10: Food, Medical, and Insurance Program Clustering Gap Tests

Dependent variable: Probability of State s	(1) CA	(2) TX	(3) FL	(4) AZ	(5) Other
Food Aid (food stamps or WIC):					
naturalized*used program	-0.090**	-0.018***	-0.027***	0.007	0.235***
	(0.037)	(0.004)	(0.005)	(0.008)	(0.036)
Green Card*used program	-0.071***	-0.008*	0.006	-0.001	0.155***
	(0.025)	(0.005)	(0.013)	(0.002)	(0.027)
other author.*used program	-0.042	-0.009	-0.002	-0.002	0.1
	(0.046)	(0.008)	(0.013)	(0.002)	(0.061)
illegal*used program	-0.084***	-0.015***	-0.021***	-0.002	0.221***
	(0.022)	(0.004)	(0.005)	(0.002)	(0.024)
Medical (Medicaid or public health):					
naturalized*used program	-0.038	-0.012*	-0.027***	0.005	0.143***
	(0.051)	(0.006)	(0.006)	(0.008)	(0.052)
Green Card*used program	-0.049	-0.013***	0.008	-0.004***	0.086**
	(0.034)	(0.004)	(0.016)	(0.001)	(0.035)
other author.*used program	-0.114**	0.002	0.000	-0.002	0.124
	(0.054)	(0.019)	(0.027)	(0.004)	(0.087)
illegal*used program	-0.121***	-0.007	-0.016**	-0.005***	0.202***
	(0.025)	(0.005)	(0.007)	(0.001)	(0.030)
Social Security or disability insurance:					
naturalized*used program	-0.044	0.018	-0.023**	0.052	0.027
	(0.065)	(0.028)	(0.010)	(0.041)	(0.086)
Green Card*used program	-0.003	-0.013*	-0.026***	0.055	0.074
	(0.042)	(0.007)	(0.007)	(0.034)	(0.056)
other author.*used program	0.136	-0.005	-0.018	-0.003	-0.013
	(0.102)	(0.015)	(0.013)	(0.003)	(0.110)
illegal*used program	-0.107**	-0.005	-0.015	0.083	0.155**
	(0.047)	(0.012)	(0.016)	(0.059)	(0.069)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Probit marginal effects. Robust standard errors in parentheses.

for Arizona is most related to medical services.

5.3.4 Education

The NAWS affords the opportunity to consider how education program availability affects locational choice. A long literature in public finance and education is devoted to Tiebout choice, or geographic sorting of individuals based on preferences over a set of available public good bundles, and its potential outcomes for students, parents, and communities. Public education is costly to state government and whether it should be available to illegal immigrants is a subject of heated debate. NAWS respondents were asked if they or members of their family participated in any of a number of U.S. educational programs in the last two years, including English as a Second Language, basic education, citizenship, job training, GED/high school equivalence, migrant education, Head Start, and Migrant Head Start.

Table 11 presents estimates of education clustering gaps. Again, a series of probits are presented in which the dependent variable is the probability of residing in state s. Few clustering gap interactions in this category are significantly different from zero. Illegal immigrants who use schools, however, are less likely to reside in California and more likely to reside in other U.S. regions.

Because adult immigrants may use educational programs to a lesser extent than their children do, Table

Table 11: Education Clustering Gap Test

Dependent variable: Probability of State s	(1) CA	(2) TX	(3) FL	(4) AZ	(5) Other
naturalized citizen	0.418***	-0.019***	0.032	-0.003	-0.261***
	(0.046)	(0.003)	(0.025)	(0.003)	(0.044)
Green Card	0.487***	-0.025***	0.027	0.004	-0.380***
	(0.035)	(0.005)	(0.019)	(0.006)	(0.037)
other work author.	0.271***	-0.011*	0.030	-0.001	-0.168***
	(0.058)	(0.006)	(0.028)	(0.005)	(0.057)
illegal	0.313***	-0.062***	0.025	0.002	-0.181***
	(0.032)	(0.010)	(0.015)	(0.005)	(0.041)
used schools	-0.035	-0.001	0.006	0.002	0.012
	(0.035)	(0.006)	(0.011)	(0.004)	(0.035)
naturalized*public education	-0.038	-0.010	-0.019**	0.013	0.077
	(0.063)	(0.013)	(0.009)	(0.015)	(0.074)
Green Card*public education	-0.041	-0.007	0.001	-0.002	0.097**
	(0.041)	(0.007)	(0.015)	(0.003)	(0.041)
other author.*public education	0.028	-0.015**	0.010	-0.000	0.002
	(0.099)	(0.007)	(0.027)	(0.006)	(0.105)
illegal*public education	-0.090**	0.022	-0.002	0.001	0.090**
	(0.035)	(0.014)	(0.011)	(0.005)	(0.044)
Observations	23727	22583	23703	22954	23727

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Probit marginal effects. Robust standard errors in parentheses.

Table 12: Child Education Clustering Gap Test

Dependent variable: Probability of State s	(1) CA	(2) TX	(3) FL	(4) AZ	(5) Other
naturalized citizen	0.417***	-0.025***	0.039	-0.006**	-0.173*
	(0.088)	(0.003)	(0.047)	(0.002)	(0.090)
Green Card	0.371***	-0.037***	0.052	0.001	-0.204***
	(0.069)	(0.008)	(0.033)	(0.007)	(0.072)
other work author.	0.302***	-0.013	0.037	-0.003	-0.141
	(0.110)	(0.012)	(0.039)	(0.005)	(0.110)
illegal	0.282***	-0.061***	0.018	-0.002	-0.103
	(0.054)	(0.019)	(0.021)	(0.007)	(0.070)
used public aid	-0.015	-0.018*	0.013	-0.016*	0.077*
	(0.035)	(0.009)	(0.011)	(0.009)	(0.040)
naturalized*public education	-0.011	0.036	-0.025**	0.085	-0.016
	(0.069)	(0.042)	(0.012)	(0.098)	(0.086)
Green Card*public education	0.094*	0.023	-0.039***	0.016	-0.108**
	(0.052)	(0.015)	(0.009)	(0.013)	(0.052)
other author.*public education	-0.059	-0.015	-0.021	0.064	0.056
	(0.076)	(0.011)	(0.013)	(0.051)	(0.109)
illegal*public education	-0.001	0.012	-0.004	0.012	-0.060
	(0.039)	(0.011)	(0.014)	(0.008)	(0.046)
Observations	11089	10112	10961	10272	11089

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Probit marginal effects. Robust standard errors in parentheses.

12 restricts the sample to agricultural workers with children. The public education participation variable is redefined as the response to a more specific question as to whether a child of the farmworker attended school within the last year. Of the 26,982 children represented in NAWS responses, 66 percent used schools in the last year. Few of the clustering gap estimates are statistically significantly different from zero. This is consistent with children of illegal and legal immigrants attending school roughly as frequently as children of U.S. born parents do.

5.4 Welfare Clustering in the U.S. Census

Because the NAWS is a survey of agricultural workers, the question arises as to whether the results are generalizable to the rest of the population and how these results can be reconciled with those of Borjas (1999). The Census does not distinguish illegal from legal immigrants. Instead, the only citizenship-related question asked to immigrants is whether they are naturalized citizens. Thus, naturalized citizens can be distinguished from noncitizens, but legal permanent residents cannot be distinguished from illegal persons, and within the legal permanent resident category, Green Card holders cannot be distinguished from those with other work authorization. The broadest definition of welfare benefits available in the Census is used here, which is based on usage of TANF, FSP, or SSI within the last year. Thus, the welfare participation variable is more restrictive (both temporally and in terms of program specificity) than that used in the analysis using the NAWS.

Borjas (1999) finds that welfare recipients cluster in benefit-generous California using 1980 and 1990 Census data. The 2000 Census is the first available decennial Census in the post-PRWORA period. Therefore, it is useful to establish if the patterns Borjas observed are still evident after changes in eligibility requirements. Column (1) of Table 13 confirms Borjas' result using the latest Census data: the welfare clustering gaps of naturalized citizens and of noncitizens relative to the U.S. born population are positive and significant. Naturalized citizens who used public aid were 2.2 percent more likely to be observed in California than were U.S. born welfare participants, and noncitizen participants were 7.7 percent more likely to be observed in California than were native participants.

One difference between the NAWS and the Census is that NAWS only includes employed persons in agriculture, while the Census is representative of both those in the labor force and those apart from it. If Borjas' result is driven by welfare use by unemployed persons then this would explain the conflicting evidence using like-methodology with the NAWS data. Column (2) of Table 13 restricts the U.S. Census sample to those active in the labor force.[29] Borjas' result still holds. The clustering gap estimate for unemployed

[29] In 2000, the reference period for this question was one week. Respondents were asked if they worked for pay last week. If the response was negative, additional questions examined if this was a temporary situation.

Table 13: 2000 Census Clustering Gap Test

Dependent variable: Probability of California	**full sample**	**in labor force**	**unemployed**	**not in labor force**
	(1)	(2)	(3)	(4)
	CA	CA	CA	CA
naturalized citizen	0.072***	0.060***	0.075***	0.092***
	(0.003)	(0.003)	(0.016)	(0.005)
noncitizen	0.071***	0.058***	0.072***	0.098***
	(0.002)	(0.002)	(0.011)	(0.004)
used public aid	0.027***	0.016***	0.005	0.031***
	(0.002)	(0.006)	(0.015)	(0.002)
naturalized*used public aid	0.022***	0.090***	0.029	-0.014*
	(0.008)	(0.018)	(0.033)	(0.007)
noncitizen*used public aid	0.077***	0.077***	0.115***	0.049***
	(0.008)	(0.013)	(0.031)	(0.010)
Observations	1054372	685641	26022	342709

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: 2000 U.S. Census, 1% sample of full population.
Probit marginal effects. Robust standard errors in parentheses.

Table 14: 1990 Census Clustering Gap Test – Farmworkers

Dependent variable: Probability of State s	(1)	(2)	(3)	(4)	(5)
	CA	TX	FL	AZ	Other
naturalized citizen	-0.036	-0.013	-0.011	0.976***	0.111
	(0.038)	(0.035)	(0.028)	(0.004)	(0.080)
noncitizen	0.025	-0.051*	-0.028	0.957***	0.066
	(0.050)	(0.027)	(0.022)	(0.002)	(0.089)
used public aid	0.026**	-0.009	-0.010**	-0.006**	0.007
	(0.012)	(0.008)	(0.005)	(0.003)	(0.015)
naturalized*used public aid	-0.025	0.071*	-0.029**	0.004	-0.038
	(0.029)	(0.042)	(0.012)	(0.012)	(0.087)
noncitizen*used public aid	-0.025	0.089***	-0.038***	0.001	-0.047
	(0.018)	(0.029)	(0.005)	(0.008)	(0.046)
Observations	31747	31747	31747	31747	31747

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: 1990 U.S. Census, 5% sample of farm laborers.
Probit marginal effects. Robust standard errors in parentheses.

Table 15: 2000 Census Clustering Gap Test – Farmworkers

Dependent variable: Probability of State s	(1)	(2)	(3)	(4)	(5)
	CA	TX	FL	AZ	Other
naturalized citizen	-0.037	-0.023	-0.003	0.002	0.125
	(0.048)	(0.033)	(0.032)	(0.013)	(0.101)
noncitizen	-0.004	-0.039	-0.007	0.007	0.091
	(0.054)	(0.033)	(0.032)	(0.014)	(0.111)
used public aid	0.098***	-0.002	0.011	-0.006	-0.082***
	(0.019)	(0.010)	(0.008)	(0.004)	(0.020)
naturalized*used public aid	-0.063**	0.049	-0.031***	0.011	0.006
	(0.026)	(0.035)	(0.010)	(0.016)	(0.059)
noncitizen*used public aid	-0.061***	0.065**	-0.019*	-0.008	0.021
	(0.017)	(0.027)	(0.011)	(0.006)	(0.035)
Observations	33368	33368	33368	33368	33368

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: 2000 U.S. Census, 5% sample of farm laborers.
Robust standard errors in parentheses.

persons (Column (3)), however, is more pronounced than that for employed persons. Unemployed noncitizen welfare participants are 11.5 percent more likely to be observed in California than are unemployed U.S. born welfare participants, while employed noncitizen participants are 7.7 percent more likely to be in California than are employed U.S. born participants.

Occupation-related questions in the Census allow farm laborers to be identified. Because farm laborers in the Census are a relatively small sample (partially due to undersampling as noted earlier), the five percent version of both the 1990 and 2000 Census is used to repeat the exercise and to check for differences before and after PRWORA. Tables 14 and 15 present the results. The negative welfare clustering gaps across legal status groups found using the NAWS also appear using this subsample. Therefore, while unemployed workers may still engage in welfare migration (as suggested by positive clustering gap estimates for immigrants in the overall Census results), the difference between the results using the NAWS and those in Borjas (1999) are not primarily due to differences between the unemployed and the employed. Instead, the similar results when using Census agricultural workers and when using the NAWS suggest that differences between the main results in Borjas (1999) and this paper are due to a fundamental difference between agricultural workers and the rest of the immigrant population in regards to welfare-induced migration.

Additional occupations traditionally taken by illegal immigrants in the U.S. were also considered with Census data. Regressions using data restricted to construction workers, service workers, and private household workers were examined (not shown). The interaction variables between program participation and immigration status are primarily insignificantly different from zero across destination state regressions, indicating that these professions represent an intermediate between the agricultural workers results and those based on the full population Census.

6 Self-Selection and Locational Choice

A consideration not yet discussed is whether illegal migrants in one state systematically differ from those in another state. The theoretical model in Section 3 suggests that immigrants within each legal status group should sort based on their skill levels in response to differences in the wage-skill relationship across states. Therefore, selection might shed further light on the agricultural worker results and their relationship to Borjas (1999) if illegal and legal immigrants within a state differ from those elsewhere in the country. For example, the lack of welfare clustering in California in the NAWS might be associated with selection by higher skilled immigrant farmworkers into California as opposed to elsewhere.

Table 16: Selection in Observable Characteristics

		(1) CA	(2) TX	(3) FL	(4) AZ	(5) Other
Nat. X Citizen	female	0.332***	-0.005	0.004	-0.003	-0.266***
		(0.065)	(0.012)	(0.017)	(0.002)	(0.057)
	age	0.002	-0.000	-0.000	0.000	-0.002
		(0.002)	(0.001)	(0.001)	(0.000)	(0.003)
	spouse	0.048	-0.003	-0.029***	-0.001	0.173***
		(0.059)	(0.014)	(0.005)	(0.003)	(0.049)
	children	0.015	-0.001	-0.010*	0.001	0.001
		(0.016)	(0.004)	(0.005)	(0.001)	(0.017)
	education	0.021***	0.001	0.001	0.002***	-0.032***
		(0.006)	(0.002)	(0.002)	(0.000)	(0.007)
	U.S. farmwork experience	0.005**	0.001	0.001	0.000	-0.011***
		(0.003)	(0.001)	(0.001)	(0.000)	(0.003)
	work network	-0.114***	0.018	-0.019***	0.006	0.104**
		(0.026)	(0.016)	(0.007)	(0.007)	(0.044)
Green X Card	female	0.096***	-0.011**	0.029*	-0.001	-0.128***
		(0.037)	(0.005)	(0.017)	(0.002)	(0.033)
	age	0.002	0.000	-0.001**	0.000***	-0.002
		(0.001)	(0.000)	(0.001)	(0.000)	(0.002)
	spouse	0.041	-0.007	0.013	-0.002	-0.032
		(0.035)	(0.006)	(0.014)	(0.001)	(0.034)
	children	-0.007	0.001	-0.004	0.001	0.009
		(0.010)	(0.002)	(0.003)	(0.001)	(0.010)
	education	0.016***	0.005***	0.001	0.001***	-0.040***
		(0.004)	(0.001)	(0.001)	(0.000)	(0.005)
	U.S. farmwork experience	0.000	-0.000	-0.001	-0.000	-0.000
		(0.001)	(0.000)	(0.001)	(0.000)	(0.002)
	work network	-0.042**	-0.001	-0.011	-0.002	0.073***
		(0.021)	(0.005)	(0.008)	(0.002)	(0.026)
Other X Author.	female	0.123*	0.007	0.070**	-0.003**	-0.259***
		(0.065)	(0.019)	(0.030)	(0.001)	(0.071)
	age	0.006***	0.000	-0.001*	0.000*	-0.004
		(0.002)	(0.001)	(0.001)	(0.000)	(0.003)
	spouse	0.024	-0.003	0.021	0.008	-0.058
		(0.047)	(0.010)	(0.016)	(0.006)	(0.058)
	children	-0.001	-0.001	-0.008***	-0.001	0.022
		(0.014)	(0.002)	(0.003)	(0.001)	(0.019)
	education	0.015**	0.003*	0.004**	0.000	-0.035***
		(0.006)	(0.002)	(0.002)	(0.000)	(0.008)
	U.S. farmwork experience	-0.006**	0.001*	0.000	-0.000	-0.000
		(0.003)	(0.001)	(0.001)	(0.000)	(0.004)
	work network	-0.109***	0.019	-0.016**	-0.002*	0.157***
		(0.024)	(0.015)	(0.006)	(0.001)	(0.042)
Illegal X	female	0.007	0.012	0.011	-0.003	-0.059*
		(0.028)	(0.009)	(0.009)	(0.002)	(0.031)
	age	0.002	0.000	-0.001***	0.000***	-0.000
		(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	spouse	-0.004	-0.010*	0.014	0.003	0.015
		(0.029)	(0.005)	(0.009)	(0.003)	(0.030)
	children	-0.008	-0.002	-0.007***	-0.001*	0.027**
		(0.009)	(0.003)	(0.002)	(0.001)	(0.011)
	education	0.010***	0.005***	0.003***	0.001***	-0.035***
		(0.004)	(0.001)	(0.001)	(0.000)	(0.004)
	U.S. farmwork experience	-0.005***	0.001***	0.001*	-0.000	0.000
		(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
	work network	0.020	-0.005	-0.015***	-0.005***	0.020
		(0.021)	(0.005)	(0.006)	(0.002)	(0.025)
	Observations	36091	35005	36091	36020	36091

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Probit marginal effects. Robust standard errors in parentheses. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Again extending the strategies employed in Borjas (1999), consider:

$$\Pr(S_i) = \Phi[X_i'\theta + \delta_1 I_i + \delta_2 N_i + \delta_3 G_i + \delta_4 O_i \tag{14}$$
$$+\delta_5(I_i \times X_i) + \delta_6(N_i \times X_i) + \delta_7(G_i \times X_i) + \delta_8(O_i \times X_i)]$$

Variables are defined as before. The vectors δ_5 through δ_8 capture differential effects of socioeconomic characteristics on the probability that workers in the various legal status groups reside in state s.

As far as education can be interpreted as a proxy for skill, Table 16 suggests that self-selection differences between agricultural workers and the rest of the population of immigrants may drive differences between results in this paper and those in previous studies. The significant coefficients on the legal status interactions with education suggests positive selection in terms of education to the border states. This is especially true for California where legal status/education interactions are positive and significant for all legal status groups. Workers are negatively selected in each legal status group to other U.S. states, consistent with the appearance of a welfare clustering gap in those locations. Borjas (1999) found evidence for welfare clustering and for negative selection to California among legal immigrants in the 1980 and 1990 Census samples. This result is not confirmed with the NAWS. Instead, immigrant agricultural workers positively select to California.

As noted previously, Chiquiar and Hanson (2005) and Orrenius and Zavodny (2005) find that Mexican immigrants are selected from the intermediate or high end of the Mexican education distribution. More educated agricultural migrants (the majority of whom are from Mexico) are found to self-select to border regions while less educated persons sort to northern states. This finding extends the selection literature to consider how migrants self-select within a destination country.

7 Effect of Public Aid Characteristics on Locational Choice

7.1 Conditional Logistic Regression

Conditional logistic regression allows effects of individual characteristics and state-level attributes to be estimated simultaneously.[30] This section exploits variation in state-level public aid provisions, labor market characteristics, and border patrol intensities both over time and across locations. Consistent with the welfare clustering results for agricultural workers, welfare and education program values are found to be insignificant determinants of locational choice within the border states.

Utility levels associated with each potential location, although unobservable, are assumed to be functions

[30] McFadden (1974) first developed this model. Previous migration studies papers such as Bartel (1989), Jaeger (2000), and Kaushal (2005) use variations of the methods here. In addition to the migration literature, this model has been used in studies of consumer and occupation choice (e.g Boskin (1974)).

Table 17: State-level Characteristics, 2004

	CA	TX	FL	AZ
Maximum monthly welfare (U.S. dollars)	697	201	303	347
Annual education value (U.S. dollars)	7,860	7,698	7,181	5,595
Minimum wage (U.S. dollars/hour)	6.75	5.15	5.15	5.15
Linewatch hours per mile	17,649	3,446	—	7,304
Rural unemployment rate (%)	7.12	6.23	4.90	6.36
Farm employment (1000s)	213,384	45,037	52,915	13,144
State population Hispanic share (%)	34.67	34.60	19.00	28.01
Mean hired farmworker wage (U.S. dollars/hour)	8.41	7.73	7.97	7.08

Sources described in Appendix B.

of a set of personal attributes (w_i) and locational characteristics (x_i^s). Personal attributes include gender, age, existence of a spouse and/or children, education, U.S. migration or work experience, legal status, and presence of work networks. Locational characteristics include the state's rural unemployment rate, agricultural employment totals, Hispanic share of the state's population, average agricultural wage, minimum wage laws, border patrol intensity (measured by linewatch hours per mile), maximum welfare benefits (maximum AFDC/TANF plus FSP values), and education expenditure per pupil. State characteristics are matched to individuals by year of observation. Welfare benefit and education expenditure levels are matched by year of observation and by reported family structure characteristics. Previous studies have used AFDC/TANF for a family of three (or four) as a regressor, despite differences in family sizes in the actual population. The calibration by family size used here is more appropriate since migrants may jointly decide whether or not to bring family members on a migration and where to locate in the U.S. State-level characteristics in 2004 are presented in Table 17. Appendix B presents additional description of these variables and their variation over time.

The independent variables are written: $z_i^d = [x_i^d, w_i]$ and

$$U_i^s = \alpha' x_i^s + \beta' w_i + \epsilon_i^s = \delta' z_i^s + \epsilon_i^s \tag{15}$$

where α and β (or δ) are parameters to be estimated and ϵ_i^s is the error term. Note that the x_i^s's can vary across choices and across individuals. The w_i's on the other hand vary by individual only. Rewriting:

$$P_i^s = \Pr(\delta' z_i^s + \epsilon_i^s > \delta' z_i^{s'} + \epsilon_i^{s'}, \forall s' \in S, s \neq s') \tag{16}$$

In this model, the data are grouped by unordered receiving states and the likelihood is calculated relative to each group. Specifically, the data are reformated into a panel across individuals and across states. The data consist of $N \times S$ observations where N is the number of individuals in the sample and S is the number of locations in the choice set. The estimation strategy involves interacting individual attributes with dummy variables for the choices in order to examine how individual attributes apply to choices. As there are S observations corresponding to each individual, the dependent variable is an indicator for the realized location taking the form:

$$y_i^s = 1 \text{ if individual } i \text{ locates in } s$$

$$y_i^{s'} = 1 \text{ if individual } i \text{ locates in } s' \neq s$$

The model estimates via maximum likelihood:

$$\Pr(y_i^s = 1 | z_i^s) = F(\nu_i + \alpha' x_i^s + \beta' w_i) \tag{17}$$

where $F(\cdot)$ is the cumulative logistic distribution (i.e. $F(\cdot) = \frac{\exp(\cdot)}{1+\exp(\cdot)}$) and ϵ_i^s is distributed i.i.d. Weibull.[31] The probability of being employed in s is a function of individual and state characteristics:

$$\Pr(y_i^s = 1) = \frac{e^{\delta' z_i^s}}{\sum_{s=1}^{S} e^{\delta' z_i^s}} \quad where\ s = 1, 2, ..., S \tag{18}$$

The equation is the likelihood function for any individual i observed in location s. Parameters estimated from maximizing the log likelihood show the impact of the vector of variables in a particular state on the individual's underlying utility associated with the particular location. Positive coefficients indicate that variables increase utility and have a positive effect on the probability that a specific location is chosen over the other possibilities in the choice set. Substituting for z_i^s yields:

$$\Pr(y_i^s = 1) = \frac{e^{\alpha' x_i^s + \beta' w_i}}{\sum_{s=1}^{S} e^{\alpha' x_i^s + \beta' w_i}} = \frac{e^{\alpha' x_i^s}}{\sum_{s=1}^{S} e^{\alpha' x_i^s}} \tag{19}$$

The fixed effects ν_i and individual specific characteristics cannot be estimated without modification. In order to allow for individual-specific effects, dummy variables for the choices are interacted with each w_i. Because a complete set of interaction terms creates a singularity, defining a reference category is necessary: California is the base category in the analysis. Standard errors are robust and account for multinomial correlation, heteroscedasticity, and clustering at the state level.

Table 18 presents coefficients, odds ratios, and their respective standard errors from the regression for

[31] The Weibull distribution is an extreme value distribution. McFadden (1974) argues for the use of extreme value errors to exploit computational advantages.

the determinants of state choice over the location set of California, Texas, Florida, and Arizona using NAWS data.[32] Results are reported relative to California.

7.2 Individual Characteristics

Agricultural immigrant workers are found in Table 18 to be significantly more likely to choose California than any other border state: compared to the base case, illegal workers are 98.4 percent less likely to choose Texas, 52.2 percent less likely to choose Florida, and 75.5 percent less likely to choose Arizona. Similar results hold for other legal status categories. This is consistent with previous evidence that immigrants in various legal status categories cluster in border areas and is independent of public aid related effects. The magnitudes of these coefficients reflect both the restriction to four states for this exercise and the nature of agricultural work in these states.[33]

Female migrants are significantly more likely to choose Florida over California and are less likely to choose Texas or Arizona over California. Older workers are most likely to choose Arizona. The presence of children in the U.S. is of little consequence to locational choice. The presence of a spouse is similarly insignificant, but married migrants are slightly less likely to choose Florida over California than are single migrants. More highly educated workers are less likely to choose Texas or Florida and more likely to choose Arizona than California. More experienced workers, however, are less likely to choose any alternative over California.

The work network variable deserves special consideration in this framework. The coefficients and odds ratios indicate that those using work networks to obtain employment are less likely to choose any of the alternative states over California. This indicates that personal-level network effects are most prominent in California migrants. This result is highly statistically significant indicating, as argued by Zavodny (1999), personal networks are an important determinant of locational choice.

7.3 State Attributes

Effects of various state attributes are estimated holding individual characteristics such as age, gender, and family structure constant. State fixed effects account for unobserved attributes affecting locational choice.

The effects of welfare benefit levels and education expenditure on locational choice are not significantly different from zero in Table 18. As far as these variables are valid proxies for program values, state-level

[32] Odds ratios are defined:

$$\frac{\Pr(y_i^s = 1|z_i^s)}{\Pr(y_i^s = 0|z_i^s)} = e^{\nu_i + \alpha' x_i^s + \beta' w_i}$$

The odds ratio increases with the probability of a positive outcome and decreases with the probability of a negative outcome. An odds ratio of one is interpreted as the variable having no effect on locational choice.

[33] For example, California's farm labor force is magnitudes larger than the other states considered. See Figure A-7 in Appendix B.

Table 18: Conditional Logistic Model of Locational Choice–Full Sample (CA, AZ, TX, FL), Reference Category: California

	Texas		Florida		Arizona	
	coef	odds ratio	coef	odds ratio	coef	odds ratio
naturalized	-3.761***	0.023***	-0.982***	0.374***	-1.960***	0.141***
	(0.328)	(0.008)	(0.088)	(0.033)	(0.250)	(0.035)
green card	-3.859***	0.021***	-1.304***	0.271***	-1.525***	0.218***
	(0.150)	(0.003)	(0.106)	(0.029)	(0.069)	(0.015)
other work author.	-3.366***	0.035***	-0.797***	0.451***	-1.154***	0.315***
	(0.223)	(0.008)	(0.136)	(0.061)	(0.113)	(0.036)
illegal	-4.132***	0.016***	-0.738***	0.478***	-1.406***	0.245***
	(0.103)	(0.002)	(0.082)	(0.039)	(0.036)	(0.009)
female	-0.308***	0.735***	0.429***	1.535***	-0.440***	0.644***
	(0.083)	(0.061)	(0.072)	(0.111)	(0.147)	(0.095)
age	0.007	1.007	-0.007	0.993	0.027***	1.027***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
spouse	0.178	1.195	-0.079*	0.924*	0.112	1.119
	(0.121)	(0.144)	(0.042)	(0.039)	(0.076)	(0.086)
children (#)	0.011	1.011	0.004	1.004	-0.016	0.984
	(0.026)	(0.026)	(0.015)	(0.015)	(0.020)	(0.020)
education (yrs)	-0.093***	0.911***	-0.079***	0.924***	0.011***	1.011***
	(0.019)	(0.018)	(0.013)	(0.012)	(0.001)	(0.001)
U.S. farmwork experience (yrs)	-0.029***	0.972***	-0.010***	0.990***	-0.020***	0.981***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
used work network	-0.234***	0.791***	-0.523***	0.593***	-1.377***	0.252***
	(0.033)	(0.026)	(0.063)	(0.037)	(0.092)	(0.023)
summer	0.219*	1.244*	-0.760***	0.468***	-0.450***	0.638***
	(0.129)	(0.161)	(0.027)	(0.013)	(0.049)	(0.031)
fall	0.146	1.158	-0.729***	0.482***	-0.081	0.922
	(0.127)	(0.146)	(0.056)	(0.027)	(0.076)	(0.070)
time trend	0.018	1.018	0.029	1.029	0.021	1.021
	(0.044)	(0.045)	(0.052)	(0.054)	(0.041)	(0.042)
constant	2.387*		9.167***		2.275**	
	(1.369)		(2.432)		(0.936)	
			State	Attributes		
monthly welfare (100s USD)			0.017	1.017		
			(0.015)	(0.015)		
annual education value (1,000s USD)			-0.029	0.972		
			(0.018)	(0.018)		
minimum wage			0.506*	1.659*		
			(0.272)	(0.451)		
linewatch hours per mile (1,000s)			-0.050***	0.951***		
			(0.008)	(0.008)		
rural unemployment rate			0.143***	1.154***		
			(0.053)	(0.061)		
farm employment (10,000s)			0.043**	1.043**		
			(0.021)	(0.022)		
state population Hispanic share			0.487***	1.627***		
			(0.138)	(0.224)		
mean hired farmworker wage			0.068	1.071		
			(0.177)	(0.189)		
Observations			76308			

Robust standard errors in parentheses
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004, sample restricted to CA, AZ, TX, FL. Robust standard errors in parentheses, clustered at the state level. Regressions include Mexican state of origin dummies. Labor market variables are lagged one year.

welfare and education program generosity is not an important determinant of locational choice for workers in the border states.[34] This is consistent with the empirical evidence in Section 5 and provides further evidence for a lack of welfare migration by agricultural workers to these areas.[35] This study finds strong, positive, rural unemployment rate and farm employment effects. All else equal, migrants are 15.4 percent more likely to choose a state with a one percent higher unemployment rate and 4.3 percent more likely to choose a state with 10,000 more people in the farm workforce. Previous studies (e.g. Buckley (1996), Zavodny (1997)) find similar positive correlations between unemployment rates and migration choices. Dodson (2001) hypothesizes that either the time lag on the unemployment variable used in these studies is inappropriate, or that if all U.S. state-level unemployment rates are of much lower magnitude than unemployment rates in origin countries, differentials between states may not be relevant in locational decision-making. It is unclear whether this argument should hold in this case given that the majority of NAWS workers are from Mexico. Official Mexican unemployment rates are generally much lower than U.S. rates, but the accountability of these rates is controversial. The labor market variables in the model (rural unemployment rate, farm employment, and mean hired farmworker wage) are included as one-year lags. Including these variables at their current levels or at two-year lags (not shown) leads to similar results, as does using statewide unemployment rates in current or lagged form instead of rural rates. Labor market variables such as rural unemployment rates represent general equilibrium outcomes. Therefore, the nonintuitive positive coefficient associated with the rural unemployment rate should not be interpreted only in light of farm labor supply. The supply and demand factors driving the sign and magnitude of this coefficient are not separately identified here.

Differences in minimum wages and the Hispanic percentage of the population are positive determinants of locational choice within the border states. Migrants are 65.9 percent more likely to choose regions with a dollar higher minimum wage. This suggests that minimum wages may be a more relevant policy instrument related to migrant flows than are welfare and education program values as measured here. A strong positive effect is also noted for state population Hispanic share. The odds ratio for state population percent Hispanic indicates that migrants are 62.7 percent times more likely to choose a state with a one percent higher Hispanic share. A strong negative effect is noted for linewatch hours per mile. Migrants are almost five percent less likely to choose a state with 1,000 more linewatch hours per mile than a state with less rigid border enforcement all else equal.[36] Gathmann (2004) and Angelucci (2005) argue that there is an endogenous relationship between migrant flows and border enforcement. These authors instrument for border enforce-

[34] The implicit assumption here is that education expenditure and quality are positively correlated (or at least expected to be positively correlated by migrants). Continuing work examines additional characteristics of education programs such as standardized test scores that may be more directly related to educational outcomes.

[35] Pena (2007) finds that Central American migrants are sensitive to welfare and education values while Mexican migrants are not.

[36] Boeri, Hanson, and McCormick (2002) document that non-border patrol apprehensions are low in comparison with border apprehensions. Florida border patrol values are approximated using Texas values.

ment with Drug Enforcement Administration budgets. Gathmann (2004) finds that enforcement has shifted illegal migrant flows to more remote crossing places. The results of this paper are consistent with her story. Angelucci (2005) finds that the overall effect of enforcement on total illegal migrant flows is ambiguous after instrumentation. Adding instrumental variables to the conditional logistic framework is an area warranting further econometric research.

7.4 Note Regarding Independence of Irrelevant Alternatives

Conditional logistic regression imposes an Independence of Irrelevant Alternatives (IIA) assumption. This imposition may not be desirable. Regressions under different assumptions of the state options set S yield similar results. These results are reported and further discussed in Pena (2007).

8 Conclusions

This paper examines whether individual states are welfare magnets for immigrants in various legal status groups. Previous studies of welfare migration have excluded illegal immigrants, yet legislation suggests that welfare migration by this population is of concern to individual states within the U.S. A focus of this paper is to extend the literature to this group. While there is strong evidence that illegal immigrants cluster in certain states, particularly those of the border, this study does not find that these patterns are systematically related to state welfare generosity. The locational clustering behavior that is evident among the illegal population is more the result of labor market conditions, network effects, and border enforcement than the result of the availability or generosity of welfare benefits at the state level. Still, this paper finds that the result of Borjas (1999) that legal immigrants who participate in welfare programs are geographically clustered in California continues to hold using the most recent U.S. Census data. These data correspond to four years after PRWORA. This result, however, does not hold for those in agriculture, a traditionally low skilled occupation and frequent employer of illegal workers. Because much of the empirical analysis is descriptive, this paper only begins to characterize the relationship between public economic activity (provision of goods and services, transfers, and taxes) at state and local levels and immigrant geographical decisions.

References

Ai, C., and E. C. Norton (2003): "Interaction Terms in Logit and Probit Models," *Economics Letters*, 80, 123–129.

Angelucci, M. (2005): "U.S. Border Enforcement and the Net Flow of Mexican Illegal Migration," Discussion Paper 1642, IZA.

Bartel, A. P. (1989): "Where Do the New U.S. Immigrants Live?," 7(4), 371–391.

Berry, W. D., R. C. Fording, and R. L. Hanson (2000): "An Annual Cost of Living Index for the American States, 1960-2000," *Journal of Politics*, 60(2), 550–567.

——— (2003): "Cost of Living Index for the United States, 1960-2000," Computer File, Inter-University Consortium for Political and Social Research, Ann Arbor.

Boeri, T., G. Hanson, and B. McCormick (eds.) (2002): *Immigration Policy and the Welfare System.* Oxford University Press, Oxford.

Borjas, G. J. (1999): "Immigration and Welfare Magnets," *Journal of Labor Economics*, 17(4.1), 607–637.

Borjas, G. J., S. G. Bronars, and S. J. Trejo (1992): "Self-Selection and Internal Migration in the United States," *Journal of Urban Economics*, 32, 159–185.

Boskin, M. J. (1974): "A Conditional Logit Model of Occupational Choice," *The Journal of Political Economy*, 82(2), 389–398.

Buckley, F. (1996): "The Political Economy of Immigration Policies," *International Review of Law and Economics*, 16, 81–99.

Camarota, S. A. (2004): "The High Cost of Cheap Labor: Illegal Immigration and the Federal Budget," Discussion Paper 23, Center for Immigration Studies.

Chiquiar, D., and G. H. Hanson (2005): "International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States," *Journal of Political Economy*, 113(2), 239–281.

Davenport, P. (2006): "Workers' Comp Benefits at Issue: Entrant's Claim to Disability Pay Sparks Questions," *Arizona Daily Star*.

Dodson III, M. E. (2001): "Welfare Generosity and Location Choices among New United States Immigrants," *International Review of Law and Economics*, 21, 47–67.

Flores, E. T. (1984): "Research on Undocumented Immigrants and Public Policy: A Study of the Texas School Case," *International Migration Review*, 18(3), 505–523.

Gabbard, S. M., R. Mines, and J. M. Perloff (1991): "A Comparison of the CPS and NAWS Surveys of Agricultural Workers," Discussion paper, Institute of Industrial Relations Working Paper Series, University of California, Berkeley.

Gathmann, C. (2004): "The Effects of Enforcement on Illegal Markets: Evidence from Migrant Smuggling along the Southwestern Border," Stanford Center for International Development Working Paper No. 227.

Jaeger, D. A. (2000): "Local Labor Markets, Admission Categories, and Immigrant Location Choice," Discussion paper.

Kaushal, N. (2005): "New Immigrants' Location Choices: Magnets without Welfare," *Journal of Labor Economics*, 23(1), 59–80.

Levinson, D. R. (2005): "Self-Declaration of U.S. Citizenship for Medicaid," Department of Health and Human Services, Office of Inspector General, Report OEI-02-03-00190.

Martin, P. L. (1996): *Promises to Keep: Collective Bargaining in California Agriculture*. Iowa State University Press, Ames, Iowa.

McFadden, D. (1974): "Conditional Logit Analysis of Qualitative Choice Behavior," in *Frontiers in Econometrics*, ed. by P. Zarembka, pp. 105–142. Academic Press, New York.

Moretti, E., and J. M. Perloff (2000): "Use of Public Transfer Programs and Private Aid by Farm Workers," *Industrial Relations*, 39, 26–47.

Orrenius, P. M., and M. Zavodny (2005): "Self-Selection among Undocumented Immigrants from Mexico," *Journal of Development Economics*, 78, 215–240.

Passel, J. S. (2006a): "Estimates of the Unauthorized Migrant Population for States based on the March 2005 CPS," Discussion paper, Pew Hispanic Center.

——— (2006b): "The Size and Characteristics of the Unauthorized Migrant Population in the U.S.: Estimates Based on the March 2005 Current Population Survey," Discussion paper, Pew Hispanic Center.

Pena, A. A. (2007): "Locational Choices of the Legal and Illegal: Mexican Agricultural Workers in the U.S.," Discussion paper.

Tiebout, C. M. (1956): "A Pure Theory of Local Expenditures," *The Journal of Political Economy*, 64(5), 416–424.

Zavodny, M. (1997): "Welfare and the Locational Choices of New Immigrants," *Federal Reserve Bank of Dallas, Economic Review*, pp. 2–10.

——— (1999): "Determinants of Recent Immigrants' Locational Choices," *International Migration Review*, 33(4), 1014–1030.

A Data Appendix

A.1 NAWS Sampling Methodology

The sampling procedure of the National Agricultural Workers Survey is based on four levels: region, crop reporting district, county, and employer with probabilities proportional to size at each level. Specifically, NAWS uses 12 geographic regions based on USDA Quarterly Agricultural Labor Survey of farm employers. The 12 regions are defined in Table 1 earlier in the paper. USDA information is also used for cyclical allocation (based on the relative proportions of workers each cycle). There are 47 Crop Reporting Districts (aggregates of counties with similar agricultural characteristics) from which sampling locations are selected. Within Crop Reporting District, counties are selected randomly without replacement with probabilities proportional to the county's farm labor expenses. Employer lists are from the Bureau of Labor Statistics Agricultural Soil and Conservation Service and are updated with information from county extension agencies, local employment agencies, grower organizations, and farmworker service programs. Employers are selected using probabilities proportional to the square root of the seasonal farm workforce. Once permission to interview is obtained, the maximum number of interviews per grower is determined with probabilities proportional to square root size. The number of interviews per site of a particular grower is also determined by a proportional distribution to total number of crop workers at each work site. Workers are selected and approached randomly when arriving for work, at lunch, or when leaving and interviews are scheduled for convenient times away from work site at locations chosen by the workers.

A.2 Supplementary State Policy, Labor Market, and Demographic Data

State policy variables include welfare values, education expenditure, minimum wages, and border patrol intensity. Maximum monthly AFDC/TANF benefit levels and FSP values are from the U.S. House of Representatives Committee of Ways and Means. Figure A-1 presents the case of a family of four. Values of these variables for other family structures are parallel shifts up or down of these curves for each state. Welfare data for 1995, 1997, 1999, 2002, and 2003 were imputed linearly, as these data are otherwise unavailable. Figure A-2 presents the welfare data for a family of four in real terms. The series is deflated by a state-level cost of living deflator, the CPI2000, developed by Berry, Fording, and Hanson (2003). Values are in year 2000 dollars based on the median cost of living state in 2000. The two middle states in terms of cost of living in that year, South Dakota and Delaware, were averaged and serve as the base for the index.

Data on current expenditure per pupil in public elementary and secondary schools in Figure A-3 are from the U.S. Department of Education, Digest of Education Statistics and from the National Education

Association, Rankings and Estimates. As the value of the welfare and education variables to the individual migrant varies with his or her family size, these variables are matched to respondents based on reported family characteristics.

Minimum wage data are from the Department of Labor and are presented in Figure A-4. Arizona, Texas, and Florida did not have state-level minimum wages in place during the time period corresponding to NAWS data. Federal minimum wage rates are used for these states.

Border Patrol linewatch hours per mile, in Figure A-5, are from unpublished INS/Homeland Security data shared by Gordon H. Hanson and Christina Gathmann. The Department of Homeland Security (formerly the INS) divides the U.S.-Mexico border into nine sectors: San Diego and El Centro in California, Yuma and Tucson in Arizona, and El Paso, Marfa, Del Rio, Laredo, and McAllen in Texas. Linewatch hours are adjusted for border mile coverage and averaged by state, where state is defined as that state housing the sector's central city.

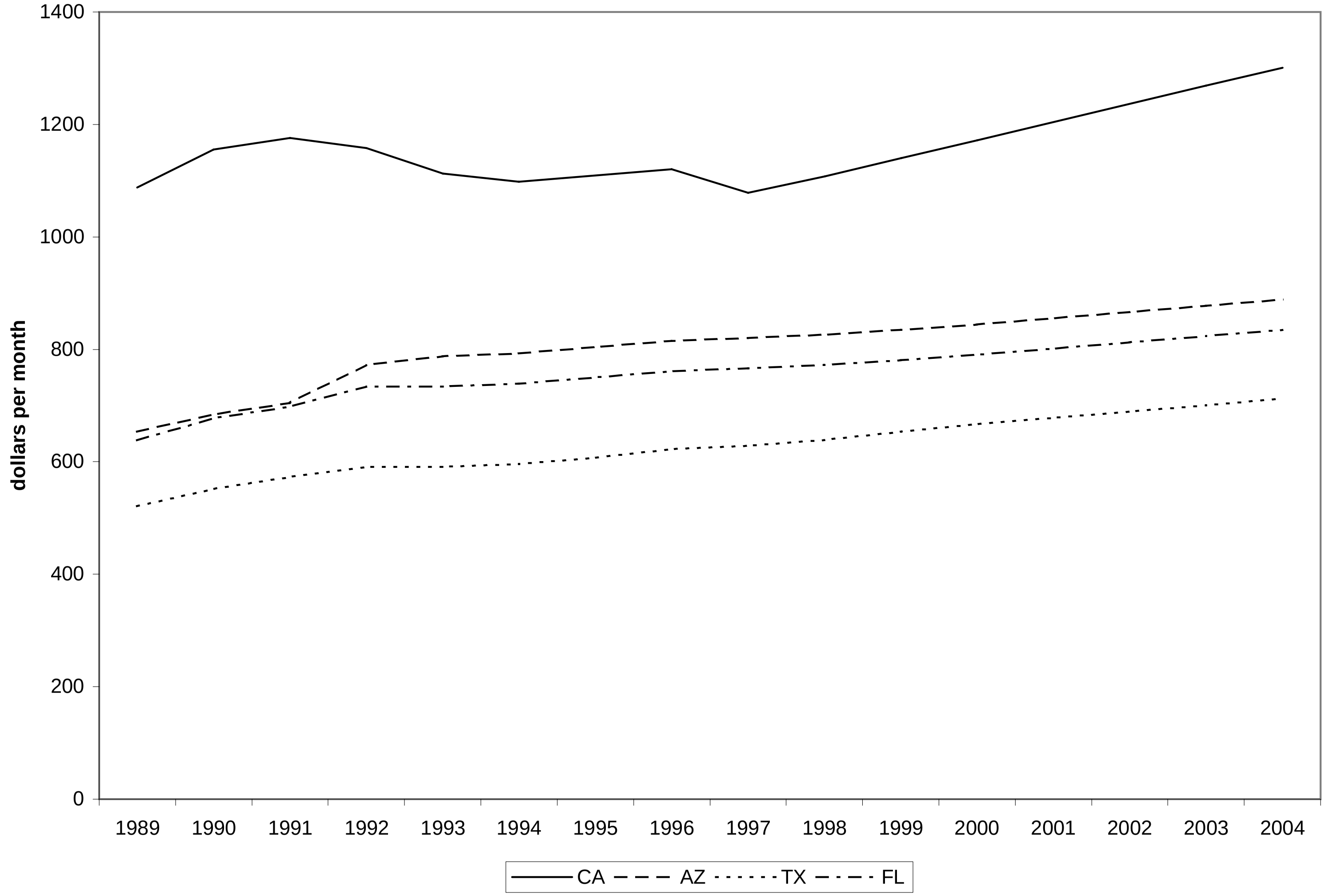
State labor market and demographic variables include rural unemployment rates, farm employment, Hispanic share of the state's population, and average wage rates. Rural unemployment rates are calculated using inputs from Economic Research Service of USDA. Rates are based on 2003 non-metro classifications. The 2003 rural classifications should represent the most rural areas, as these areas have remained in the rural classification over time. Rural unemployment rates based on 1983 and 1993 classifications were also calculated and are available from the author. Figure A-6 shows these rates over time.

Farm employment, presented in Figure A-7, are from Economic Research Service of USDA and the Bureau of Economic Analysis of the Department of Commerce. California employment totals are presented on the left hand side axis, while data for the other states follow the right axis.

Hispanic share of state's population is from the U.S. Census (Figure A-8). Data for year 2000 on include those classifying themselves as "Latino." This difference in definition drives the nonlinearity in the data in year 2000.

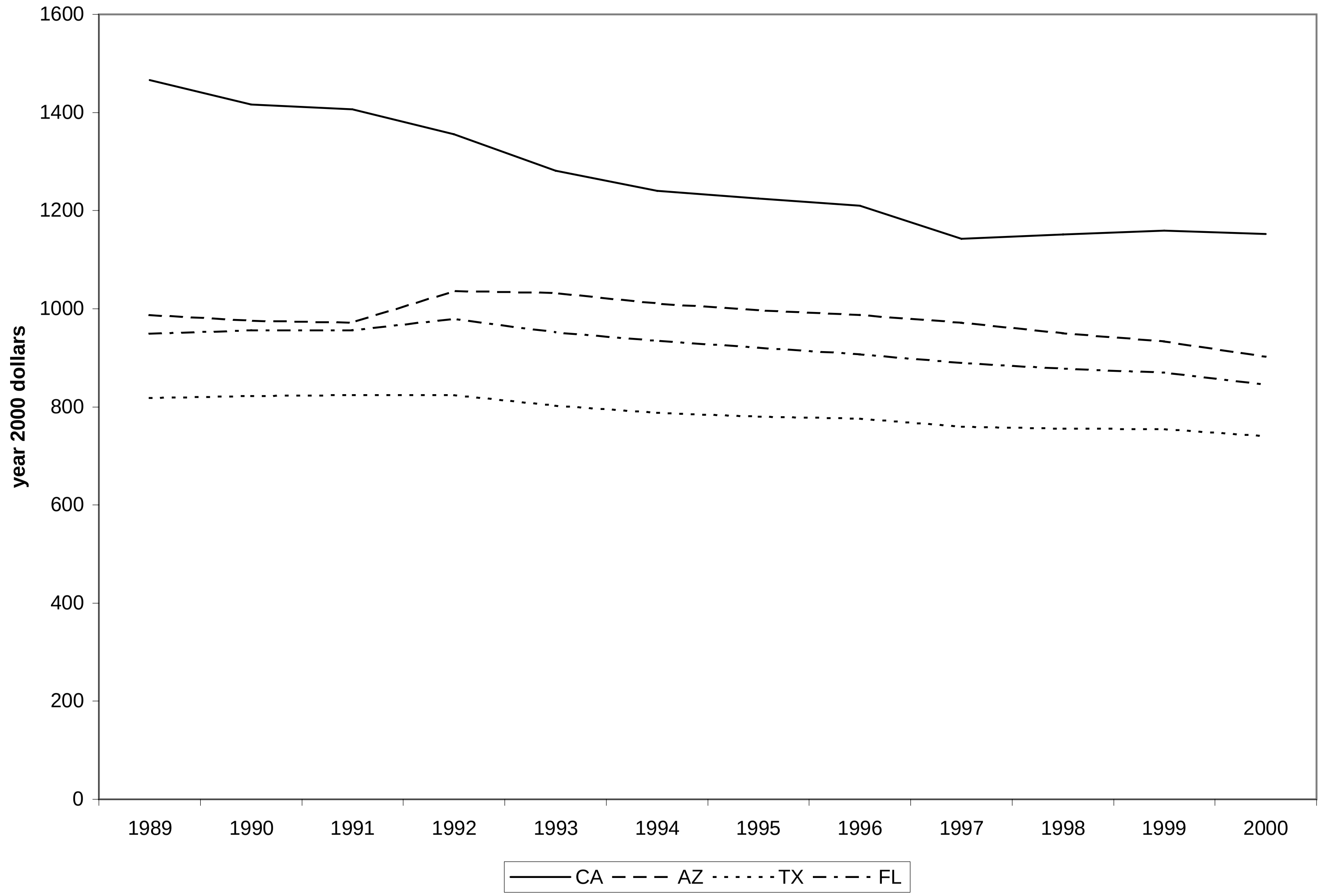
Annual average wage rates of hired field workers are from USDA (Figure A-9). The wages reported for Arizona and Texas in the 1989-1991 period are averages of wages in the USDA agricultural regions including these states. Data for later years correspond to average wages specific to those states.

Figure A-1: (Nominal) Maximum Monthly AFDC/TANF plus FSP Benefits for a Family of Four



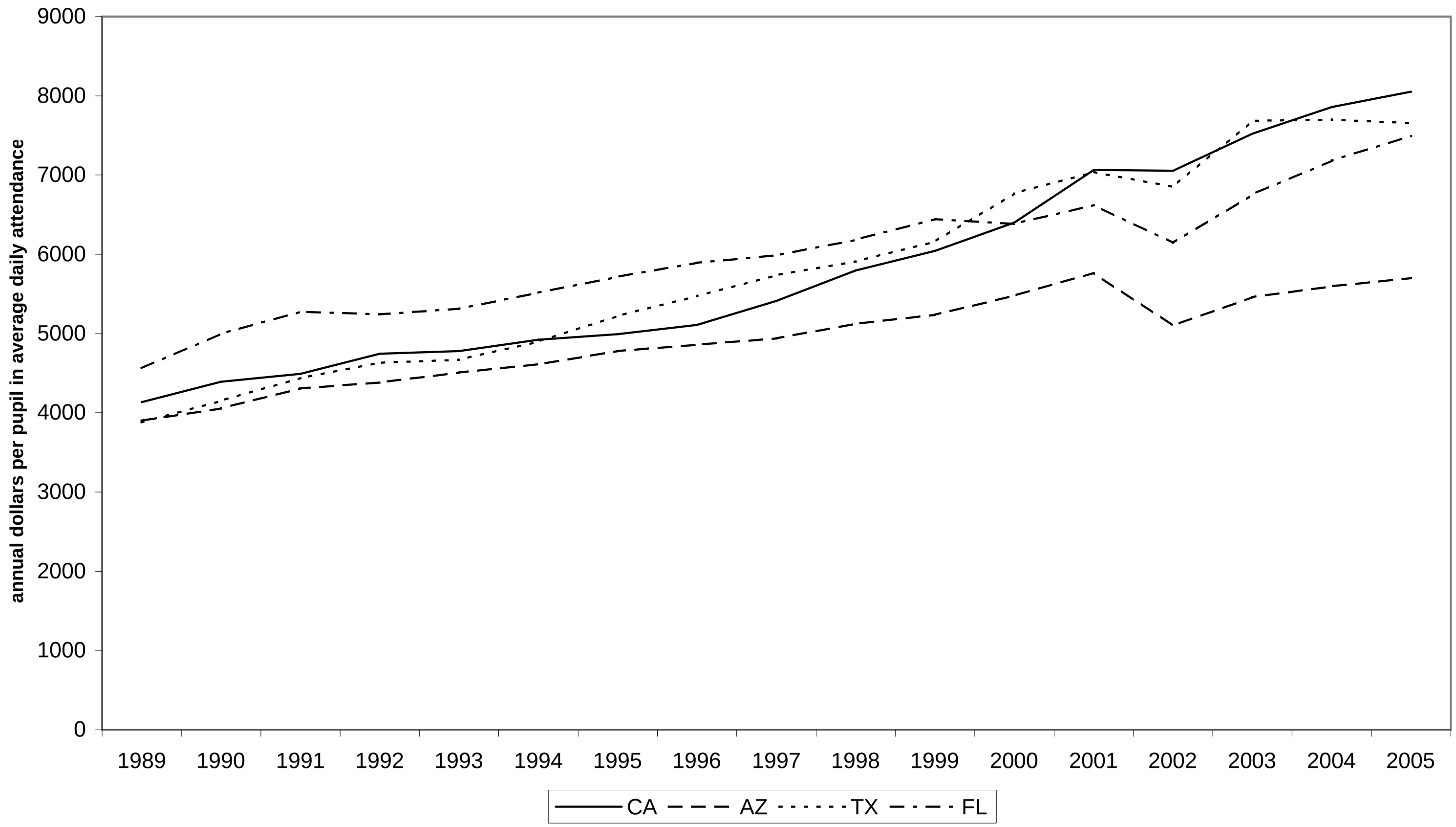
Source: U.S. House of Representatives Committee of Ways and Means, Green Book, selected years

Figure A-2: (Real) Maximum Monthly AFDC/TANF plus FSP Benefits for a Family of Four



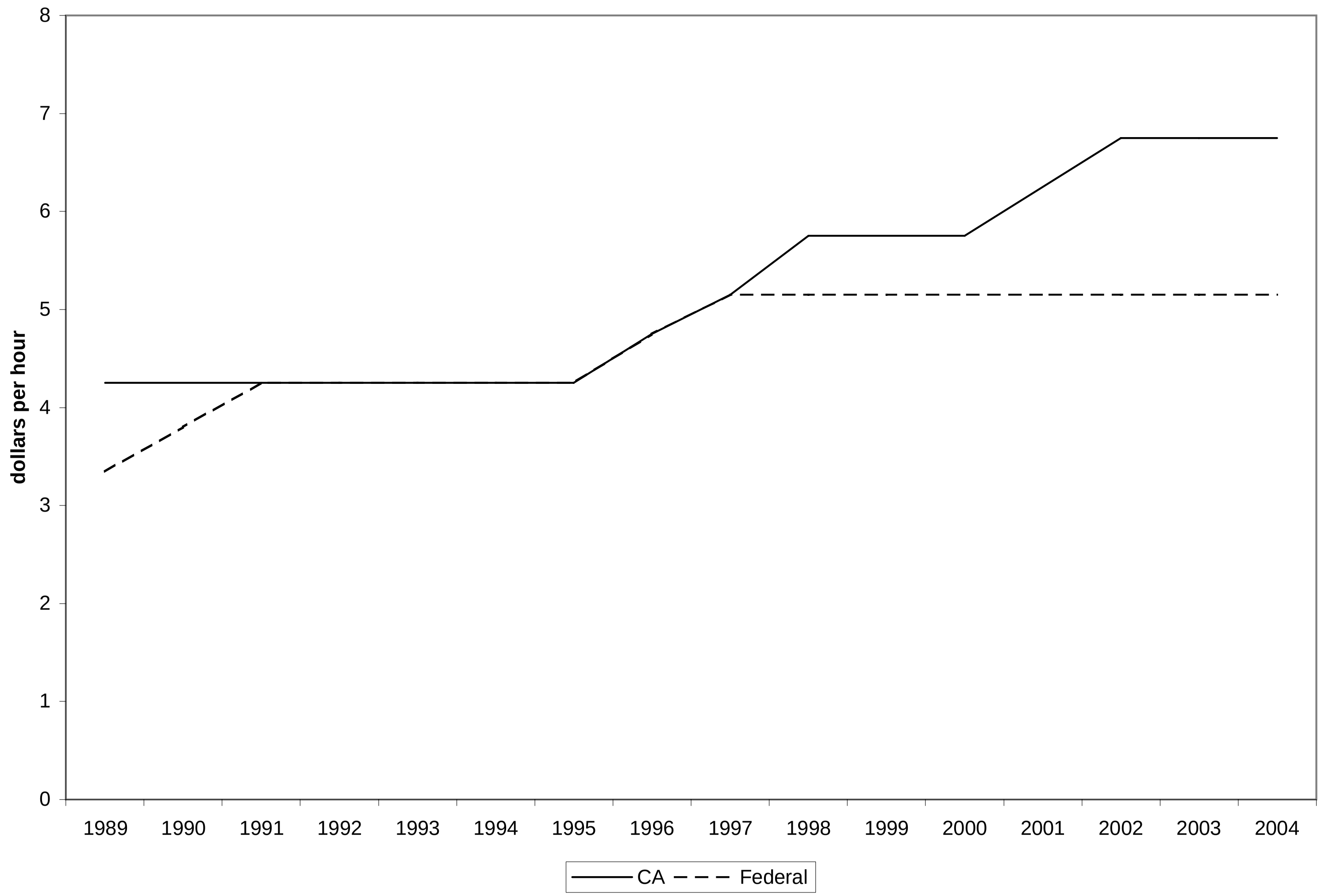
Source: U.S. House of Representatives Committee of Ways and Means, Green Book, selected years
Note: Deflated using the CPI2000 from Berry, Fording, and Hanson (2003)

Figure A-3: (Nominal) Current Expenditure in Public Elementary and Secondary Schools



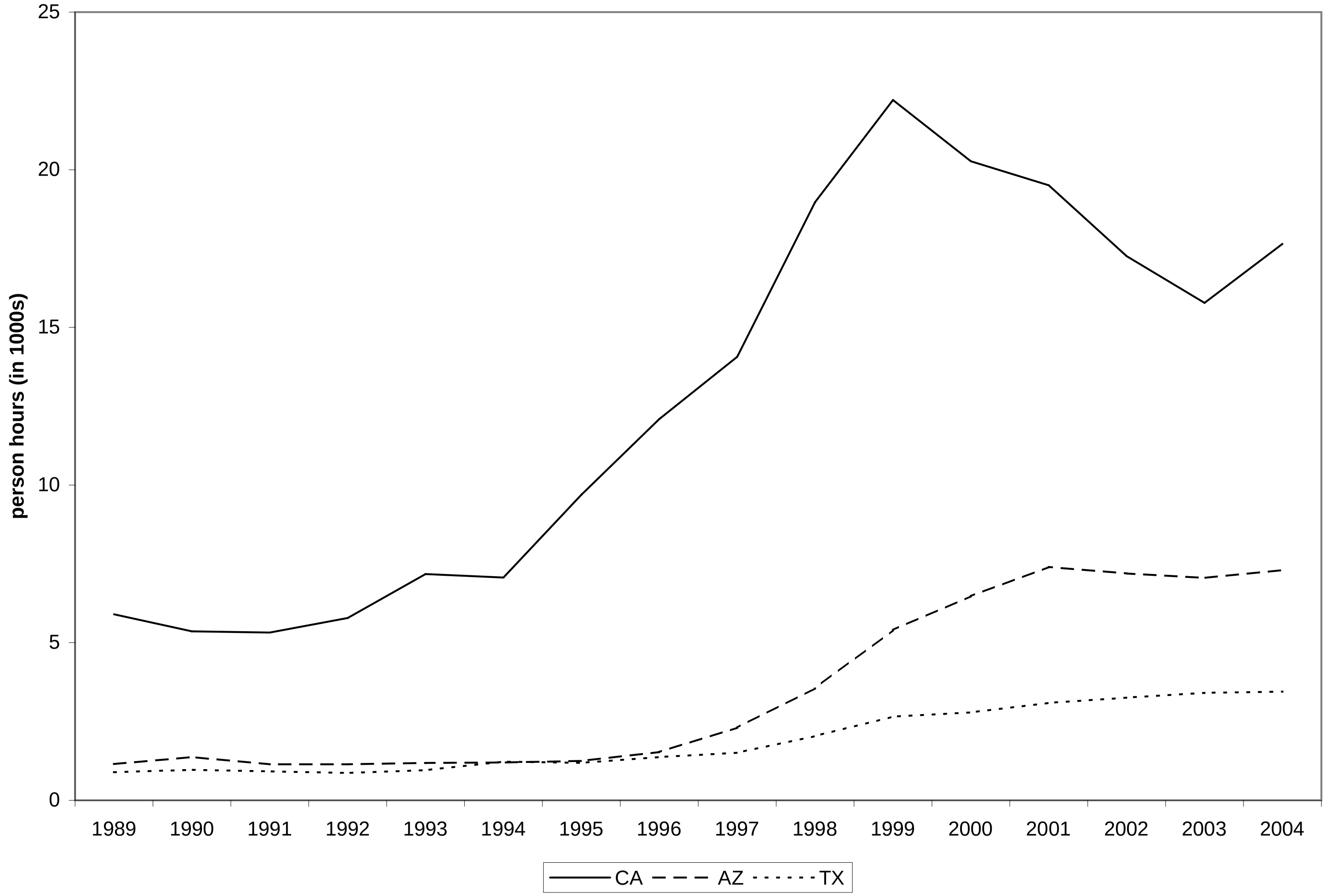
Sources: U.S. Department of Education, Digest of Education Statistics, selected years and National Education Association, Rankings and Estimates, selected years

Figure A-4: (Nominal) Federal versus State Minimum Wages



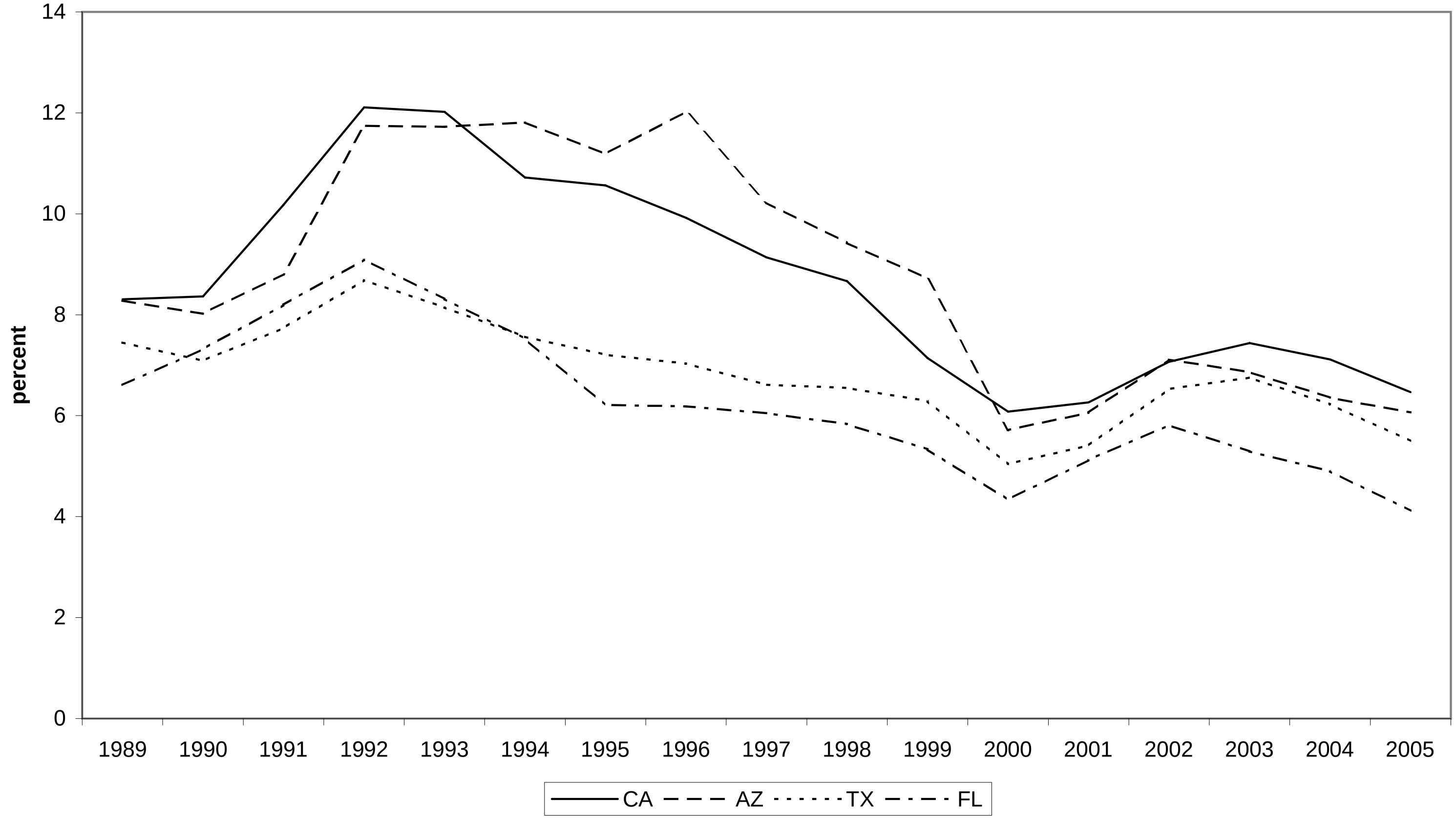
Source: Department of Labor

Figure A-5: Border Patrol Linewatch Hours per Mile



Source: INS/Homeland Security via Gordon Hanson and Christina Gathmann

Figure A-6: Rural Unemployment Rates

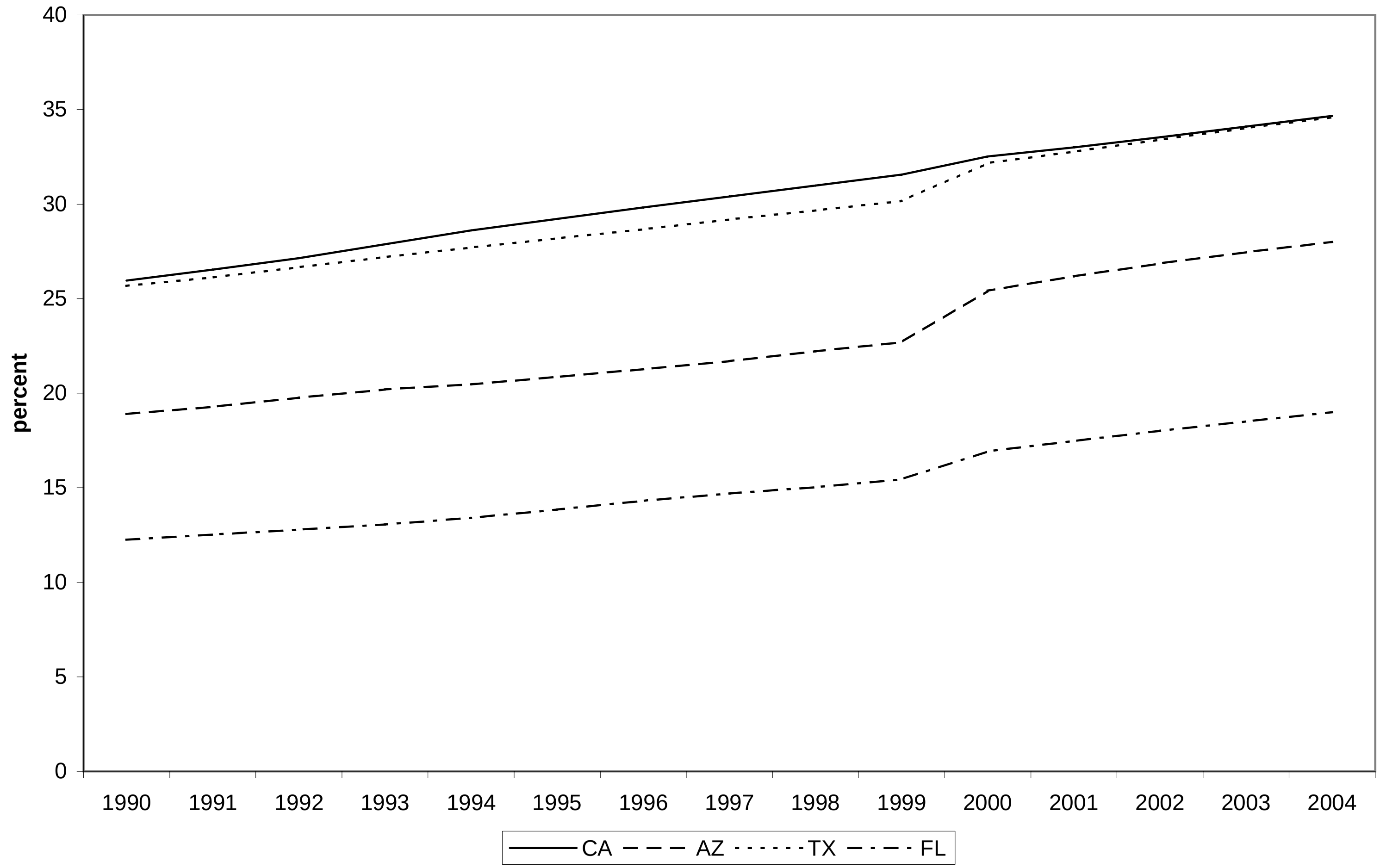


Sources: Economic Research Service, USDA and author's calculations
Note: based on 2003 Metro/Nonmetro classifications

Figure A-7: Farm Wage and Salary Workers Employment

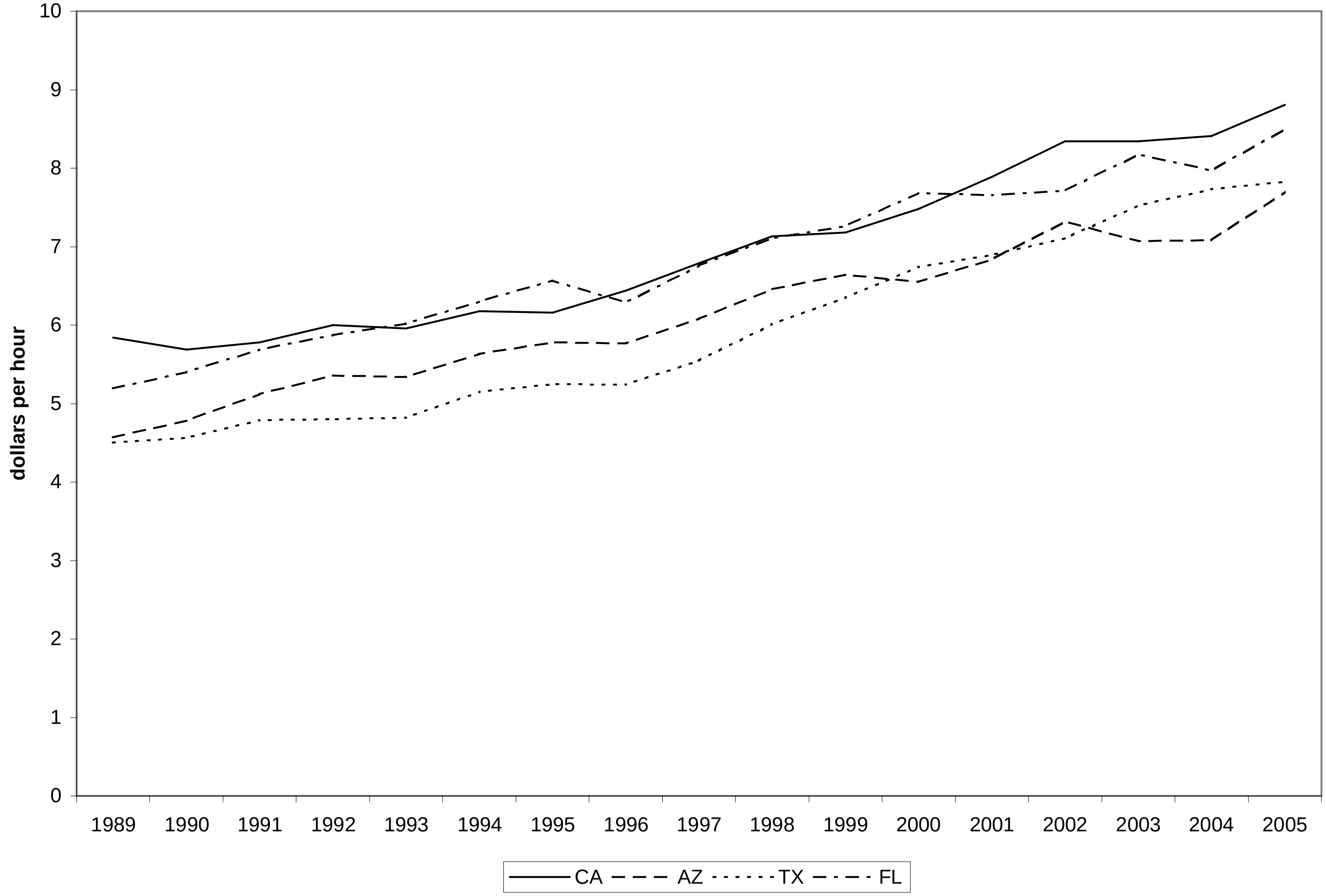
Sources: Economic Research Service, USDA and Bureau of Economic Analysis, Department of Commerce

Figure A-8: Hispanic Share of State's Population



Source: U.S. Census Bureau

Figure A-9: (Nominal) Annual Average Wage Rates of Hired Field Workers



Source: USDA

Note: 1989-1991 “AZ” and “TX” wages based on USDA agricultural regions