Immigration, Legal Status, and Public Aid Magnets: Evidence from Agricultural Labor

Anita Alves Pena

Colorado State University

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Email: anita.pena@colostate.edu

Address: 1771 Campus Delivery

Department of Economics

Colorado State University

Fort Collins, CO 80523-1771

Phone: 970-491-0821

Fax: 970-491-2925

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Abstract

A common perception is that immigrants use disproportionate amounts of public and that immigrants select locations based on characteristics of services offered. This paper asks to what extent geographic clustering of immigrant agricultural laborers is attributable to differences in generosity of state-provided public aid. Evidence from a nationally-representative farmworker survey does not support welfare migration for immigrants in any legal status group, including illegal immigrants who have been previously unidentifiable in the literature. The paper therefore challenges existing notions of welfare migration by both legal and illegal immigrants.

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

JEL codes: H53, I38, J43, O15

I Introduction

A common perception is that immigrants are costly in terms of public expenditures, especially at the state level. When states face budget tradeoffs, immigrants (and particularly illegal immigrants) are often among the proposed scapegoats. As public aid and education participation imposes direct costs on state governments, states are concerned about attracting a disproportionate number of program participants. In 2008, for example, state legislators introduced 1,305 immigration-related bills and resolutions, many of which focused on restricting access to welfare, education, and medical service.[1] Current budget shortfalls make these issues even more salient.

Migrants are said to engage in welfare migration if they choose residence in response to public aid differentials across locations. Analogously, a state is a "welfare magnet" if it attracts 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.[2] Despite common public perceptions, little statistical evidence exists concerning how these mechanisms compare across illegal and legal immigrant categories.

The hypothesis of welfare migration within the undocumented population may seem irrelevant given that extensive eligibility requirements for many U.S. welfare programs exclude those without documents. Empirical evidence, however, 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. In addition, public medical services and education programs often are not subject to legal status verification. Camarota (2004), for example, 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,[3] and \$1.4 billion in federal aid to schools in 2002. It is worth noting that these expenditures occurred well after the 1996 passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) that strengthened immigrant eligibility requirements for means-tested benefits.

California, known for welfare generosity, is usually suspected to be a welfare magnet for immigrants. Different states, however, may be magnets based on other public 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. Contributions of this paper therefore are (1) to extend a theoretical model of locational choice by incorporating legal status and (2) to test for the presence of welfare migration (a) by refined legal status groups: illegal immigrants, naturalized citizens, green card holders, immigrants with other work authorization, and U.S. born citizens; (b) based not only on traditional welfare, but also on food aid, medical service, and education programs; and (c) in each of four immigrant destinations: California, Arizona, Texas, and Florida. Documenting the existence (or absence) of welfare migration for different groups by 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, and the budgetary effects of legal and illegal immigrant clusters.

Primary data in this paper come from the National Agricultural Workers Survey (NAWS), a nationally-representative dataset conducted by the U.S. Department of Labor. While restricting to one industry, the sample design of the NAWS, unlike traditional micro-level data sources, specifically accounts for migratory behavior and directly asks about both usage of public aid and education and, most importantly, about 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, especially among the migrant population from Mexico.

Illegal immigrants may be less likely than legal immigrants to respond to public aid incentives both due to the eligibility issues noted above and due to temporary migration (if for example, application processing times discourage take-up among transitory persons). Raw tabulations from the NAWS confirm this pattern with 13.8 percent of illegal immigrants between 1989 and 2004 reporting some form of public aid use and higher percentages among legal immigrants. Specifically, 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) indicate use. Figure 1 shows aggregate welfare participation rates for agricultural workers by legal status in the sample over time. 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 clinics, Medicaid, and WIC.

[Figure 1 about here]

The rest of this paper is organized as follows. Section II presents motivation and context from state-level program characteristics and policy initiatives relating to immigration and the welfare state. Section III illustrates how the Borjas-Roy self-selection model can be extended to include a multi-region setup and differences in legal status, and how original conclusions from the model are sensitive to specification. Section IV presents empirical evidence of the extent of geographic clustering of public aid and education participants in the NAWS. Participants are compared with non-participants both within and across legal status groups unconditionally and conditional on socioeconomic controls. Results do not support welfare-induced migration for any legal status group. Using conditional logistic regression, Section V examines the effects of state specific labor market and public policy attributes, including public aid benefit and education values, on migration decisions, and Section VI concludes.

II 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 2006, the maximum monthly TANF benefit for a family of four in California was $862 compared with $418 in Arizona, $364 in Florida, and $268 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 food stamp 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.[4] In addition to its higher absolute benefits, California uses state funds to provide cash welfare, food stamps, 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.[5]

[Figure 2 about here]

Given that provision of welfare, medical, and education programs is costly, several states have taken action to limit the use of these programs by illegal immigrants. For example, 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, 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 was California's Proposition 187 in 1994 that 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. 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 just two examples of state-level responses to illegal immigration. A more recent example, 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.

III Theoretical Model

A theoretical model illustrating how the existence of various welfare programs and other public services may differently influence locational choices of U.S. born citizens, legal immigrants, and illegal immigrants is developed in this section. If mobility costs and expected welfare benefits differ between legal and illegal immigrants, then there may exist a greater degree of welfare clustering for one group than the other. This is shown here in a model that builds on that of Borjas et al. (1992) and Borjas (1999).

Borjas et al. (1992) present a multi-region 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 into 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. The intuition behind the general result is that immigrants face similar costs of migrating to any U.S. state while current native residents of a state have a zero cost of staying but positive cost of moving, indicating that natives will not be responsive to small differences in state-level public aid and immigrants will. Borjas confirms this pattern with U.S. Census data.[8]

In the model presented here and in contrast to previous models, immigrants are distinguished by legal status. While regions with high returns to skills again attract higher skilled workers (and 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. In particular, 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. In fact, relaxing this assumption leads to a multiplicity of possible equilibria. This robs the model of its predictive power.

Consider a country consisting of s=1,...,S mutually-exclusive states. The expected net benefits from migrating to state 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 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 migration (and opportunity) cost from an origin o to destination s; $C_{ss} = 0$ 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]

Utility-maximizing (or income-maximizing) agents prefer to locate in the state s for which the expected net benefits from making a migration is highest.[11] 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:

$$w_s = \mu_s + \nu_s \tag{2}$$

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 the skill measure ν determines each individual's earnings in each state allows further characterization of equilibrium sorting. The wage earnings equation is rewritten:

$$w_s = \mu_s + \eta_s \nu \tag{3}$$

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 and 3. 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. Alternative sorting conditions are derived under different assumptions regarding the functional form of $B_s(w_s)$. The equations are conditions describing individual sorting. At the margin, the descriptive result generated by the model parallels that of Borjas et al. (1992): the least skilled workers choose the region with the lowest return to skills while higher skilled workers locate in higher return areas.[12] Public aid benefits and costs affect the skill distribution cutoff points corresponding to different locational choices and therefore have implications for equilibrium sorting.

A Introduction of Legal Status

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:

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

Earnings of illegal immigrants are likely distributed differently because 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. The case where the wage-skills curve of illegal immigrants is lower than that of legal immigrants and natives is considered in what follows. This is consistent with observable positive wage differentials between legal and illegal immigrants in the data. Furthermore, 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.

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,[13] and 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.

Illegal immigrant skill-level cutoffs are defined analogously to those for the legal immigrant and U.S. born populations. Illegal immigrants prefer region s over region s' when:

$$\nu < \frac{\mu^I_s - \mu^I_{s'} + (B^I_s - B^I_{s'}) - (C^I_{os} - C^I_{os'})}{\eta^I_{s'} - \eta^I_s}.$$

Sorting rules 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. Specific skill-level cutoff points for illegal and legal persons differ, and levels depend on particular assumptions of the magnitudes of variable parameters for these populations.

B Example

Consider the case of two potential migration destinations (states 1 and 2) and one origin (country 0). Figure 3 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) and Orrenius and Zavodny (2005) consider self-selection among Mexican immigrants. Both studies find that immigrants are selected from the intermediate or high end of the Mexican education distribution. 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.[14]

[Figure 3 about here]

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.[15]

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, does not allow migration costs faced by an individual to vary with locations. Alternately, migration costs can be thought of as shifting the wage-skills curve down for each potential destination. This latter treatment is adopted in this paper. This difference in specification of migration costs results in different predictions. 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.

[Figure 4 about here]

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 4 presents the addition of costs and public aid benefits to state 1. The country and state 2 cost-adjustment curves are suppressed for simplicity. When expected migration costs are positive, those with skills below $\nu_{B'}$ migrate to state 1 and those with skills above $\nu_{B'}$ sort to state 2. Thus, asymmetric migration costs alter the locational distribution of migrants. 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 locate based on $\nu_{B'}$, and those who do expect to participate (or who value that 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. As drawn, the wage-skills curve including benefits is cost-adjusted. Benefits here 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.

[Figure 5 about here]

Illegal immigrants are distinguished from legal immigrants in Figure 5. If illegal immigrants face lower wage-skills curves in each destination state than do their legal counterparts, then within a state, illegal and legal immigrants will have different program participation values. 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 for legal immigrants than for illegal immigrants suggesting that welfare migration should be observed to a greater extent in the legal population than in the illegal population. Note, however, that even if costs vary by legal status, they may have no qualitative impact on migrant clustering if the difference is the same in all states. These aspects will be tested in what follows.

IV Locational Clustering

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

Buckley (1996) uses INS admissions data from 1985-1991, and 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. Consistent with a welfare migration story, Buckley finds a strongly positive, significant relationship between legal immigration flows and AFDC levels. His result holds across 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. Zavodny (1999) challenges these conclusions using INS legalization data from 1989-1994 supplemented with refugee data 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 of locational choice overall.

Dodson (2001), like Buckley (1996), argues in favor of immigrant welfare migration after regressing 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 and cross-sectional INS data from 1991. Using 1995-6 and 1998-9 INS data, Kaushal (2005) offers additional challenges. 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 and concludes that means-tested programs have "at best a weak effect on the location choices of newly arrived immigrants."

To date, the empirical literature on welfare migration has primarily used two data sources: INS cross-tabular administrative record data or the U.S. Census. As INS data are primarily available in count form, 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, legal status cannot be fully controlled for in Census data and the Census may under-represent certain immigrant groups. This paper, however, diverges from the literature by using an underused but representative survey of illegal and legal, immigrant and native, U.S. agricultural workers in order to draw further conclusions.

A The National Agricultural Workers Survey

The National Agricultural Workers Survey is 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 information relating to the legal status of its respondents.[16] NAWS workers are employed by growers and farm labor contractors in crop agriculture. The NAWS is a cross-section sampled from work sites three times per year (fall, winter/spring, summer) since fall of 1988. This paper uses the restricted NAWS sample covering 1989 through 2004.[17] Of the 42,821 workers in the sample, 17,572 indicate 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. Respondents are guaranteed confidentiality and less than one percent decline to answer legal status questions. The survey has been conducted three times a year since 1988 and has never resulted in enforcement raids. The NAWS is nationally and regionally representative of agricultural workers within 12 spatial divisions (with sampling weights, which are used here). 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 comprising workers from the remaining eight regions throughout the empirical analysis.

Table 1 shows key demographic and employment variables by legal status after pooling the 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 proficiency. Illegal immigrants report fewer years of U.S. experience than do legal immigrants.[18] 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.[19]

[Table 1 about here]

Welfare participation rates by region are presented in Table 2.[20] Compared with the national average within legal status group, Southern Plains (TX, OK) residents have higher participation rates than those elsewhere. More than 41 percent of U.S. born Southern Plains workers, for example, indicate 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.

[Table 2 about here]

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.

B Public Aid Participation in the NAWS

As documented in Table 2, participation rates vary both across legal status and across states. Table 3 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 non-participants should also live there. Likewise, equal percentages of participants and non-participants in each legal status/state category are expected. The difference between the percentage of participant households living in state s and the percentage of non-participant households in state s is an unconditional estimate of the "welfare clustering gap" associated with that location. Table 3 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 non-participant percentages is an unconditional test for evidence of a welfare clustering gap.

The California panel of Table 3 shows that almost 30 percent of the U.S. farmworkers who received some aid lived in California and that 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 3 correspond to U.S. born workers, naturalized citizens, and green card holders. The data suggest 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 non-participating households than participating ones are observed among naturalized citizens and green card holders in California, indicating a negative welfare clustering gap for these legal status groups in the raw data.[21] 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 non-participants. 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 represents an intermediate.

[Table 3 about here]

The statistics presented in Table 3 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. An empirical test for the existence of a welfare clustering gap using multivariate regression analysis is developed.

C Empirical Test of Welfare Clustering

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

$$P_s = \Pr(U_s > U_{s'}, \forall s' \in S, s \neq s') \tag{5}$$

where

$$U_s = V_s + \epsilon_s \tag{6}$$

. 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.

The regression framework extends Borjas' (1999) descriptive 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 the probit specification:

$$\Pr(S_i) = \Phi[X_i'\lambda + \beta_1 I_i + \beta_2 N_i + \beta_3 G_i + \beta_4 O_i + \beta_5 B_i \tag{7}$$
$$+\beta_6(I_i \times B_i) + \beta_7(N_i \times B_i) + \beta_8(G_i \times B_i) + \beta_9(O_i \times B_i)]$$

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; and 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.

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.[22] 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 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. The NAWS also allows for the inclusion of an individual work network variable, which equals one if the worker was referred to his or her job by a relative, friend, or workmate. Survey year and season fixed effects are included in all specifications.

Table 4 presents estimates of the clustering gaps between welfare participants and non-participants for the four immigrant legal status groups relative to natives in separate regressions for California, Texas, Florida, Arizona, and remaining U.S. states as a whole.[23] Positive coefficients on legal status/participation interactions indicate evidence of welfare clustering relative to the U.S. born population. Using similar methodology, Borjas (1999) finds strong positive welfare clustering in California by immigrants overall relative to natives. As evident in Column (1) of Table 4, no such results are found for any legal status group in California for this analysis using the NAWS.[24] Instead, naturalized citizens who use public aid are 7.8 percent *less* likely to 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 non-participating counterparts; and illegal immigrants who use aid are 12.2 percent *less* likely to locate in California than are non-participating illegal immigrants.[25] Thus, the results are inconsistent with the hypothesis that California is a welfare magnet for agricultural workers. Furthermore, examining between-category differences in the California results indicate that differences between legal status groups follow a continuum, with the negative clustering results being demonstrated strongest for illegal immigrants relative to natives. Second strongest are results for those with temporary work authorizations, followed by more permanent immigrants (green card holders and naturalized citizens). This is expected if permanent immigrants are more similar to natives than are temporary immigrants in their mobility costs.

[Table 4 about here]

Redefining the dependent variable using the other border states, Table 4 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 for 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 receiving states of California, Texas, Florida, and Arizona.[26]

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. Furthermore, agricultural work is often dangerous and illegal workers may be less likely to receive full compensating wage differentials and therefore may place greater weight on public medical benefits. Table 5 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.

[Table 5 about here]

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 non-participating counterparts. The negative significant welfare clustering gap estimates for the Texas and Florida regressions in Table 4 appear primarily driven by food aid participation, while that for Arizona is most related to medical services.

Education

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 6 presents estimates of education clustering gaps. Only two (of 20) clustering gap interactions in this category are positive and significantly different from zero, and both correspond to the aggregate "other" states category. Illegal immigrants who use schools, however, are less likely to reside in California and more likely to reside in other U.S. regions. [Table 6 about here]

Because adult immigrants may use educational programs to a lesser extent than their children do, the exercise was also considered restricting the sample to agricultural workers with children (not shown). 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.

D Self-Selection and Locational Choice

A related consideration that may shed light on why the Borjas results are reversed here is whether illegal migrants in one state systematically differ from those in another state. The theoretical model in Section III 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 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 7 about here]

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

$$\Pr(S_i) = \Phi[X_i'\theta + \delta_1 I_i + \delta_2 N_i + \delta_3 G_i + \delta_4 O_i + \delta_5(I_i \times X_i) + \delta_6(N_i \times X_i) + \delta_7(G_i \times X_i) + \delta_8(O_i \times X_i)] \tag{8}$$

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*.

Using education as a proxy for skill, Table 7 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 into the states examined here. This is especially true for California where legal status/education interactions are positive and significant for all legal status groups. Within each legal status group, workers are negatively selected 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 here to self-select to border regions while less educated persons sort to northern states. Another interpretation is that those who select into the northward migrant stream (as opposed to engaging in return migration) have lower skills. This finding extends the selection literature to consider how migrants self-select within a destination country.

E Farmworkers as a Study Population and Other Explanations

Questions arise as to how these results can be reconciled with those of the previous literature and whether the results are generalizable beyond the population of farmworkers. Given that previous results on welfare migration come from data predating welfare reform, differences may be attributable to time frame of study. Second, the NAWS and Census are based on sampling methodologies of different philosophies that could potentially generate discrepancies. Particularly, unemployed persons who may have higher probabilities of using welfare are not represented in the NAWS, but are included in the U.S. Census. Third, because the NAWS is a survey of agricultural workers, differences may be due to characteristics of this specific occupation. Agricultural work, for example, is often physically demanding and workers in this industry may be selectively healthy (and likewise less likely to participate in public aid programs) in comparison to the general population. These three explanations are examined in Pena (2009a) using 2000 Census data. It is shown that Borjas' 1999 results are valid across Census years for the overall population and across employed and unemployed subgroups (though to differing magnitudes). Results, however, are occupation-dependent and are shown to reverse for those in agriculture and other hypothesized illegal immigrant intensive fields such as construction and service.

V Public Aid Characteristics and Locational Choice

A Conditional Logistic Regression

Given that locational choice is not consistent with welfare migration for the NAWS sample, the question becomes what does explain the migration patterns for these workers. Conditional logistic regression allows effects of individual characteristics and state-level attributes to be estimated simultaneously, and is used here to remove the influence of state fixed effects.[27] 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 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 cash transfers 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 8 for the four states examined in this section.

[Table 8 about here]

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

$$U_i^s = \alpha' x_i^s + \beta' w_i + \epsilon_i^s = \delta' z_i^s + \epsilon_i^s \tag{9}$$

where 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, while w_i's vary by individual only. Rewriting, we have:

$$P_i^s = \Pr(\delta' z_i^s + \epsilon_i^s > \delta' z_i^{s'} + \epsilon_i^{s'}, \forall s' \in S, s \neq s') \tag{10}$$

.

In this model, the data are grouped by receiving states and the likelihood is calculated relative to each group. Specifically, the data are reformatted 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.[28] 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:

$$\Pr(y_i^s = 1|z_i^s) = F(\nu_i + \alpha' x_i^s + \beta' w_i) \tag{11}$$

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.[29] The probability of being employed in s is a function of individual and state characteristics:

$$\Pr(y_i^s = 1) = \frac{e^{\delta' z_i^s}}{\sum_{s=1}^{S} e^{\delta' z_i^s}} \quad where\ s = 1, 2, ..., S \tag{12}$$

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:

$$\Pr(y_i^s = 1) = \frac{e^{\alpha' x_i^s + \beta' w_i}}{\sum_{s=1}^{S} e^{\alpha' x_i^s + \beta' w_i}} = \frac{e^{\alpha' x_i^s}}{\sum_{s=1}^{S} e^{\alpha' x_i^s}} \tag{13}$$

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. Standard errors are robust and account for heteroskedasticity and clustering at the state level.

Table 9 presents coefficients, odds ratios, and their respective standard errors from the regression for the determinants of state choice over the location set of California, Texas, Florida, and Arizona using NAWS data.[30] The sample is limited to this four state group, and results are reported relative to California, the base category.[31] The top panel results refer to individual characteristics (x_i^s) and the bottom panel to state characteristics (w_i).

[Table 9 about here]

B Results by 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 9. As far as these variables are valid proxies for program values, state-level welfare and education program generosity is not an important determinant of locational choice for workers in the border states.[32] This is consistent with the empirical evidence in Section IV and provides further evidence for a lack of welfare migration by agricultural workers to these areas. Instead, differences in labor, demographic, and enforcement variables significantly relate to geographic distributions.

Positive farm employment and rural unemployment rate effects are found. All else equal, migrants are 4.3 percent more likely to choose a state with 10,000 more people in the farm workforce and 15.4 percent more likely to choose a state with a one percent higher unemployment rate. 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. Extensions in the context of the Mexican immigrant population are presented in Pena (2009b). Buckley (1996) and Zavodny (1997) find similar positive correlations between unemployment rates and migration choices. Rural unemployment rates represent general equilibrium outcomes and therefore should be interpreted in light of both farm labor supply and demand and frictions in equilibrium dynamics.

Minimum wages and Hispanic percentage of the population are positive determinants of locational choice within the state group of study. Farmworkers 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.[33] 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.[34] Gathmann (2008) and Angelucci (2005) argue that there is an endogenous relationship between migrant flows and border enforcement. These authors instrument for border enforcement with Drug Enforcement Administration budgets. Gathmann (2008) finds that enforcement has shifted illegal migrant flows to more remote crossing places. Results here are consistent with this story.[35]

C Results by Individual Characteristics

Agricultural immigrant workers are found 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.

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 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.

VI 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 ongoing legislative initiatives 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. These findings are important for quantifying fiscal costs of immigration.

A final question is why agricultural immigrants across *all* legal status groups (and therefore across eligibility levels) appear to exhibit less welfare clustering than do other immigrants. One reason, alluded to in the introduction, is that many immigrants in this occupation are transitory and therefore less likely to settle permanently in an area and to integrate into local communities. While lack of permanence may suggest lower mobility costs (and therefore increased probabilities of welfare migration), decreased probabilities of receiving benefits before moving to another location may push expected benefits below expected costs. Because of application processing times, transitory workers likely have low probabilities of physically receiving benefits before moving if they apply. A second reason may be that immigrant agricultural workers often face language barriers (and therefore linguistic challenges applying for benefits) at greater rates than other immigrants, thus contributing to why interactions between public aid program usage and locational choice among immigrants are sensitive to the "permanence" of the specific immigrant population of interest.

Notes

[1]National Conference of State Legislatures; 206 laws and resolutions (in 41 states) were enacted.

[2]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.

[3]These include Food Stamp Program (FSP), Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), and subsidized school lunches. FSP changed names to Supplemental Nutrition Assistance Program (SNAP) in October 2008.

[4]The series is deflated by a state-level cost of living index from Berry et al. (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.

[5]Kaushal (2005).

[6]Flores (1984).

[7]Martin (1996).

[8]Pena (2009a) finds that this result is sensitive to occupation and that occupations for which the result reverses specifically are those though to have higher illegal immigrant percentages.

[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.

[11]Risk-neutrality is implicitly assumed.

[12]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:

$$\frac{\mu_{s-1} - \mu_s + (B_{s-1} - B_s) - (C_{os-1} - C_{os})}{\eta_s - \eta_{s-1}} < \frac{\mu_s - \mu_{s+1} + (B_s - B_{s+1}) - (C_{os} - C_{os+1})}{\eta_s - \eta_{s+1}}$$

[13]See Gathmann (2008).

[14]An alternative is that education is a proxy for family wealth in Mexico and that this alternate mechanism is correlated with the development of skills.

[15]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.

[16]The NAWS sampling procedure 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. There are 47 crop reporting districts (county aggregates with similar characteristics) from which sampling locations are selected. Within crop reporting district, counties are selected randomly without replacement. The number of interviews per site is determined by a proportional distribution to total workforce. Workers are chosen randomly and interviews are scheduled at times and locations chosen by respondents. Respondents receive a small payment for participation.

[17]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. As the locational identifiers are limited in the public use version of the data, estimations were conducted on-site at the Aguirre office in Burlingame, California.

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

[19]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.

[20]For this and subsequent exercises, it is assumed that workers work and reside in the same state.

[21]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.

[22]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 III, public aid is assumed to be a supplement to income, as opposed to a replacement of income, thus minimizing this concern.

[23]From this point forward, “Texas” refers to the “Southern Plains” and “Arizona” to Arizona/New Mexico.

[24]All NAWS respondents are employed (at least part-time) by definition. Pena (2009a) shows a similar result for both employed and unemployed Census respondents.

[25]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.

[26]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. Of children reported by NAWS farmworkers, 45.2 percent are native. Considering the exercise for the subpopulation of NAWS workers with U.S. born children (not shown). 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. 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.

[27]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.

[28]Conditional logistic regression imposes an Independence of Irrelevant Alternatives (IIA) assumption, which if violated would indicate inconsistent coefficient estimates. Regressions under different assumptions of the state options set S, however, yield similar results. Specifically, Florida and Arizona were independently dropped and the model was reestimated in three destination form.

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

[30] 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.

[31]Because a complete set of interaction terms creates a singularity, defining a reference category is necessary.

[32]The implicit assumption here is that education expenditure and quality are expected by migrants to be positively correlated.

[33]It should be noted, however, that higher minimum wages may favor more skilled workers and simultaneously indicate increased unemployment among more unskilled types.

[34]Boeri et al. (2002) document that non-border patrol apprehensions are low in comparison with border apprehensions. Florida border patrol values are approximated using Texas values.

[35]Angelucci (2005) finds that the overall effect of enforcement on total illegal migrant flows is ambiguous after instrumentation. Instrumental variables in the conditional logistic framework is an area for further econometric research.

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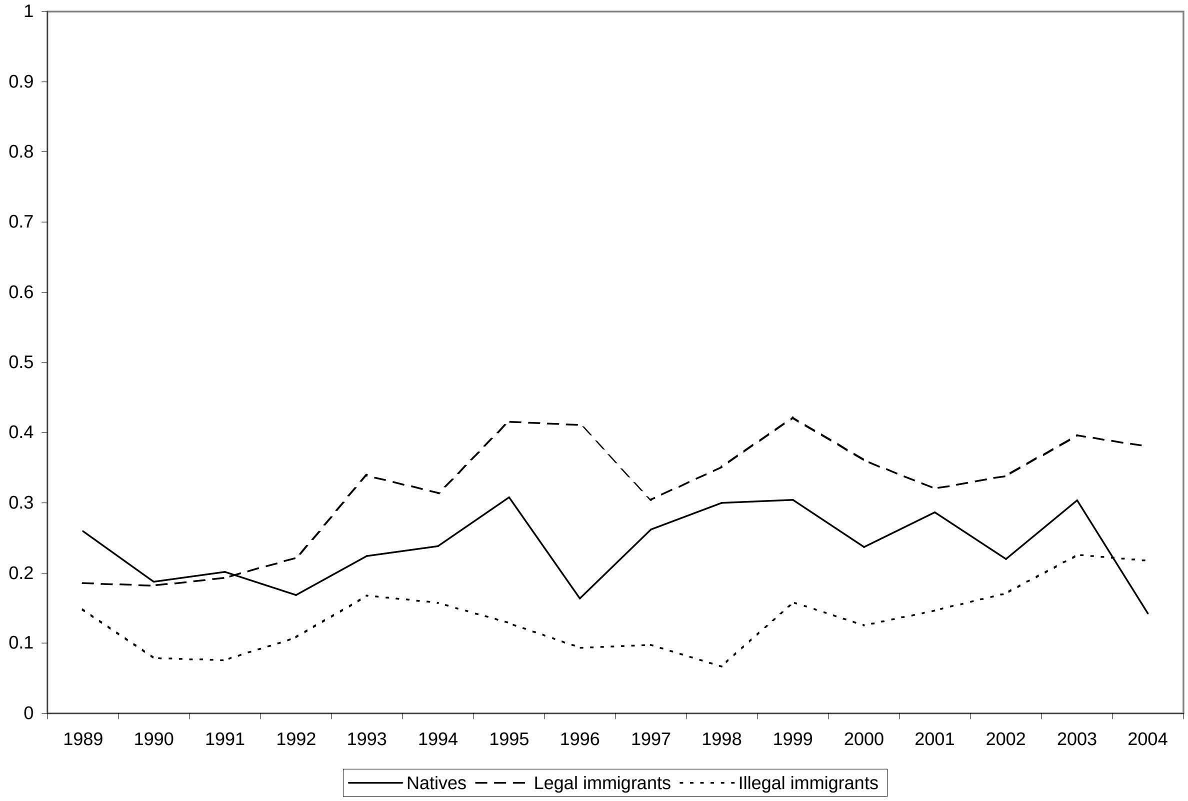

Fig. 1 –Welfare Participation Rates of U.S. Farmworkers, by Legal Status

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

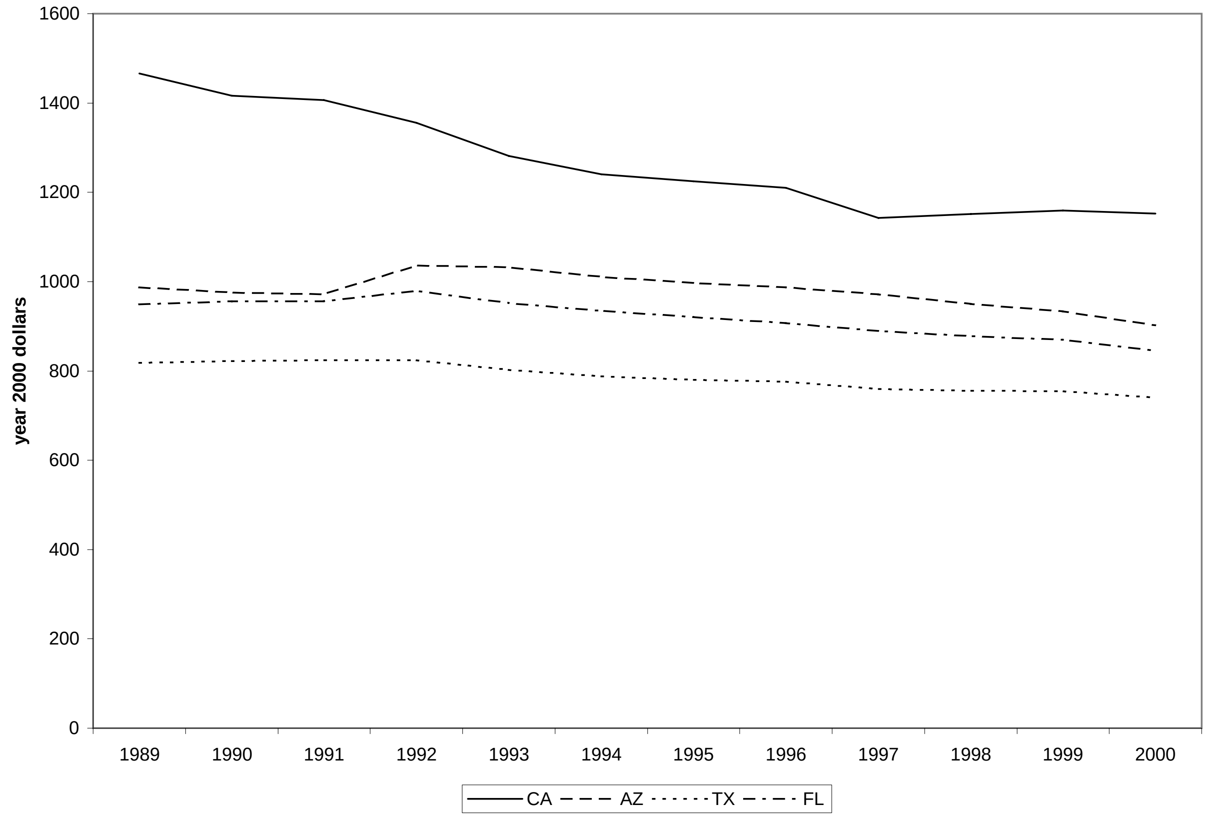

Fig. 2 –(Real) Maximum Monthly AFDC/TANF plus FSP for Family of Four

SOURCE– U.S. House of Representatives Committee of Ways and Means, *Green Book*, and author's calculations NOTE– Deflated using the CPI2000 from Berry et al. (2003)

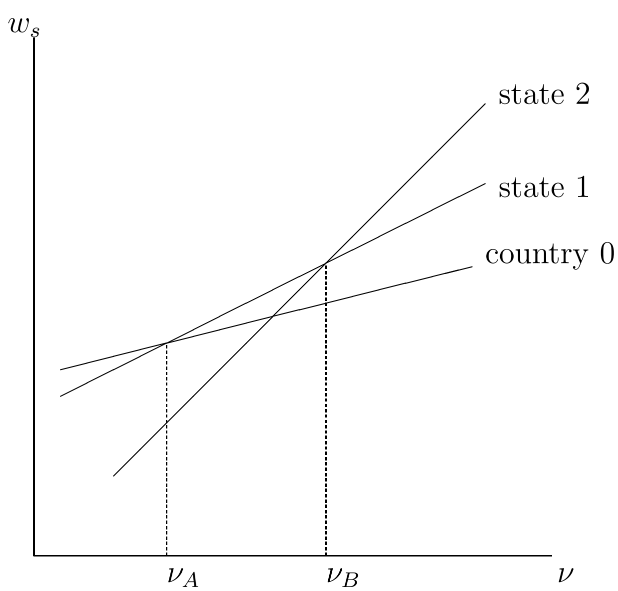

Fig. 3 –Wage-skills Curves of Two Destination States and One Origin Country

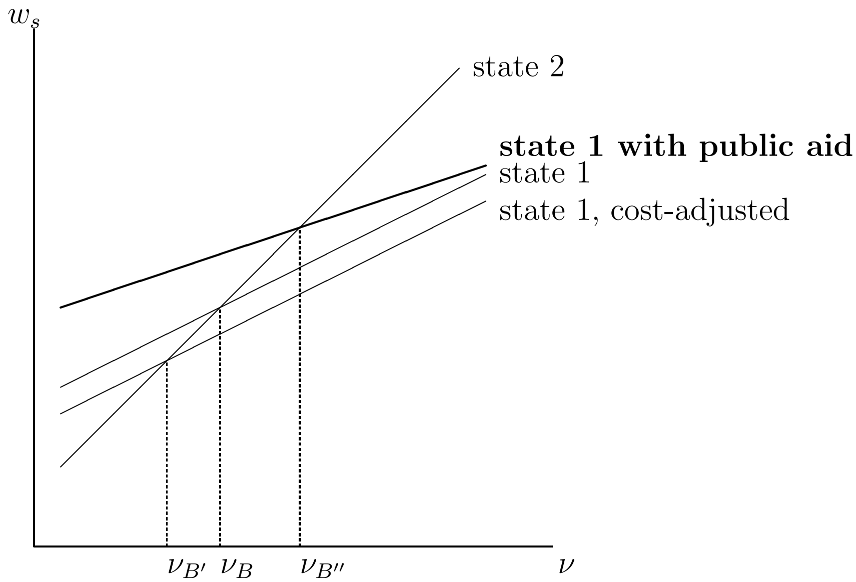

Fig. 4 –Migration Costs plus Public Aid in State 1

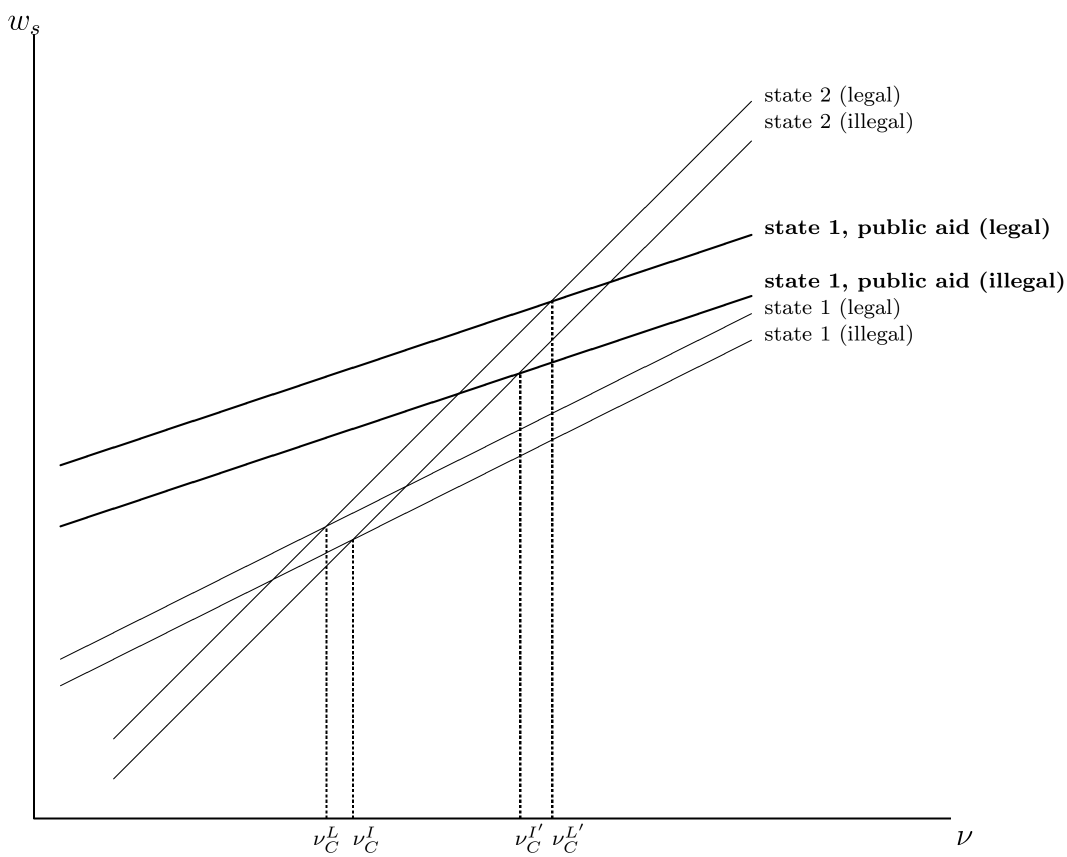

Fig. 5 –Illegal versus Legal Immigrants, Public Aid in State 1

Table 1 Means of Key Demographic and Employment Variables, by Legal Status

	Native	Illegal	Nat. Citizen	Green Card	Other Author.
Female (%)	36.7	15.5	18.5	23.2	13.7
Age (yrs)	32.4	27.6	38.7	38.1	31.5
Married, spouse in U.S. (%)	42.3	18.4	46.4	56.7	33.6
Married, spouse anywhere (%)	44.7	46.3	61.0	76.2	63.7
Children in U.S. (#)	0.8	0.4	1.1	1.4	0.9
None (%)	64.7	83.1	58.2	48.1	65.9
One (%)	12.6	6.5	9.3	12.1	10.1
More than one (%)	22.7	10.5	32.6	39.8	24.0
Children anywhere (#)	0.8	0.9	1.2	1.7	1.0
Education (yrs)	10.7	6.2	7.5	5.9	5.5
U.S. farmwork experience (yrs)	13.5	4.1	16.5	15.5	9.5
Hourly wage ($1982-4)	4.0	3.7	4.1	4.1	4.1
Speaks English (%)	94.9	7.3	42.5	22.5	16.3
Reads English (%)	93.1	5.7	34.8	18.2	11.7
Has work network (%)	56.6	77.8	61.7	59.7	62.3
Paid below min wage (%)	7.6	12.7	7.3	6.6	7.5
Hispanic (%)	36.0	98.6	95.0	96.6	98.3
in California (%)	7.1	33.8	24.7	51.4	35.0
in Southern Plains (TX, OK) (%)	9.8	2.8	6.5	7.7	5.4
in Florida (%)	3.1	7.9	13.0	5.0	8.2
in Arizona or New Mexico (%)	0.9	1.7	1.8	4.2	3.2
from Mexico (%)		93.7	51.2	94.7	94.9
Observations	5664	16514	1598	9622	2547

SOURCE– National Agricultural Workers Survey, pooled cross sections 1989-2004.

Table 2 Welfare Program Participation, by Legal Status and Location (% of total)

	Native	Illegal	Nat. Citizen	Green Card	Other Author.
California	33.13	13.12	32.40	33.10	15.21
Southern Plains (Texas, OK)	41.41	23.17	54.72	48.84	24.55
Florida	30.24	11.46	23.62	39.38	19.51
Mountain III (Arizona, NM)	19.45	7.24	41.12	16.23	6.84
United States	23.12	13.81	39.43	34.52	15.84

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

Table 3 Geographic Clustering of Welfare Recipients (percentage of households)

California migrants				
	have used welfare	have not used welfare	t-test equality	p-value
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				
	have used welfare	have not used welfare	t-test equality	p-value
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				
	have used welfare	have not used welfare	t-test equality	p-value
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				
	have used welfare	have not used welfare	t-test equality	p-value
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				
	have used welfare	have not used welfare	t-test equality	p-value
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.

Table 4 Welfare Clustering Gap Hypothesis Test Revised

Dependent variable: Probability of State s	(1)	(2)	(3)	(4)	(5)
	CA	TX	FL	AZ	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

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

Note– Probit marginal effects. Robust standard errors in parentheses. Regressions also include controls for gender, age, spouse, children, education, farmwork experience, presence of work networks, season, survey year, and country and state of origin.

$*p < 0.1$

$**p < 0.05$

$***p < 0.01$

Table 5 Food, Medical, and Insurance Program Clustering Gap Tests

Dependent variable: Probability of State s	(1)	(2)	(3)	(4)	(5)
	CA	TX	FL	AZ	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)

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

Note– Probit marginal effects. Robust standard errors in parentheses. Regressions also include controls for gender, age, spouse, children, education, farmwork experience, presence of work networks, season, survey year, and country and state of origin.

$*p < 0.1$

$**p < 0.05$

$***p < 0.01$

Table 6 Education Clustering Gap Test

Dependent variable: Probability of State s	(1)	(2)	(3)	(4)	(5)
	CA	TX	FL	AZ	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

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

Note– Probit marginal effects. Robust standard errors in parentheses. Regressions also include controls for gender, age, spouse, children, education, farmwork experience, presence of work networks, season, survey year, and country and state of origin.

$*p < 0.1$

$**p < 0.05$

$***p < 0.01$

Table 7 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. Regressions also include survey year, season, country and state of origin, and non-interacted socioeconomic characteristics.
Note– Probit marginal effects. Robust standard errors in parentheses.
$*p < 0.1$
$**p < 0.05$
$***p < 0.01$

Table 8 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– Maximum monthly AFDC/TANF benefit levels and FSP values are from the U.S. House of Representatives Committee of Ways and Means. Data on current expenditure per pupil in public elementary and secondary schools are from the U.S. Department of Education, Digest of Education Statistics and from the National Education Association, Rankings and Estimates. Minimum wage data are from the Department of Labor. Border Patrol linewatch hours per mile are from unpublished INS/Homeland Security data shared by Gordon H. Hanson and Christina Gathmann. Rural unemployment rates are calculated using inputs from Economic Research Service of USDA. Farm employment figures are from Economic Research Service of USDA and the Bureau of Economic Analysis of the Department of Commerce. Hispanic share of state's population is from the U.S. Census. Annual average wage rates of hired field workers are from USDA.

Table 9 Conditional Logistic Model of Locational Choice–Full Sample (CA, AZ, TX, FL), Reference Category: California

	Texas		Florida		Arizona	
	coef	odds	coef	odds	coef	odds
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		
			coef	odds		
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			

SOURCE– National Agricultural Workers Survey, pooled cross sections 1989-2004, sample restricted to CA, AZ, TX, FL.
NOTE– Robust standard errors in parentheses, clustered at the state level. Regressions also include Mexican state of origin dummies. Labor market variables are lagged one year.
$*p < 0.1$
$**p < 0.05$
$***p < 0.01$