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Locational Choices of the Legal and Illegal: Mexican Agricultural Workers in the U.S.

by

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Abstract

The paper examines if and how state-level labor market, agricultural, and demographic conditions, public aid provisions, minimum wages, and border patrol intensities persuade or dissuade illegal and legal farmworker migration from Mexico. The study uses a nationally-representative survey of farmworkers that provides direct data on legal status, and qualitative choice modeling of individual locational choices. Results indicate that, consistent with social capital literature, personal and community networks are primary determinants of individual locational choices. Conversely, border enforcement significantly deters migration to certain areas. Results are strongest for California migrants and for experienced migrants relative to new ones. Potential welfare and education program values are found uncorrelated with the locational choices of Mexican migrants, but are positively correlated with the destinations of those from Central America.

Keywords: illegal immigration, farmworkers, locational choice

JEL codes: K42, O15, Q12, R12

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The migrant workers' year is a string of beads-a week of employment here, another there, uncertainly tied together with travel in search of work. Away from home for months at a time, many take their families with them. In a sense they work not for Employer A or Employer B; they work a crop. Lacking capital, they often unite loosely as crews, and travel in whatever vehicles the leader can provide. Where they work, many find indifferent housing. Planning has helped them-the planning that relates employers' demands to crews' availability. And public opinion has helped to temper the worse of their woes. But much more needs to be done. The migrant farm worker occupies the lowest level of any major group in the American economy.

(U.S. Department of Labor *Farm Labor Fact Book* (1959) p. 110)

1 Introduction

Immigration policy, especially that relating to illegal immigration, is a hot topic in current United States policy debates.[1] Proponents of opening the borders argue that illegal immigrants form a crucial part of the labor force of the U.S. as a whole, or of individual states, and contribute to the greater economy. Opponents worry about fiscal burdens, decreases in public safety, ethnic segregation, and linguistic and cultural barriers. While many recent policy discussions have focused on potential federal-level actions such as the introduction of a new guest worker program reminiscent of the Bracero-era, questions regarding if and how individual states can, do, or might persuade or dissuade migration are also relevant.

Migrants to the U.S. form a mobile and many times circumspect population. Therefore, direct data on these persons and their activities are often unreliable if not completely unavailable. The estimates that do exist of the magnitude of the illegal population present in the U.S. and its dispersion (or lack there of) across receiving states are striking. Passel (2006b) estimates that 11.1 million illegal immigrants were present in the U.S. in March 2005. This estimate is up from 9.3 million in 2002 (Passel (2004)) and 10.3 million in 2003 (Passel, Capps, and Fix (2005)). Of this total, approximately 6.2 million (56 percent) were from Mexico. In terms of spatial distribution within the country, 2.5-2.75 million illegal immigrants resided in California, followed by Texas (1.4-1.6 million), Florida (0.8-0.95 million), New York (0.55-0.65 million), and Arizona (0.4-0.45 million). These five states account for more than 50 percent of the estimated total.[2]

Patterns for legal immigrants parallel those for the illegal population. Of the 175,364 persons from Mexico who became legal permanent residents in fiscal year 2004, for example, more than 75 thousand

[1] "Illegal" and "undocumented" refer to those unauthorized to reside and work in the U.S. These terms are used interchangeably in this paper. "Legal" and "documented" refer to naturalized citizens, Green Card holders, and those with other authorization.

[2] The estimation strategy involves subtracting an estimate of legal foreign-born residents from one of the total foreign-born population. Asylum applicants and those with temporary protected status comprise as much as 10 percent of the estimate.

took residence in California, followed by 42 thousand in Texas. More than 10 thousand became Arizonians, and three thousand became Floridians.[3] Naturalizations from Mexico totaled 63,840. Almost 30 thousand newly-naturalized citizens lived in California, and 12 thousand lived in Texas.

This paper examines state-level locational choices of legal and illegal Mexican migrants with a focus on how state-level factors such as changes in labor market conditions, public service provisions, and law enforcement efforts influence the decision-making process of not only whether to come to the U.S., but also where to locate if and after successfully crossing the border. Specifically, this paper asks what variables explain immigrant locational distributions and whether determinants differ for legal and illegal populations. Analysis focuses on the key immigrant-receiving states of California, Texas, Florida, and Arizona.

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. In addition to spatial characteristics, individual demographic (such as family structure differences) and temporal factors associated with migration decisions are explored. Results indicate that personal and community networks are primary determinants of locational choice, and that border enforcement significantly deters migration by agricultural workers to certain areas. These results are strongest for California migrants and for experienced migrants relative to new ones. Potential welfare and education program values are found uncorrelated with the locational choices of Mexican migrants, but positively correlated with the locations of Central American migrants and U.S. born farmworkers.

The paper is organized as follows. Section 2 reviews academic literature relating to international migration, illegal immigration, and locational choice. Section 3 develops a theoretical framework for questions of locational choice. Section 4 describes supplemental data of economic and labor market conditions over time in key U.S. destination states, the structure and characteristics of seasonal agricultural work, and border enforcement intensity, and how these data can be matched to the NAWS. Section 5 presents empirical strategies. Section 6 presents results and interpretations. Section 7 concludes.

2 Literature

Academic literature on international migration and illegal migrant flows points to complexities regarding domestic and international labor market interactions and the empirical estimation of these relationships. General literature on international migration, on illegal immigration specifically, and on immigrant locational choice is presented in turn.

[3] U.S. Department of Homeland Security.

2.1 International Migration

Literature on the determinants of international migration is prolific. Massey, Arango, Hugo, Kouaouci, Pellegrino, and Taylor (1998) and Massey and Espinosa (1997) present comprehensive surveys of existing studies. These authors discuss contemporary literature as falling within five categories. The first relates to neoclassical framework in which potential migrants make cost-benefit calculations, migrating in cases of positive net benefits. Policy initiatives that decrease migrant flows reduce net benefits while benefit programs should have the opposite effect. A second category is the new economics of migration in which migration minimizes household risk of price inflation and currency devaluation or enables households to overcome production or consumption constraints. A third branch is social capital theory, which stresses personal and professional networks (e.g. Munshi (2003) and Mckenzie and Rapoport (2004)). Finally, segmented labor market theory conceptualizes migration as the result of a structural demand for immigrant labor in industrial societies, and world systems theory hypothesizes that immigration is driven by capitalist market penetration into the developing world.

2.2 Illegal Immigrant Flows

Academic work concerned with illegal immigration has focused on determinants of these flows and on impacts on the U.S. economy. The majority of studies have compensated for the lack of direct data on illegal migrants by using border apprehensions and enforcement data (e.g. Hanson and Spilimbergo (1999) and Hanson, Robertson, and Spilimbergo (2002)), or by using U.S. Census data on recent Mexican immigrants (some of whom are illegal) or case studies of sending or receiving communities of illegal migrants.[4] A few authors have used microdata on apprehended illegal immigrants to infer characteristics of this largely transparent population.

Among points raised in the illegal immigrant literature is that illegal immigrant flows are more sensitive to changes in Mexican wages than to changes in U.S. wages. This is in contrast to studies using U.S. interregional data that have found the opposite relationship between sending and receiving regions. Unemployment in the U.S. (or in U.S. border states) and minimum wages in Mexico and in the U.S. have been found only weakly correlated with proxies of illegal immigrant flows such as border apprehensions.

Evidence on whether border enforcement reduces illegal immigration is mixed. Some authors conclude that border enforcement causes migrants to make several attempts to cross the border as opposed to deterring migration. Others find evidence of a deterrence effect (e.g Gathmann (2004) and Dávila, Pagán, and Soydemir (2002)). Additionally, the composition of illegal migrants may respond to increases in border patrol and the

[4] See discussion in Boeri, Hanson, and McCormick (2002).

distribution of destinations may be sensitive to border patrol intensity. One contribution of this paper is to study this aspect. Hanson and Spilimbergo (2001) consider whether border enforcement affects regional economies. The authors find zero correlation between wages and enforcement in California and Texas apparel, textiles, food, and furniture industries. However, they find a negative effect of border enforcement on Mexican wages.

2.3 Immigrant Locational Choice

A handful of academic papers examine locational choices and settlement patterns of immigrants. Bartel (1989) studies the locational choices of post-1964 U.S. immigrants at the city level. She finds that immigrants are more geographically concentrated than natives while controlling for age and ethnicity and that education reduces the probability of geographic clustering and increases the probability of changing locations after arrival in the U.S.

Jaeger (2000) uses micro-level admissions data from the INS and 1980 and 1990 Census data to examine locational propensities of legal immigrants. He finds that immigrants' responsiveness to labor market and demographic conditions differs across admission categories. Employment category immigrants, for example, are more likely to locate in areas with low unemployment rates. Other determinants of locational choice are wage levels and ethnic concentrations. Neither Bartel and Jaeger restrict to specific ethnic groups of interest such as those from Mexico. Orrenius (2004), however, considers preferred border crossing sites at the state and city level and concludes that enforcement has played an important role in deterring Mexican migrants from crossing in California.

3 Theoretical Model

The following builds a theory of locational decision-making by individual migrants in the presence of state-level variation in labor market conditions and public policy attributes.

Agents (defined as the set of all people of migration age in the source country, here Mexico) maximize expected utility by choosing a destination d from their set of potential destinations D, which includes a remain-at-origin option denoted o.

Define V_i^* as the expected net benefits to person i from making a decision regarding his or her location (i.e. whether to migrate, and if migrate, to which destination).

$$V_i^* = V_i^o = 0 \;\; if \; V_i^d < 0 \;\; \forall d \neq o \in D \tag{1}$$

$$V_i^* = \max_{d \neq o \in D} V_i^d > 0 \ \ if \ V_i^d \ \ for \ at \ least \ one \ d \neq o \in D$$

Expected net benefit to person i from making a migration is defined by the difference between that agent's expected utility at the destination d and his or her expected utility at the origin plus expected migration costs. Specifically,

$$V_i^d = E(U_i^d) - E(U_i^o) - E(C_i^d) \tag{2}$$

where expected incomes and costs are mapped to expected utilities.

Equation 3 formally defines the expected utility at the destination.

$$E(U_i^d) = P_c^d Y_i^d = P_c^d[P_e^d(w_i^d H_i^d) + P_b^d B_i^d] \tag{3}$$

Here, P_c^d is the probability of successfully crossing the border into destination d (i.e. the probability of making it to the destination without being apprehended) and Y_i^d is i's expected income at location d. The expected income term comprises an expected wage earnings term and an expected public aid term, where P_e^d represents the probability of employment and P_b^d is the probability of receiving aid including education benefits at the destination. Expected wage earnings are defined by expected hourly wage rates (w_i^d) times expected hours per period (H_i^d). Expected supplemental income is denoted B_i^d. As benefit levels of many U.S. public aid programs are based on family size and characteristics, this variable is modeled as a function of the migrant's family size.

Equation 4 provides a parallel definition for expected utility at the origin.

$$E(U_i^o) = Y_i^o = P_e^o(w_i^o H_i^o) + P_b^o B_i^o \tag{4}$$

The probability of employment is denoted P_e^o and expected income at the origin is Y_i^o. Quantities are defined as expectations and are inclusive of supplemental income sources.

Equation 5 presents the cost side.

$$E(C_i^d) = C_{mi}^d + C_{pi}^d + (1 - P_c^d)C_{ai}^d \tag{5}$$

Expected costs are a function of monetary, psychological, and apprehension-related costs. C_{mi}^d is agent i's total expected monetary cost of migration including such payments to border smugglers or "coyotes" for assistance in the trip and other monetary costs associated with travel.[5] The variable is assumed to include

[5] Gathmann (2004) shows that illegal migrants may increase their probability of successfully crossing by making a costly investment in a coyote.

the opportunity cost of migrating to the U.S., namely any foregone income at the origin, and is indexed by d to account for travel time and distance. If the migrant intends to return to the sending location, then C^d_{mi} represents round-trip costs. C^d_{pi} denotes expected psychological costs associated with migration such as leaving family or one's homeland in order to undertake a (risky) migration. This may depend on travel distance or time. Finally, C^d_{ai} represents costs associated with apprehension or deportation if the migrant does not make it successfully across the border. These include court costs, opportunity costs of time, and psychological costs.

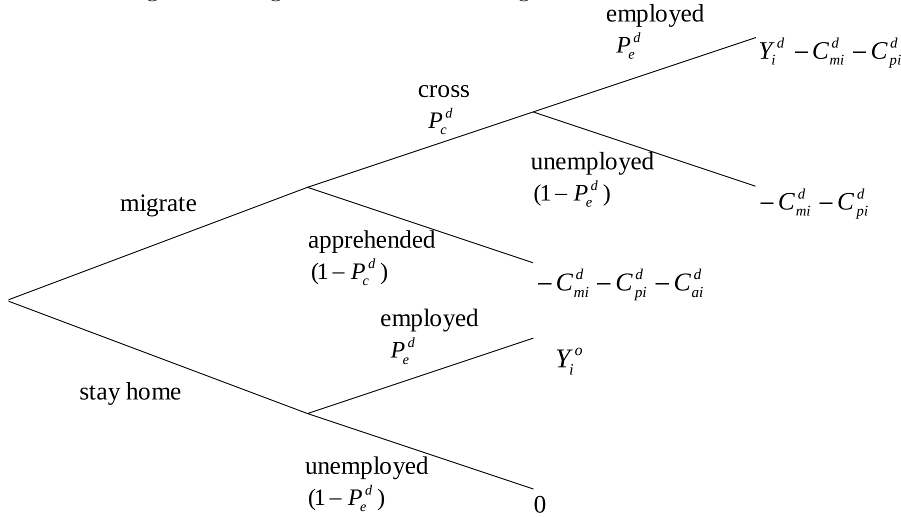
Although notation is suppressed, the values of each variable may depend on year and season. Thus, an agent is imagined to make this calculation at any point of time. He or she remains at the origin as long as the calculation remains negative. Equations 2 to 5 provide insight as to how several hypothesized determining factors influence the propensity to choose one destination over another. Specifically, increases in border patrol intensity over certain border patrol sectors (as measured by linewatch hours per mile or in apprehensions per mile for example) should be associated with a decrease in the probability of successful crossing P^d_c, and therefore with a decrease in the probability of choosing a particular location. This probability is equal to one for legal migrants (unless border enforcement has negative effects on the utility of legal migrants as well, in which case the probability is less than one). P^d_c should be strictly less than one for illegal migrants.

High unemployment rates and other negative indicators of labor market conditions should be associated with decreases in the probabilities of employment at the destination and origin P^d_e and P^o_e. Increases in average wages of similar workers and potential values received from social service programs, hospitals, and educational systems should be positively related to expected incomes Y^d_i and Y^o_i. Similarly, differences in state-level minimum wages should make certain states more attractive.

Personal and professional networks, as stressed in social capital theory literature, simultaneously enter multiple variables in the problem. Information networks may increase the probability that one crosses successfully and increase the probability of employment at a destination. Networks may increase the probability of receiving aid benefits if experienced friends and family members help in the application process. Networks may decrease both the monetary and unobserved psychological costs of crossing.

Figure 1 illustrates the migrant decision-making process under uncertainty regarding crossing success and employment at the destination. The figure compares the payoffs of the status quo option of staying at the origin to that of the destination choice d offering highest expected net benefits when compared with other destinations within the full set D.

Figure 1: Migrant Decision-making Process and Outcomes



4 Data

4.1 Data on Illegal and Legal Immigrants

Ideally, the questions addressed in this dissertation would be answered and the theoretical models tested with a household-level panel of illegal and legal, successful and unsuccessful border crossers from a number of communities and industries representative both domestically and internationally and supplemented by a rich dataset of agricultural and labor market conditions at refined local levels. This type of data is difficult to produce given the distinction between migrants who make it across the border and those who do not, and given stigmas related to migrating illegally in the first place and hence non-participation in surveys. In addition, many illegal migrants take seasonal jobs in the U.S., traveling back and forth between short-term jobs in the U.S. and family in their sending countries, introducing problems for surveys using traditional sampling techniques.

Appropriate data for studies of immigrant populations, especially illegal immigrant populations, are scarce. Johnson (2006) writes that "There are no nationally (or state) representative surveys that include questions about legal status." In the macroeconomics literature, a common solution is to proxy for numbers of illegal persons using measures of border apprehensions or enforcement. In the microeconomics literature, researchers have used data from immigrant respondents of the Current Population Survey (CPS) or U.S. Census (some of whom are illegal) or household surveys of sending or receiving communities of illegal migrants. U.S. household surveys prove problematic for the study of illegal immigrants as many in this group live in non-standard housing situations and are unlikely to be sampled.[6] Surveys specifically targeting mi-

[6] Gabbard, Mines, and Perloff (1991) explain that while CPS sampling methodology focuses on household location, NAWS

grant communities are similarly imperfect. One dataset popular in the literature is the Mexican Migration Project (MMP), which provides cross-section retrospective migration data. The MMP is problematic for studies of migrants in the U.S. at any point in time, however, due to small sample sizes of those with U.S. migration experience. Although a series of cross-sections can be reconstructed, the data are not nationally representative of either the sending or receiving country.[7]

4.2 The National Agricultural Workers Survey

Primary data used in this paper 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.[8] 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 1.

Table 2 shows key demographic and employment variables by legal status after pooling the cross-sectional 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.[9] 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

focuses on employment and may avoid biases due to undersampling migratory and immigrant farmworkers. They write: "The CPS is based on a random sample of housing units. Though all types of housing are to be included, critics claim that agricultural workers who live in non-standard housing units or who may be illegal tenants or sub-tenants are likely to be missed." The authors compare 1988 NAWS and CPS data and find that NAWS workers are more likely foreign-born and less likely to own or rent houses.

[7] A newer dataset, the Mexico National Rural Household Survey (Encuesta Nacional a Hogares Rurales de Mexico (ENHRUM)) conducted by El Colegio de Mexico and the University of California, Davis may be more appropriate as that data are reported to be nationally and regionally representative of rural Mexico.

[8] 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.

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

Table 1: 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

Table 2: 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.

native counterparts. The opposite is true of Southern Plains (TX, OK) farmworkers.[10]

In some sense, the data in this paper represents 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.

[10]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.

Table 3: Summary Statistics for Mexican Farmworkers, by Legal Status

	Legal		Illegal	
4 States–CA, AZ, TX, FL	Mean	Std. Err.	Mean	Std. Err.
Female	0.234	0.008	0.177	0.008
Age (yrs)	37.869	0.180	28.479	0.176
Spouse in U.S.	0.585	0.008	0.260	0.008
Spouse anywhere	0.768	0.007	0.498	0.010
Children in U.S. (#)	1.436	0.027	0.509	0.021
Children anywhere (#)	1.587	0.025	0.964	0.027
Education (yrs)	5.723	0.060	6.186	0.060
U.S. farmwork experience (yrs)	15.818	0.149	5.939	0.117
Speaks English	0.177	0.007	0.053	0.004
Reads English	0.143	0.006	0.043	0.004
Has work network	0.552	0.008	0.729	0.008
Has used public aid	0.339	0.008	0.177	0.007
Has used education	0.304	0.008	0.144	0.007
Observations	8651		8256	

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

4.3 Farmworker Characteristics, by Location

In light of the basic theoretical model, the data reveal a selection problem. Workers in the data are only a subset of those appearing in Figure 1. Specifically, they are those who have decided to migrate, who successfully crossed the border, and who found employment. Seventy-one percent of the NAWS sample report origins in Mexico. Of those from Mexico, 16,907 were sampled in the California, Texas, Florida, and Arizona regions. Means and linearized standard errors by legal status and U.S. receiving state are presented in Tables 3 and 4.

In the full sample, each of the reported variables displays significant differences in a two-sample t-test on the equality of means between the legal and illegal populations present in the U.S. Gender is largely male overall, and a higher percentage of illegal workers than of legal workers are male. The mean age for legal workers is 37.9 years compared with 28.5 years in the illegal population. Following their younger age, illegal survey respondents are less likely to be married and have fewer children on average both within and outside the U.S.[11] Legal workers have on average almost 10 additional years of U.S. farmwork experience, again consistent with their older age. They have fewer years of education, however, on average. This could be due to cohort effects and secular trends of education increases in Mexico. Legal workers are more likely to possess English language speaking and reading ability and are more likely to use public aid and education services.[12] Illegal workers are more likely to report the presence of a work network in the U.S. These general patterns of the demographic characteristics of legal versus illegal Mexican workers in the U.S. holds true for most of the state-level subsamples. Exceptions tend be associated with high p-values in the two-sample

[11] Previous to 1992, workers were asked how many children they had total, as opposed to how many within and outside the U.S. The mean number of children reported by Mexican workers in 1991 to 1992 was 1.05. For those answering the specific questions in 1993 to 2004, the mean was 1.10.

[12] Workers were asked to rate their English speaking and writing ability on a scale of one to four. The variable for language ability pools responses one and two as “no” and three and four as a “yes” answer.

Table 4: Summary Statistics for Mexican Farmworkers, by Legal Status and State

	Legal		**Illegal**	
California sample	Mean	Std. Err.	Mean	Std. Err.
Female	0.235	0.008	0.178	0.009
Age (yrs)	37.759	0.184	27.936	0.192
Spouse anywhere	0.767	0.008	0.490	0.011
Children anywhere (#)	1.604	0.029	0.971	0.032
Education (yrs)	5.682	0.063	6.225	0.068
U.S. farmwork experience (yrs)	16.146	0.144	5.840	0.134
Speaks English	0.162	0.007	0.044	0.004
Has work network	0.564	0.008	0.766	0.009
Observations	6109		5642	
Arizona sample				
Female	0.140	0.017	0.123	0.027
Age (yrs)	40.395	0.525	34.233	0.945
Spouse anywhere	0.752	0.022	0.655	0.035
Children anywhere (#)	1.596	0.075	0.967	0.080
Education (yrs)	6.169	0.181	6.588	0.363
U.S. farmwork experience (yrs)	17.399	0.520	7.910	0.567
Speaks English	0.140	0.017	0.111	0.032
Has work network	0.294	0.021	0.366	0.035
Observations	803		421	
Texas sample				
Female	0.190	0.022	0.212	0.036
Age (yrs)	39.025	0.659	32.597	1.073
Spouse anywhere	0.804	0.022	0.533	0.041
Children anywhere (#)	1.591	0.077	0.969	0.109
Education (yrs)	5.849	0.256	5.741	0.276
U.S. farmwork experience (yrs)	15.325	0.570	7.393	0.651
Speaks English	0.250	0.026	0.129	0.023
Has work network	0.631	0.026	0.686	0.037
Observations	847		483	
Florida sample				
Female	0.382	0.051	0.171	0.015
Age (yrs)	34.877	1.031	27.935	0.381
Spouse anywhere	0.730	0.030	0.477	0.023
Children anywhere (#)	1.407	0.103	0.918	0.064
Education (yrs)	5.537	0.243	6.027	0.130
U.S. farmwork experience (yrs)	11.896	0.683	5.204	0.226
Speaks English	0.246	0.047	0.053	0.010
Has work network	0.536	0.044	0.645	0.022
Observations	892		1710	
Other U.S. states sample				
Female	0.158	0.011	0.146	0.010
Age (yrs)	35.382	0.320	28.546	0.216
Spouse anywhere	0.712	0.014	0.506	0.011
Children anywhere (#)	1.392	0.060	1.026	0.045
Education (yrs)	5.993	0.101	6.328	0.073
U.S farmwork experience (yrs)	13.689	0.246	5.719	0.129
Speaks English	0.288	0.013	0.118	0.007
Has work network	0.665	0.013	0.754	0.010
Observations	3374		7567	

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

t-test of equality. Compared with national averages, legal California workers are slightly older and illegal workers slightly younger. In the Texas sample, an education difference between illegal and legal workers is not evident and the work network difference between the groups is small. Also notable are the small percentages of Arizonians reporting work networks in both legal and illegal categories. Only 29 percent of legal workers and 37 percent of illegal workers in Arizona report a network. Floridian workers are slightly younger and have fewer years of experience.

Because the NAWS does not provide data on state-level attributes, the data are supplemented with historical data from external sources. These data describe supply and demand shifters relevant to the U.S. agricultural sector and preview sources of state-level variation to be exploited in the empirical section.

4.4 State Economic and Demographic Conditions

State labor market and demographic variables include rural unemployment rates, farm employment, Hispanic share of the state's population, and average wage rates.

Unemployment rates serve as indicators of employment probabilities (and of more general labor market conditions) in various locations at given times. If migrants are attracted to tighter labor markets (those with lower unemployment rates), then higher unemployment rates in a state should dissuade migrants. Figure 2 presents state-level rural unemployment rates for the key border states of California, Arizona, and Texas and for Florida respectively.[13] The state-level unemployment rates have generally moved together cyclically and are highly correlated with statewide unemployment rates (not shown). Unemployment rates, however, are based on the legal workforce only.

Total farm wage and salary workers employment is presented in Figure 3. California is presented on the left axis while Arizona, Texas, and Florida are presented on the right. While Texas and Florida farm employment is of similar magnitude, California employment is notably higher and Arizona lower. Further description of state agricultural market characteristics is presented in Appendix B.

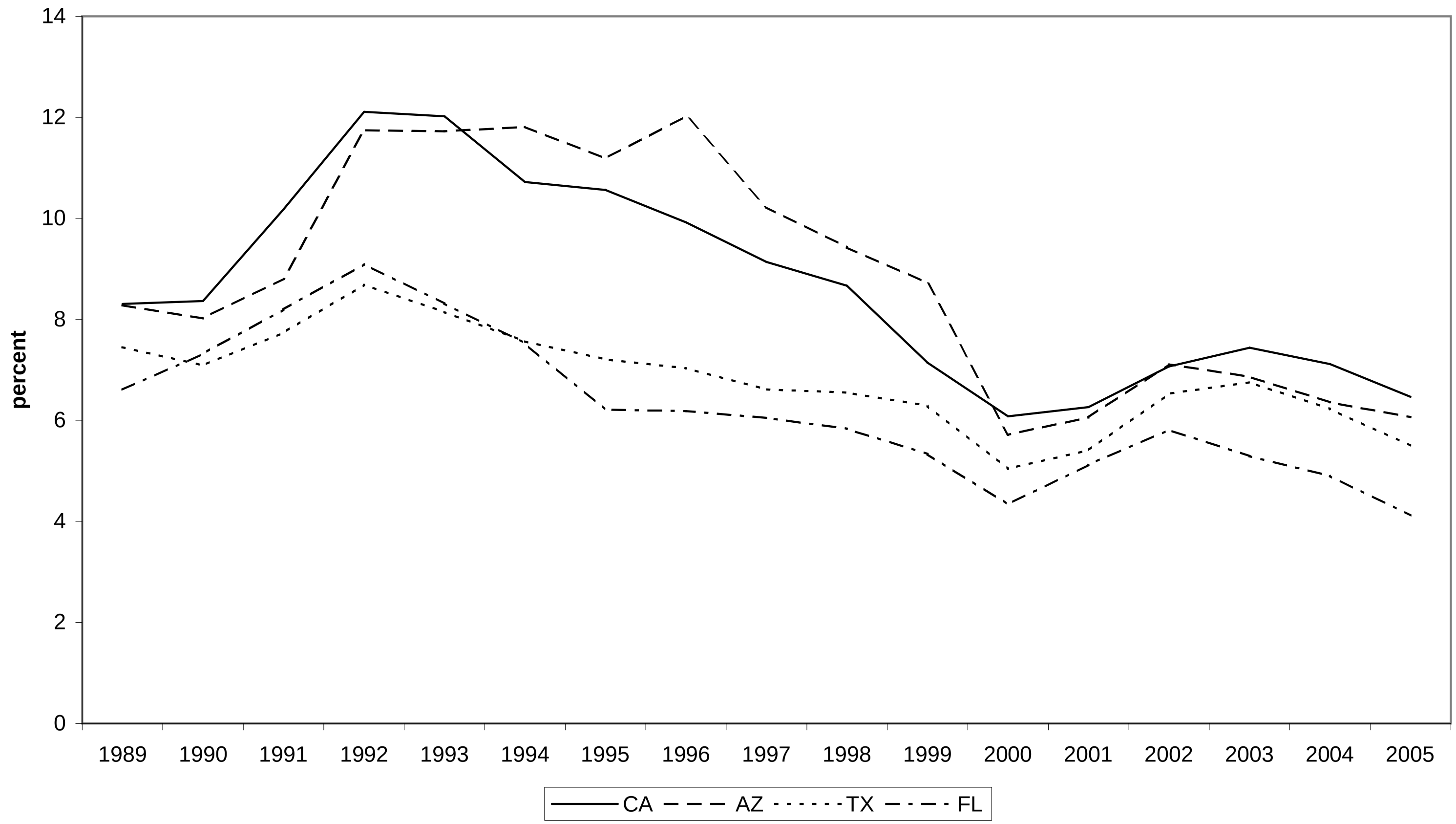
Hispanic share of the population in the border-states approximates the general size of the cultural and linguistic network available in a state and proxies for the potential size of a migrant's greater social network in the U.S. Figure 4 shows that these percentages increased at similar rates over the 1990s. Texas has moved closer to California since 1999.[14]

Annual average wage rates for hired field workers are presented in Figure 5. Wages move together over time with little variation. California and Florida agricultural wages have been slightly higher than those in

[13] Reported rural rates are based on 2003 non-metro classifications and the author's calculations. The 2003 groupings should represent the most rural areas, as these have remained classified non-metro over time.

[14] Data for year 2000 on include those classifying themselves as Latino. This definition difference drives the nonlinearity in the data in year 2000.

Figure 2: Rural Unemployment Rates

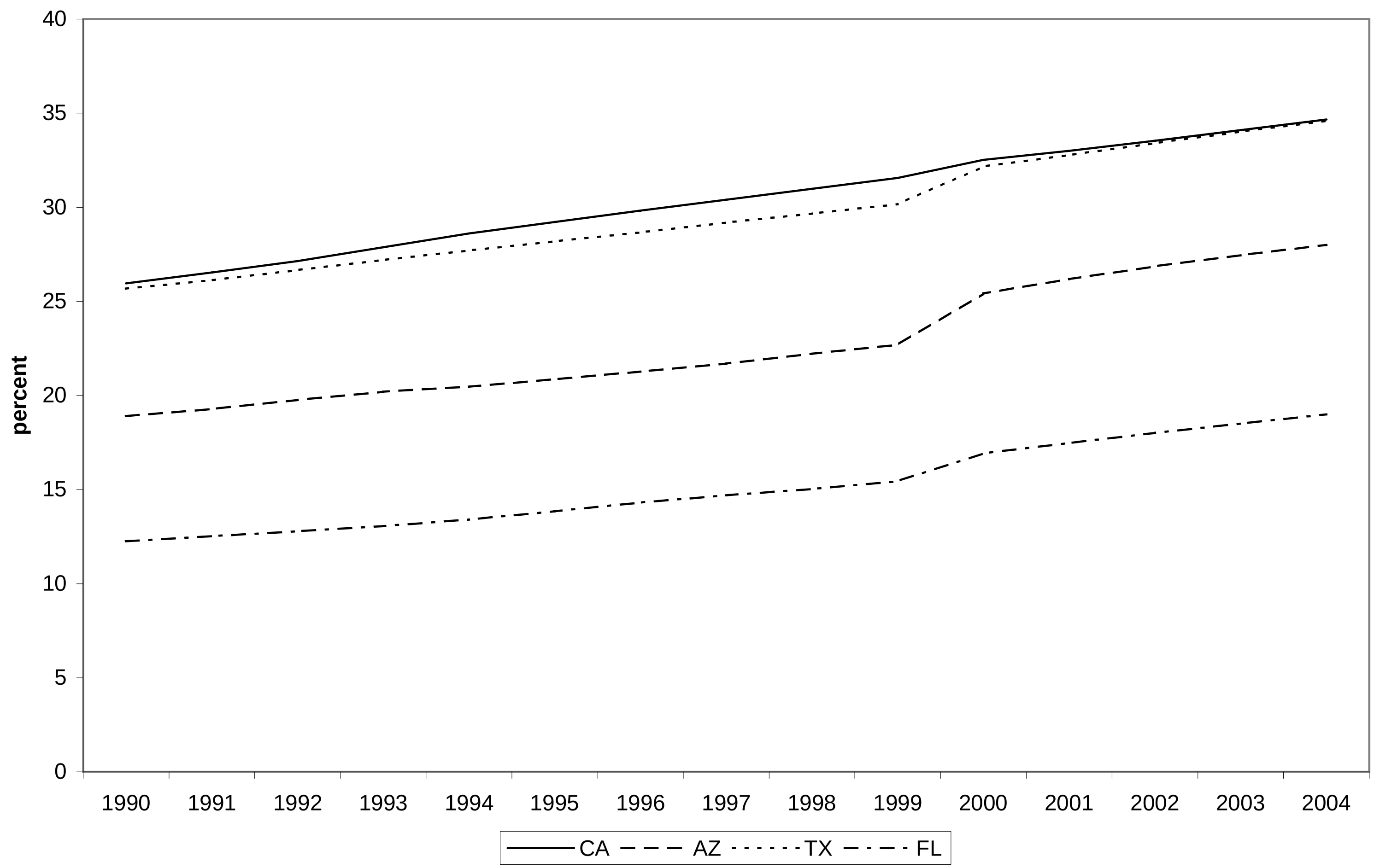


Sources: Economic Research Service, U.S. Department of Agriculture and author's calculations
Note: based on 2003 Metro/Nonmetro classifications

Figure 3: Farm Wage and Salary Workers Employment

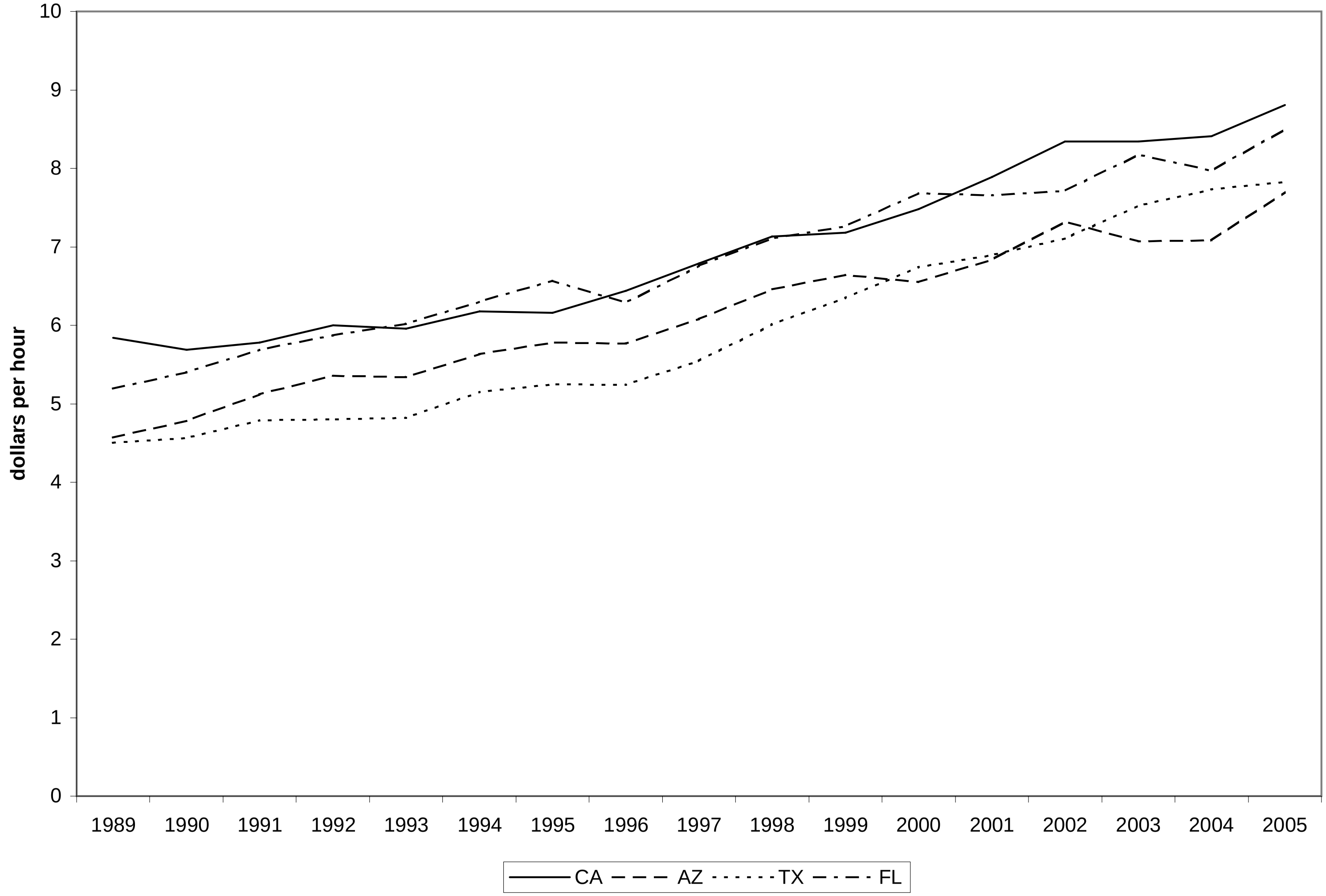
Sources: Economic Research Service, U.S. Department of Agriculture and Bureau of Economic Analysis, U.S. Department of Commerce

Figure 4: Hispanic Share of State's Population



Source: U.S. Census Bureau

Figure 5: Annual Average Wage Rates of Hired Field Workers



Source: U.S. Department of Agriculture
Note: 1989-1991 AZ and TX wages based on USDA agricultural regions

Arizona and Texas.

4.5 State Policy Instruments

State policy variables include public aid program generosities, education expenditure, minimum wages, and border patrol intensity.

U.S. hired farmwork is a low wage occupation. The federal minimum wage was created as part of the 1938 Fair Labor Standards Act. The minimum wage was originally set at 25 cents per hour and has been increased 26 times. Certain states, and in some cases certain cities, have enacted their own minimum wages. In cases that a local government sets a minimum wage in addition to the federally mandated one, the greater prevails. Arizona and Texas do not currently have a state minimum wage. Florida raised its minimum wage for the first time (to 6.15) in May 2005.[15] In contrast, California has re-set its rate 20 times since February 1943, five times since the start of the NAWS. The current minimum wage in California is 6.75 as of January 2002, and the current federal minimum wage is 5.15 per hour. Minimum wages are presented in Figure 6. While the agricultural sector is excluded from minimum wage legislation, observed wage rates roughly approximate these values and minimum wages may be important in expected income calculations.

Another potential determining factor is state differences in public aid payments. If migrants expect to receive forms of welfare while in the U.S., interstate differences in welfare payments also affect the expected income calculation. Although many illegal immigrants are excluded from receiving payments from such programs as AFDC/TANF and food stamps, there are ways around this. For example, the presence of U.S. born children may allow illegal families to receive assistance legally. In addition, workers who have obtained false documents may be able to take-up benefits. Table 3 shows that a sizable fraction of illegal sampled farmworkers used welfare or education programs while in the U.S. Specifically, 18 percent of the illegal immigrant four state sample reported using some form of public aid. Fourteen percent reported using U.S. education programs.

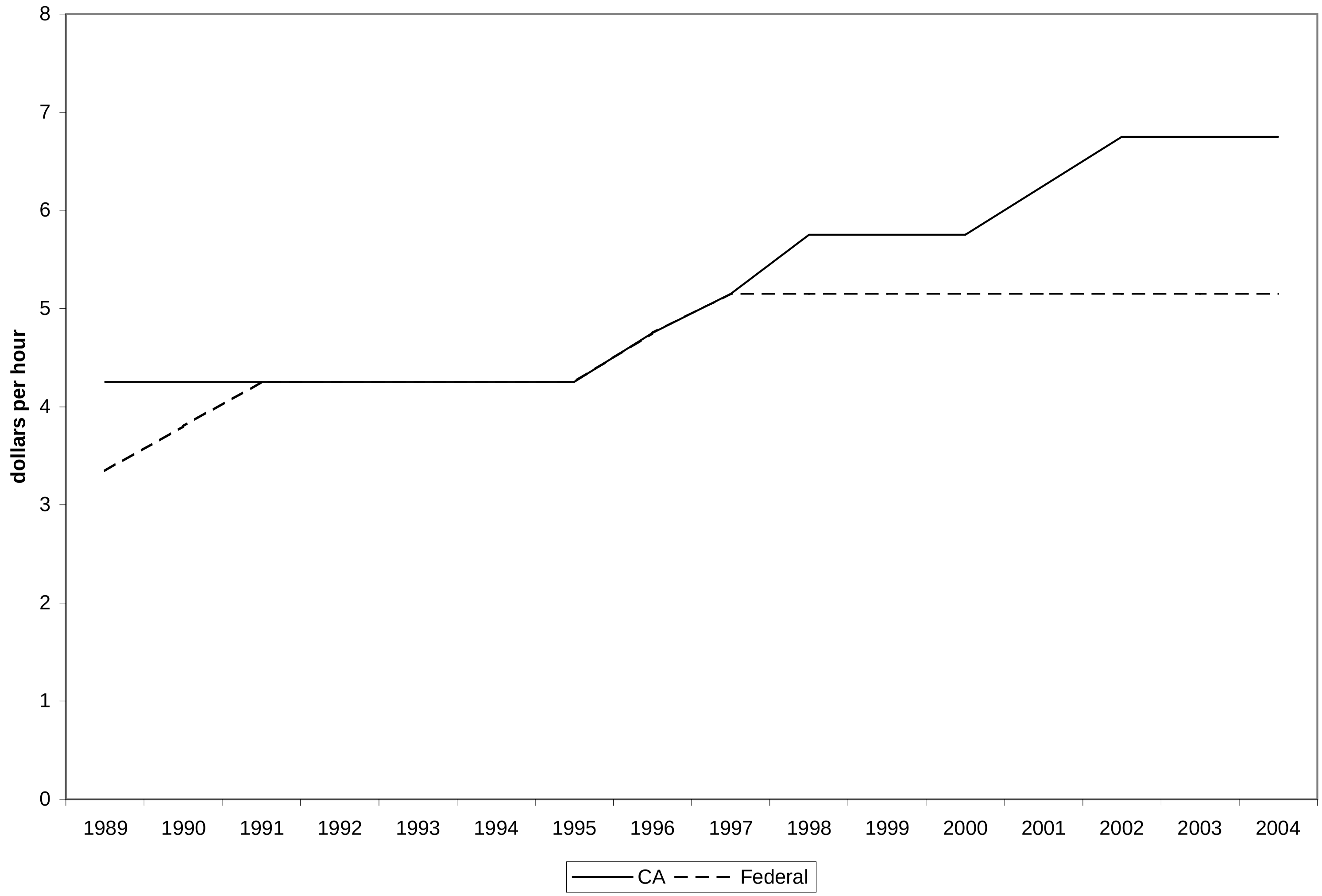
Figures 10 and 11 illustrate the maximum monthly AFDC/TANF payments plus FSP benefits for a family of four for the states of California, Arizona, Texas, and Florida respectively in both nominal and real terms as published by the U.S. House of Representatives Committee on Ways and Means.[16] The AFDC/TANF program provides cash assistance. FSP provides vouchers redeemable for food products. Face values of these vouchers are set as a percentage of the federal poverty line. Maximum monthly FSP benefits are constant across states but vary across family structures.[17]

[15] Federal minimum wage rates are matched to Arizona, Texas, and Florida migrants in the empirical section since these states did not have state-level minimum wages during the NAWS sample period.

[16] The *Green Book* was published annually from 1982-1994 at which point it was published biannually until 2000, followed by early in 2004. It was necessary to linearly impute values for missing years.

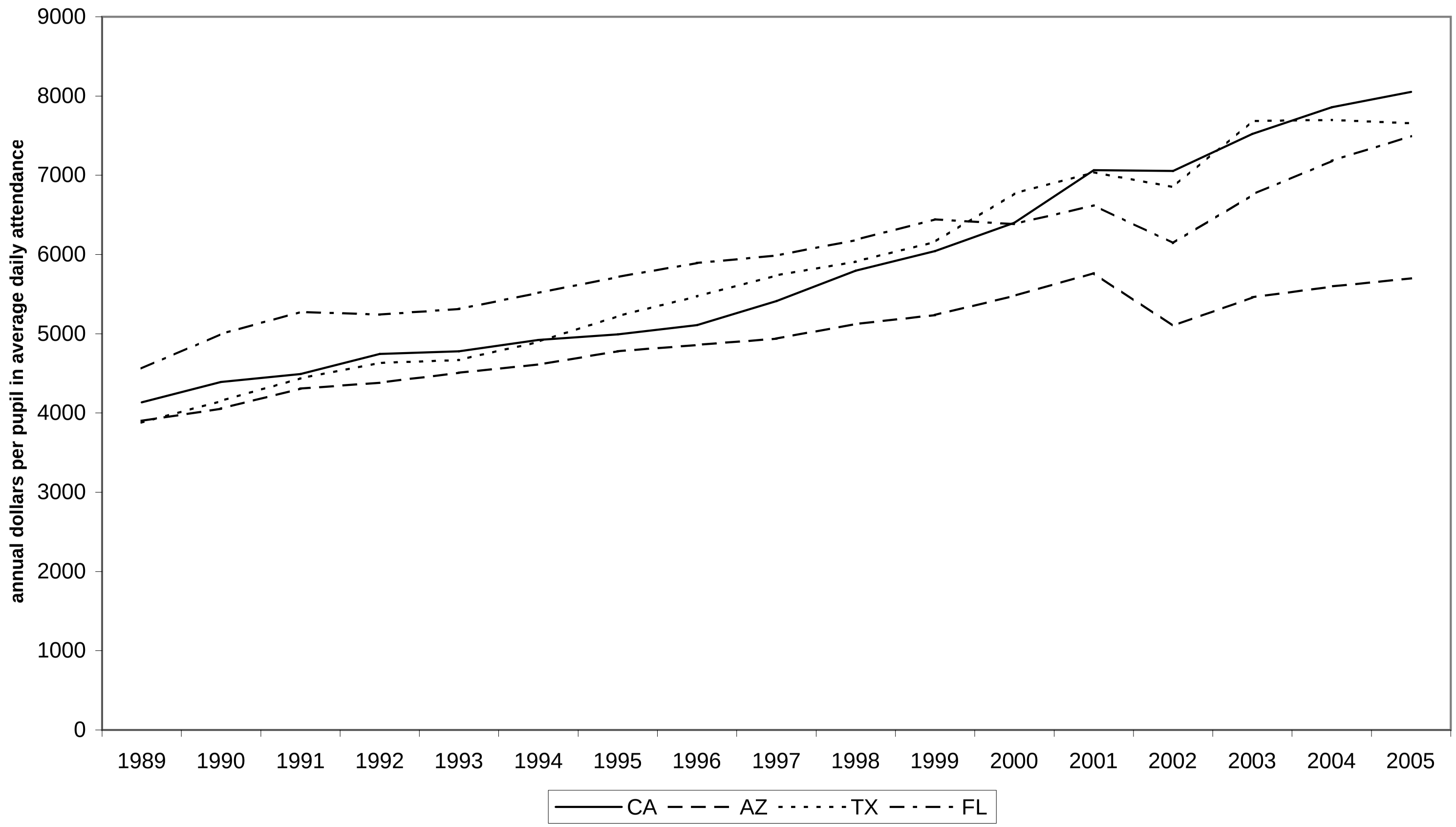
[17] Alaska and Hawaii have higher food stamp allotments. These states are not examined here.

Figure 6: Federal versus State Minimum Wages



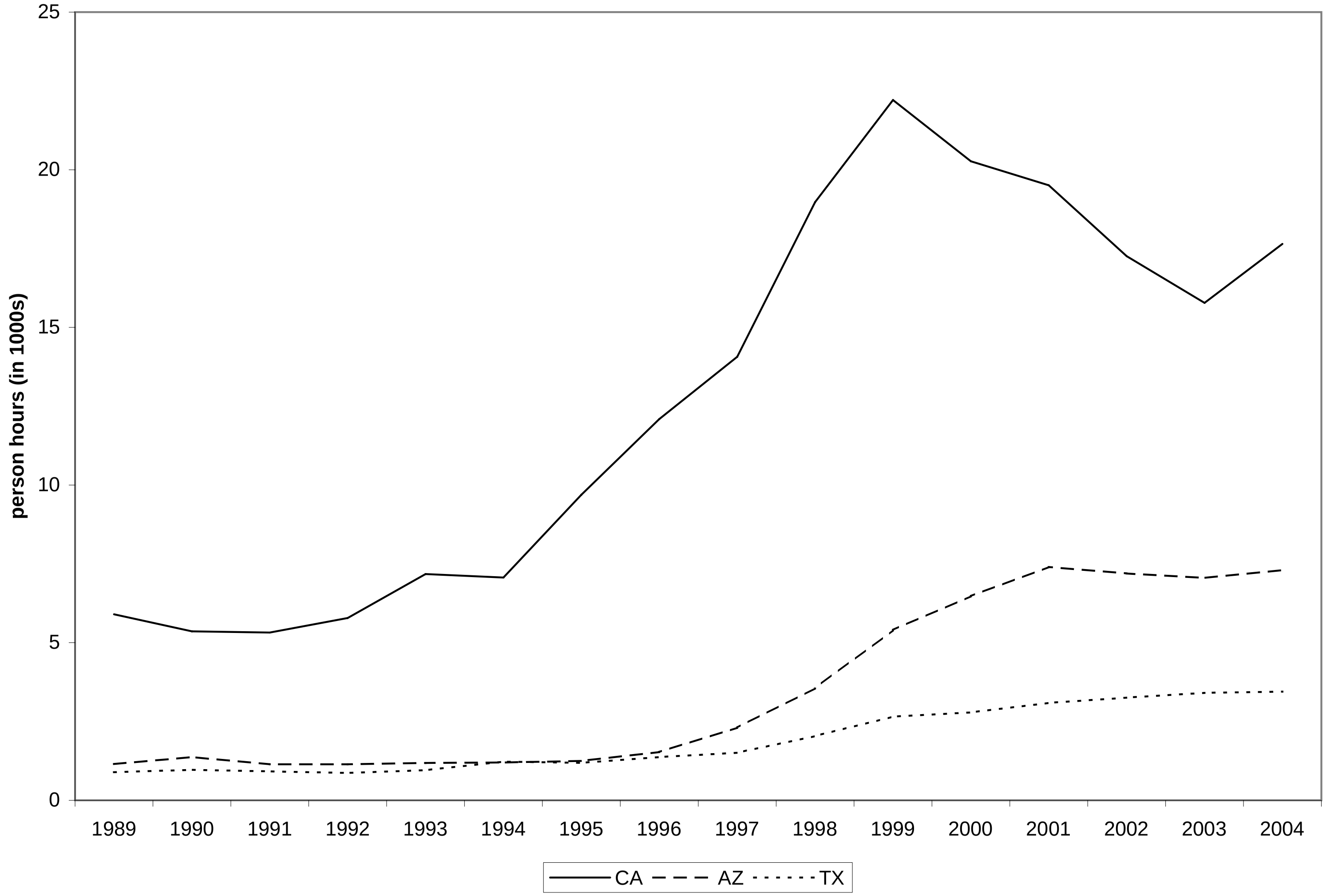
Source: U.S. Department of Labor

Figure 7: Current Expenditure in Public Elementary and Secondary Schools



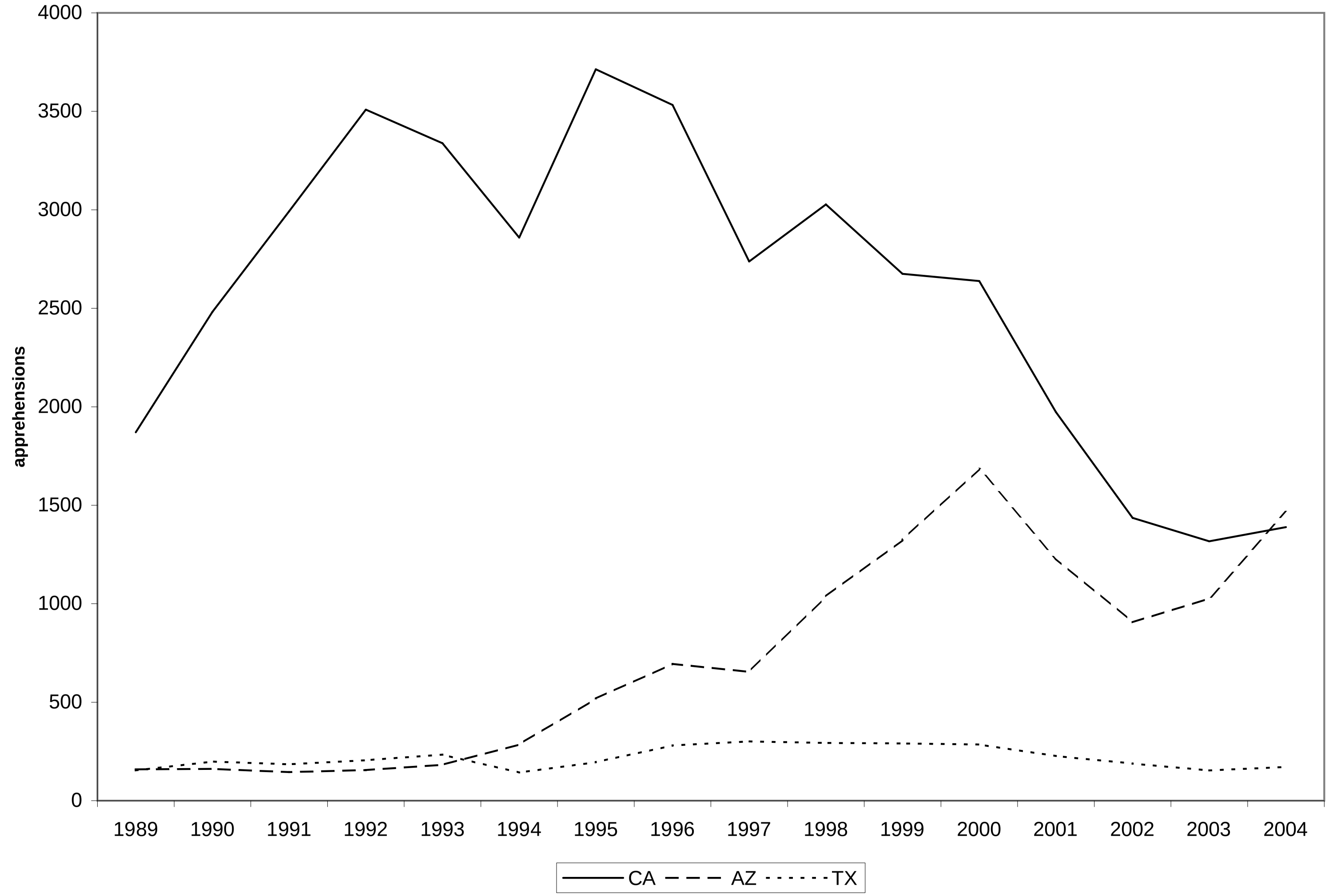
Sources: U.S. Department of Education, *Digest of Education Statistics* and National Education Association, *Rankings and Estimates*, selected years

Figure 8: Border Patrol Linewatch Hours per Mile



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

Figure 9: Border Patrol Apprehensions per Mile

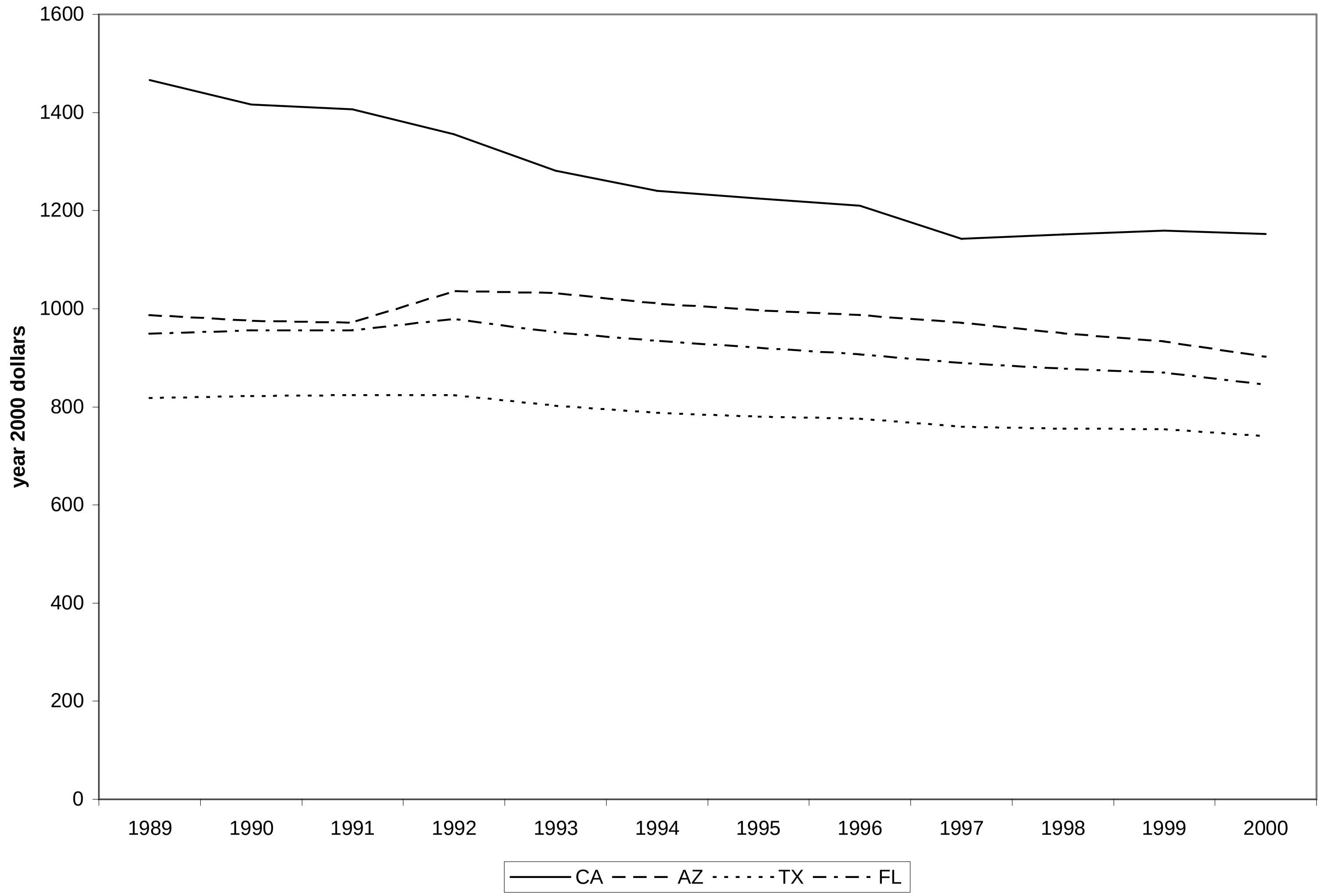


Source: INS/Homeland Security via Gordon Hanson and Christina Gathmann

Figure 10: (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 11: (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)

Figure 10 shows that offered benefit levels in Arizona, Florida, and Texas are low and have been relatively constant over the last two decades for a family size of four. While Arizona has traditionally offered benefits similar to the median U.S. state (not shown), Florida and Texas have had strictly lower benefits than the median state (Texas to the greatest extent). California has traditionally offered above the median state level of benefits suggesting that any welfare migration that does exist should be most evident in that state. The figure suggests that welfare is arguably exogenous given the small degree of change in payment levels over time in many of the presented series.

Another public service program dimension on which a state can diverge is that of public education. Like welfare, education may be considered in the expected benefits calculation of choosing one state over another. Figure 7 shows current expenditure per pupil based on average daily attendance in public elementary and secondary schools.[18] Current expenditure per pupil based on fall enrollment is similar (not shown). Although the series move together throughout the period, there are notable switch points. Texas increased current expenditure per student at an increasing rate over the period and surpassed Arizona in the late 1980s, and California in the early 1990s.

Unrefunded hospital visits are another state-borne cost of illegal migration. These are not explicitly modeled here. While migrants may plan to utilize welfare and education programs to supplement their expected net benefits from migration, it is unlikely that migrants predict the use of emergency room services, except potentially in the case of pregnancy, and the value of unrefunded emergency room care to a migrant across states is largely equivalent (even if costs to the state are not). Regressions adding Medicaid value per patient (not shown) found Medicaid to be an insignificant factor of locational choice.

A final state dimension examined is that of border enforcement intensity. Differences in state border patrol efforts measured via linewatch hours (person hours spent patrolling the border) and apprehensions are related to the probability of successful crossing the border. The Department of Homeland Security 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. Figures 8 and 9 respectively present linewatch hours per mile and apprehensions per mile for the states of California, Arizona, and Texas.[19] Notable in the figures is how California's border patrol intensity, especially that in the San Diego sector, increased greatly during the 1990s.

[18]Current expenditures for elementary/secondary education are "expenditures for operating local public schools, excluding capital outlay and interest on school debt. These expenditures include such items as salaries for school personnel, fixed charges, student transportation, schoolbooks and materials, and energy costs...expenditures for state administration are excluded." Average daily attendance is "The aggregate attendance of a school during a reporting period (normally a school year) divided by the number of days school is in session during this period" (Digest of Education Statistics).

[19]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. Note that the New Mexico portion of the border is implicitly included since the nine border sectors cover the entire U.S.-Mexico border.

5 Empirical Model

The empirical migration data are modeled in a discrete choice framework following Bartel (1989) and Jaeger (2000). Utility for person i migrating to alternative d comprises two components, a systematic observable utility term and a random error term:

$$U_i^d = V_i^d + \epsilon_i^d \tag{6}$$

As in the theoretical model, V_i^d is the expected net benefit to person i from making a migration to destination d.[20] Demographic characteristics of the sampled farmworkers and destination choice specific attributes are included in V_i^d. The probability that destination option d is chosen by person i (P_i^d) is an increasing function of V_i^d by assumption. Namely, $\frac{\partial P_i^d}{\partial V_i^d} > 0$ and

$$P_i^d = Pr(U_i^d > U_i^{d'}, \forall d' \in D, d \neq d') \tag{7}$$

where D denotes the choice set available to agent i. Thus, the migrant selects that location d in his or her individual choice set which offers the highest utility.[21]

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^d). 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 wages, 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. Independent variables can be written $z_i^d = [x_i^d, w_i]$ and

$$U_i^d = \alpha' x_i^d + \beta' w_i + \epsilon_i^d = \delta' z_i^d + \epsilon_i^d \tag{8}$$

where α and β (or δ) are parameters to be estimated and ϵ_i^d is the error term.

[20] Note that equation 2 reduces to $V_i^d = E(U_i^d) - E(C_i^d)$ in the presence of the NAWS data since those who choose the default option of remaining at the origin are not observed.

[21] A potential concern with using the state as the unit of geographic observation is that smaller geographic units may be better approximations to homogeneous labor markets. See discussion in Bartel (1989).

Note that the x_i^d's can vary across choices but are allowed to vary only at the individual level. The w_i's only vary by individual. Rewriting equation 7:

$$P_i^d = Pr(\delta' z_i^d + \epsilon_i^d > \delta' z_i^{d'} + \epsilon_i^{d'}, \forall d' \in D, d \neq d') \tag{9}$$

5.1 Conditional Logistic Regression

Conditional logistic regression allows effects of individual characteristics and state-level attributes to be estimated simultaneously.[22] 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.

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 $N \times D$ observations where N is the number of individuals in the sample and D 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 D observations corresponding to each individual, the dependent variable is an indicator for the realized location taking the form:

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

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

The model estimates via maximum likelihood:

$$\Pr(y_i^d = 1 | z_i^d) = F(\nu_i + \alpha' x_i^d + \beta' w_i) \tag{10}$$

where $F(\cdot)$ is the cumulative logistic distribution (i.e. $F(\cdot) = \frac{\exp(\cdot)}{1+\exp(\cdot)}$) and ϵ_i^d is distributed i.i.d. Weibull.[23] The probability of being employed in d is a function of individual and state characteristics:

$$\Pr(y_i^d = 1) = \frac{e^{\delta' z_i^d}}{\sum_{d=1}^{D} e^{\delta' z_i^d}} \quad where\ d = 1, 2, ..., D \tag{11}$$

[22] 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)).

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

The equation is the likelihood function for any individual i observed in location d. 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^d yields:

$$\Pr(y_i^d = 1) = \frac{e^{\alpha' x_i^d + \beta' w_i}}{\sum_{d=1}^{D} e^{\alpha' x_i^d + \beta' w_i}} = \frac{e^{\alpha' x_i^d}}{\sum_{d=1}^{D} e^{\alpha' x_i^d}} \tag{12}$$

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.

Given the data complexities surrounding empirical work on illegal immigration, it is useful to consider the structural econometric experiment before presenting reduced form results. In the presence of ideal data, parameters from the following structural econometric model for the probability of migration of person i to destination d would be estimated:

$$Pr(choice_i^d = 1) = \frac{e^{a_0 + a_1 E(U_i^d) + a_2 E(U_i^o) + a_3 E(C_i^d)}}{\sum_{d=1}^{D} e^{a_0 + a_1 E(U_i^d) + a_2 E(U_i^o) + a_3 E(C_i^d)}} = \frac{e^Q}{\sum_{d=1}^{D} e^Q} \tag{13}$$

where

$$\begin{aligned} E(U_i^d) = {} & b_0 + b_1 female_i + b_2 age_i + b_3 educ_i + b_4 US\_exper_i + b_5 illegal_i \\ & + b_6 worknetwork_i + b_7 unemploy\_rate_d + b_8 farm\_employ_d \\ & + b_9 percent\_Hispanic_d + b_{10} avg\_wage_d + b_{11} min\_wage_d \\ & + b_{12} welfare_d + b_{13} ed\_ben_d + b_{14} linewatch_d + b_{15} season_i \\ & + b_{16} year_i + b_{17} US\_state_i + b_{18} MX\_state_i + \epsilon_i^d \end{aligned} \tag{14}$$

$$\begin{aligned} E(U_i^o) = {} & c_0 + c_1 female_i + c_2 age_i + c_3 educ_i + c_4 season_i + c_5 year_i \\ & + c_6 MX\_state_i + \epsilon_i^o \end{aligned} \tag{15}$$

$$
\begin{aligned}
E(C_i^d) = d_0 &+ d_1 female_i + d_2 age_i + d_3 educ_i + d_4 US\_exper_i + d_5 illegal_i \\
&+ d_6 worknetwork_i + d_7 spouse_i + d_8 children_i + d_9 percent\_Hispanic_d \\
&+ d_{10} linewatch_d + d_{11} season_i + d_{12} year_i + d_{13} MX\_state_i + \epsilon_i^c
\end{aligned} \tag{16}
$$

and

$$
\begin{aligned}
Q = \sum_{d \neq CA}^{D} 1(d=1) * (f_0 &+ f_1 female_i + f_2 age_i + f_3 spouse_i + f_4 kids_i \\
&+ f_5 educ_i + f_6 US\_exper_i + f_7 illegal_i + f_8 worknetwork_i \\
&+ f_9 season_i + f_{10} year_i + f_{11} MX\_state_i) + f_{12} unemploy\_rate_d \\
&+ f_{13} farm\_employ_d + f_{14} percent\_Hispanic_d + f_{15} avg\_wage_d \\
&+ f_{16} min\_wage_d + f_{17} welfare_d + f_{18} ed\_value_d + f_{19} linewatch_d
\end{aligned} \tag{17}
$$

Equations 14 to 16 map expected utility into income and likewise for the cost equation. Given the NAWS data, the reduced form coefficients in equation 17 can be estimated, but the structural coefficients presented in equations 14 to 16 cannot. Reduced form coefficients are expressed as linear combinations of the structural coefficients.

5.2 Reduced Form versus Structural Coefficients

While suppressed here, each individual characteristic coefficient should be indexed by $d \neq CA$, as individual characteristics are estimated relative to the base category of California in the conditional logistic model. The individual characteristics can be expressed as follows:

Constant: $f_0 = a_0 + b_0 + c_0 + d_0$

Female: $f_1 = a_1 b_1 + a_2 c_1 + a_3 d_1$

Age: $f_2 = a_1 b_2 + a_2 c_2 + a_3 d_2$

Spouse: $f_3 = a_3 d_7$

Children: $f_4 = a_3 d_8$

Education: $f_5 = a_1 b_3 + a_2 c_3 + a_3 d_3$

U.S. farmwork experience: $f_6 = a_1 b_4 + a_3 d_4$

Illegal: $f_7 = a_1 b_5 + a_3 d_5$

Work network: $f_8 = a_1 b_6 + a_3 d_6$

Season: $f_9 = a_1 b_{15} + a_2 c_4 + a_3 d_{11}$

Time trend: $f_{10} = a_1 b_{16} + a_2 c_5 + a_3 d_{12}$

Mexican state of origin: $f_{11} = a_1 b_{18} + a_2 c_6 + a_3 d_{13}$

The state attributes can be expressed:

Rural unemployment rate: $f_{12} = a_1 b_7$

Farm employment: $f_{13} = a_1 b_8$

State population Hispanic share: $f_{14} = a_1 b_9 + a_3 d_9$

State average wage: $f_{15} = a_1 b_{10}$

State minimum wage: $f_{16} = a_1 b_{11}$

Maximum welfare value: $f_{17} = a_1 b_{12}$

Maximum education value: $f_{18} = a_1 b_{13}$

Linewatch hours per mile: $f_{19} = a_1 b_{14} + a_3 d_{10}$

The error structure is expressed:

$\eta_i^d = a_1 \epsilon_i^d + a_2 \epsilon_i^o + a_3 \epsilon_i^c + \epsilon_i$

5.2.1 Signing the Structural Parameters

Although the structural parameters cannot be identified, many can be signed. From the theoretical model, $a_1 > 0$, $a_2 < 0$, and $a_3 < 0$. The b coefficients refer to effects on expected utility at a given destination, the c coefficients refer to effects on expected utility at a given origin, and the d coefficients refer to effects on expected costs.

6 Reduced Form Results

Table 5 presents both reduced-form coefficients and odds ratios (exponentiated coefficients), and their respective standard errors, from the regression for the determinants of state choice over the destination set of California, Texas, Florida, and Arizona.[24] Odds ratios are defined:

$$\frac{Pr(y_i^d = 1|z_i^d)}{Pr(y_i^d = 0|z_i^d)} = e^{\nu_i + \alpha' x_i^d + \beta' w_i} \tag{18}$$

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 a zero effect.

[24] Odds ratios are reported instead of marginal effects for computational reasons.

Table 5: Conditional Logit Model – Mexican Farmworkers (CA, AZ, TX, FL)

Reference Category: California	Texas		Florida		Arizona	
	coef	odds	coef	odds	coef	odds
female	-0.525***	0.591***	0.368***	1.444***	-0.508***	0.602***
	(0.114)	(0.067)	(0.078)	(0.113)	(0.182)	(0.109)
age	0.012***	1.012***	-0.010*	0.991*	0.034***	1.035***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
spouse	0.158	1.171	0.034	1.035	0.126	1.134
	(0.165)	(0.194)	(0.081)	(0.084)	(0.079)	(0.089)
children (#)	-0.059*	0.942*	-0.047**	0.954**	-0.062***	0.940***
	(0.031)	(0.029)	(0.019)	(0.019)	(0.017)	(0.016)
education (yrs)	-0.072***	0.930***	-0.055***	0.946***	0.030***	1.030***
	(0.019)	(0.017)	(0.008)	(0.008)	(0.008)	(0.008)
U.S. farmwork experience (yrs)	-0.036***	0.964***	-0.024***	0.976***	-0.021***	0.979***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
illegal	-0.511***	0.600***	0.191**	1.211**	0.192**	1.212**
	(0.013)	(0.008)	(0.097)	(0.117)	(0.079)	(0.096)
used work network	-0.128**	0.880**	-1.416***	0.243***	-0.535***	0.586***
	(0.050)	(0.044)	(0.098)	(0.024)	(0.089)	(0.052)
summer	0.147	1.159	-0.821***	0.440***	-0.514***	0.598***
	(0.147)	(0.170)	(0.075)	(0.033)	(0.043)	(0.026)
fall	-0.110	0.896	-0.746***	0.474***	-0.174**	0.840**
	(0.114)	(0.102)	(0.096)	(0.045)	(0.073)	(0.061)
time trend	-0.066	0.936	-0.063	0.939	-0.091**	0.913**
	(0.061)	(0.057)	(0.078)	(0.073)	(0.045)	(0.041)
constant	-0.754		8.072**		0.351	
	(1.332)		(3.820)		(1.897)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.165***	1.180***		
			(0.041)	(0.048)		
farm employment (10,000s)			0.019	1.019		
			(0.037)	(0.038)		
state population percent Hispanic			0.473**	1.605**		
			(0.206)	(0.331)		
mean hired farmworker wage			-0.313	0.731		
			(0.284)	(0.207)		
minimum wage			0.265	1.303		
			(0.406)	(0.529)		
monthly welfare value (100s USD)			0.003	1.003		
			(0.020)	(0.020)		
annual education value (1,000s USD)			-0.040	0.961		
			(0.025)	(0.024)		
linewatch hours per mile (1,000s)			-0.075***	0.928***		
			(0.022)	(0.020)		
Observations			64808			

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

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

6.1 Individual Characteristics

With the exception of the marital status variable, all individual level variables presented in the table are significant for at least one alternative state over the base state of California. Most individual characteristics are highly significant at the one percent level.

Illegal migrants are generally less likely to choose Texas and more likely to choose Florida or Arizona than California. This can be seen by observing the negative coefficient on *illegal* in the Texas column of the results. Likewise, the coefficients on *illegal* are positive for Florida and for Arizona relative to the base case of California. The odds of an illegal worker choosing Texas over California are 0.6 times the odds of a legal worker choosing Texas over California. The odds of an illegal worker choosing Florida over California are 1.2 times the odds of a legal worker doing so. Similarly, the odds of an illegal worker choosing Arizona over California are 1.2 times the odds of a legal worker making that decision.

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 more likely to choose Texas or Arizona and less likely to choose Florida. The presence of children in the U.S. is of little consequence to locational choice. Mexican immigrants with more children are less likely to choose any of the alternative states over California than are those with fewer children. More highly educated immigrants 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 of these alternative states over California. Summer and fall workers are less likely to choose Florida or Arizona than springtime workers are. The time trend indicates that Mexican migrants are less likely to choose any of the alternative states over California over the period of study, but this relationship is only statistically significant at conventional levels for the Arizona case.

The work network variable deserves special consideration. The results 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. Texas workers are more than 12 percent less likely to use a work network than are those going to California. Florida workers are 86 percent less likely and Arizona workers are 41 percent less likely to use a work network than are California workers. These results are highly statistically significant indicating, as argued by Zavodny (1999), that personal networks are an important determinant of locational choice.

6.2 State Attributes

Effects of various state attributes are estimated holding individual characteristics constant. State fixed effects account for unobserved attributes affecting locational choice.

A strong positive effect is found for state population Hispanic share. The odds ratio for state population Hispanic share indicates that migrants are 60.5 percent 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 more than seven 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.[25] Gathmann (2004) 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 (2004) finds that enforcement has shifted illegal migrant flows to 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.[26]

While the identified social network and border patrol effects may be expected, the unemployment rate effect seems counterintuitive. Namely, this study finds a strong, positive, rural unemployment rate effect. All else equal, migrants are 18.0 percent more likely to choose a state with a one percent higher unemployment rate. 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 significantly 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. Another possibility is that because of the presence of personal work networks in agriculture, workers are willing to choose high unemployment areas if those areas are the same locations in which workers have connections. Another is that rural unemployment rates may vary significantly by season and the annual rates matched to workers in this paper are inappropriate.

[25] 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.

[26] Adding instrumental variables to conditional logistic regression warrants further econometric research.

Other state attribute variables (farm employment, mean wages, minimum wages, and welfare and education values) do not have significant predictive power for the Mexican immigrant sample in the NAWS. The effects of welfare benefit levels and education expenditure on locational choice, for example, are not significantly different from zero in Table 5. 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.[27] This provides further evidence for a lack of welfare migration by agricultural workers to these areas.

6.3 Robustness: Independence of Irrelevant Alternatives

Conditional logistic regression imposes an Independence of Irrelevant Alternatives (IIA) assumption. Because this may not be desirable, destination set variations are considered.

6.3.1 Excluding Texas

One consideration is that the nature of agriculture in Texas may be different than that for the rest of the sample. Texas ranks first in the nation in terms of livestock and poultry value but has a lesser rank for sales in crop agriculture despite its large land area.[28] Only 2.8 percent of illegal immigrant agricultural workers in the NAWS are surveyed in the Texas region. Almost 10 percent of native agricultural workers, seven percent of those in each of the legal immigrant groups are in the region. The regression presented in Table 6 parallels that of Table 5 with the exception that Texas observations are dropped.

The results in Table 6 are qualitatively similar to the overall results in Table 5. The rural unemployment rate and share of the state's population that is Hispanic are strong predictors of locational choice in the positive direction. Linewatch hours per mile is a strong predictor in the negative direction. Results regarding the importance of other state attributes, however, are different. When the Texas observations are dropped, state-level agricultural employment levels, minimum wage rates, and monthly welfare values are additional positive predictors of locational choice. Results for individual characteristics are similar to the full sample with the exception of the time trend variables which switch signs.

6.3.2 Excluding Florida

Table 7 presents the parallel exercise for the case of Florida. Although Florida is a key U.S. agricultural state and destination among illegal immigrants, there are several reasons why Florida is different. Most obviously,

[27]The implicit assumption here is that education expenditure and quality are positively correlated (or at least expected to be positively correlated by migrants).

[28]Appendix B presents state-level agricultural market characteristics in more detail.

Table 6: Conditional Logit Model – Robustness, excluding TX

Reference Category: California				
	Arizona		**Florida**	
	coef	odds	coef	odds
female	-0.394**	0.674**	0.519***	1.680***
	(0.161)	(0.109)	(0.077)	(0.130)
age	0.039***	1.039***	-0.011	0.989
	(0.005)	(0.006)	(0.007)	(0.007)
spouse	0.236***	1.266***	0.073	1.075
	(0.003)	(0.003)	(0.073)	(0.079)
children (#)	-0.056*	0.946*	0.008	1.008
	(0.032)	(0.030)	(0.025)	(0.025)
education (yrs)	0.035***	1.035***	-0.064***	0.938***
	(0.009)	(0.009)	(0.005)	(0.005)
U.S. farmwork experience (yrs)	-0.023***	0.978***	-0.027***	0.973***
	(0.002)	(0.002)	(0.006)	(0.006)
illegal	0.182*	1.199*	0.240*	1.271*
	(0.093)	(0.112)	(0.143)	(0.182)
used work network	-0.576***	0.562***	-1.482***	0.227***
	(0.123)	(0.069)	(0.151)	(0.034)
summer	-0.493***	0.611***	-0.881***	0.414***
	(0.029)	(0.018)	(0.071)	(0.030)
fall	-0.174***	0.840***	-0.762***	0.467***
	(0.061)	(0.051)	(0.071)	(0.033)
time trend	0.197*	1.217*	0.384**	1.468**
	(0.105)	(0.128)	(0.162)	(0.237)
constant	11.390***		25.488***	
	(1.327)		(5.561)	
			State	**Attrib.**
			coef	odds
rural unemployment rate			0.409***	1.506***
			(0.091)	(0.138)
farm employment (10,000s)			0.278***	1.320***
			(0.047)	(0.062)
state population percent Hispanic			1.571***	4.809***
			(0.405)	(1.948)
mean hired farmworker wage			0.215	1.240
			(0.794)	(0.985)
minimum wage			2.002**	7.406**
			(1.021)	(7.560)
monthly welfare value (100s USD)			0.035**	1.035**
			(0.017)	(0.018)
annual education value (1,000s USD)			-0.061	0.941
			(0.057)	(0.054)
linewatch hours per mile (1,000s)			-0.149***	0.861***
			(0.032)	(0.028)
Observations			59672	
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$				

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

Table 7: Conditional Logit Model – Robustness, excluding FL

Reference Category: California				
	Texas		**Arizona**	
	coef	odds	coef	odds
female	-0.672***	0.511***	-0.559***	0.572***
	(0.168)	(0.086)	(0.205)	(0.117)
age	0.016***	1.017***	0.035***	1.036***
	(0.006)	(0.006)	(0.005)	(0.005)
spouse	-0.042	0.959	0.065	1.067
	(0.153)	(0.147)	(0.146)	(0.156)
children (#)	-0.064	0.938	-0.076***	0.927***
	(0.060)	(0.056)	(0.017)	(0.016)
education (yrs)	-0.063**	0.939**	0.030***	1.030***
	(0.025)	(0.023)	(0.009)	(0.009)
U.S. farmwork experience (yrs)	-0.042***	0.959***	-0.022***	0.978***
	(0.006)	(0.005)	(0.004)	(0.004)
illegal	-0.502***	0.605***	0.267***	1.307***
	(0.029)	(0.017)	(0.016)	(0.021)
used work network	-0.145*	0.865*	-1.433***	0.239***
	(0.075)	(0.065)	(0.112)	(0.027)
summer	0.318***	1.374***	-0.516***	0.597***
	(0.028)	(0.039)	(0.047)	(0.028)
fall	-0.037	0.964	-0.147**	0.863**
	(0.139)	(0.134)	(0.068)	(0.059)
time trend	-0.099*	0.906*	-0.099*	0.906*
	(0.058)	(0.053)	(0.053)	(0.048)
constant	-0.446		1.418	
	(1.260)		(2.123)	
			State	**Attrib.**
			coef	odds
rural unemployment rate			0.152***	1.164***
			(0.049)	(0.057)
farm employment (10,000s)			0.024	1.025
			(0.042)	(0.043)
state population percent Hispanic			0.600***	1.822***
			(0.085)	(0.155)
mean hired farmworker wage			-0.046	0.955
			(0.768)	(0.734)
minimum wage			0.245	1.278
			(0.527)	(0.673)
monthly welfare value (100s USD)			-0.035	0.966
			(0.065)	(0.063)
annual education value (1,000s USD)			-0.045	0.956
			(0.056)	(0.054)
linewatch hours per mile (1,000s)			-0.094***	0.911***
			(0.031)	(0.028)
Observations			54952	
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$				

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

Table 8: Conditional Logit Model – Robustness, excluding AZ

Reference Category: California	Texas		Florida	
	coef	odds	coef	odds
female	-0.546***	0.579***	0.346***	1.414***
	(0.129)	(0.075)	(0.087)	(0.123)
age	0.010**	1.010**	-0.010*	0.990*
	(0.004)	(0.004)	(0.005)	(0.005)
spouse	0.127	1.136	0.011	1.011
	(0.186)	(0.212)	(0.094)	(0.095)
children (#)	-0.062**	0.940**	-0.057***	0.945***
	(0.029)	(0.028)	(0.020)	(0.019)
education (yrs)	-0.084***	0.919***	-0.059***	0.943***
	(0.014)	(0.013)	(0.006)	(0.005)
U.S. farmwork experience (yrs)	-0.039***	0.962***	-0.025***	0.975***
	(0.006)	(0.005)	(0.005)	(0.004)
illegal	-0.517***	0.596***	0.187	1.205
	(0.008)	(0.005)	(0.129)	(0.156)
used work network	-0.174***	0.840***	-0.529***	0.589***
	(0.047)	(0.040)	(0.097)	(0.057)
summer	0.102	1.107	-0.838***	0.432***
	(0.154)	(0.171)	(0.078)	(0.034)
fall	-0.234***	0.791***	-0.798***	0.450***
	(0.066)	(0.052)	(0.064)	(0.029)
time trend	-0.007	0.993	0.094***	1.099***
	(0.038)	(0.038)	(0.033)	(0.036)
constant	-1.010		18.978***	
	(1.834)		(2.807)	
			State	**Attrib.**
			coef	odds
rural unemployment rate			0.024	1.025
			(0.132)	(0.136)
farm employment (10,000s)			0.054	1.056
			(0.034)	(0.036)
state population percent Hispanic			1.280***	3.598***
			(0.263)	(0.948)
mean hired farmworker wage			-0.839***	0.432***
			(0.081)	(0.035)
minimum wage			0.897***	2.453***
			(0.225)	(0.551)
monthly welfare value (100s USD)			0.000	1.000
			(0.024)	(0.024)
annual education value (1,000s USD)			-0.002	0.998
			(0.016)	(0.016)
linewatch hours per mile (1,000s)			-0.124***	0.883***
			(0.023)	(0.020)
Observations			60104	

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

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

Florida does not share a formal land border with Mexico. Florida is removed from the destination set in Table 7.

For the Florida exclusion as with the Texas exclusion, state attribute results are qualitatively similar to the full sample results. A positive rural unemployment rate effect is found, as well as a positive state population Hispanic share effect and a negative linewatch hours effect. The magnitudes of these effects are similar to those using the full sample, with Hispanic share being an even stronger indicator of where migrants choose to locate. Individual level characteristics are similar to those in the full sample case of Table 5. The magnitude of the effect of legal status on choosing Arizona increases when Florida workers are dropped and the work network effect supporting California over Arizona increases.

6.3.3 Excluding Arizona

Arizonian workers are excluded in Table 8. Arizona may be systematically different than the other states in the sample given its lower agricultural production and workforce. The magnitude of the California work network effect over Florida decreases in this specification. Being illegal loses significance as being a positive predictor of choosing Florida over California. The coefficient, however, remains positive.

State attribute characteristics are more sensitive to the exclusion of Florida than to the exclusion of Arizona. While the coefficient on rural unemployment rate remains positive, this variable is no longer significant. State population Hispanic share remains a positive indicator of locational choice and linewatch hours per mile remains a negative predictor of state choice. Both effects are stronger when Arizona is excluded. Additionally, the minimum wage becomes a positive statistically significant indicator of destination choice. Mean hired farmworker wage is significant in a negative direction. Like rural unemployment rates, these variables are included at a one-year lag and represent general equilibrium outcomes which cannot be signed with certainty in the theoretical model.

6.4 Extension: Illegal versus Legal Mexican Farmworkers

Tables 9 and 10 restrict to illegal and legal migrants respectively using the original four state sample. Many of the individual characteristics which are highly significant in the full sample regression are not significant for the illegal only sample. Gender, age, experience, and number of children relationships between Texas and the base of California are not significant for the illegal migrant case. The same is true for the relationships between age and children and the choice of Florida. Married illegal migrants have a propensity to choose Arizona over California and illegal workers with more U.S. farmwork experience choose Florida. The time trend of fewer migrants choosing Arizona is not significant for the illegal sample. This

Table 9: Conditional Logit Model – Illegal Mexican Farmworkers

Reference Category: California	Texas		Florida		Arizona	
	coef	odds	coef	odds	coef	odds
female	0.079	1.082	0.410***	1.506***	-0.442*	0.643*
	(0.184)	(0.199)	(0.118)	(0.177)	(0.228)	(0.147)
age	0.003	1.003	-0.013	0.987	0.045***	1.046***
	(0.014)	(0.014)	(0.010)	(0.010)	(0.007)	(0.008)
spouse	0.071	1.074	-0.009	0.991	0.654***	1.923***
	(0.079)	(0.085)	(0.051)	(0.050)	(0.109)	(0.210)
children (#)	-0.080	0.923	-0.029	0.972	-0.287***	0.750***
	(0.074)	(0.068)	(0.020)	(0.020)	(0.009)	(0.006)
education (yrs)	-0.086**	0.918**	-0.033**	0.967**	0.058***	1.060***
	(0.034)	(0.031)	(0.014)	(0.014)	(0.018)	(0.019)
U.S. farmwork experience (yrs)	0.014	1.015	0.026***	1.026***	-0.023**	0.977**
	(0.013)	(0.013)	(0.003)	(0.003)	(0.009)	(0.009)
used work network	-0.637**	0.529**	-1.815***	0.163***	-0.674***	0.510***
	(0.253)	(0.134)	(0.316)	(0.051)	(0.097)	(0.049)
summer	-0.276	0.759	-0.987***	0.373***	-0.817***	0.442***
	(0.224)	(0.170)	(0.157)	(0.059)	(0.115)	(0.051)
fall	-0.738***	0.478***	-0.809***	0.445***	-0.826***	0.438***
	(0.161)	(0.077)	(0.136)	(0.060)	(0.141)	(0.062)
time trend	0.019	1.019	0.099	1.104	0.029	1.030
	(0.114)	(0.117)	(0.141)	(0.155)	(0.076)	(0.078)
constant	0.540		11.837*		1.996	
	(0.414)		(6.897)		(3.368)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.342***	1.408***		
			(0.059)	(0.083)		
farm employment (10,000s)			0.120**	1.127**		
			(0.059)	(0.067)		
state population percent Hispanic			0.618	1.855		
			(0.427)	(0.793)		
mean hired farmworker wage			-0.475***	0.622***		
			(0.112)	(0.070)		
minimum wage			1.045	2.843		
			(0.692)	(1.968)		
monthly welfare value (100s USD)			0.038**	1.039**		
			(0.015)	(0.016)		
annual education value (1,000s USD)			-0.004	0.996		
			(0.058)	(0.058)		
linewatch hours per mile (1,000s)			-0.066	0.936		
			(0.046)	(0.043)		
Observations			32244			

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

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

Table 10: Conditional Logit Model – Legal Mexican Farmworkers

Reference Category: California

	Texas		**Florida**		**Arizona**	
	coef	odds	coef	odds	coef	odds
female	-0.900***	0.407***	0.283***	1.327***	-0.552***	0.576***
	(0.111)	(0.045)	(0.070)	(0.093)	(0.191)	(0.110)
age	0.017***	1.017***	-0.009***	0.991***	0.031***	1.031***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
spouse	0.248	1.282	0.005	1.005	-0.136	0.873
	(0.228)	(0.293)	(0.100)	(0.100)	(0.116)	(0.102)
children (#)	-0.057**	0.945**	-0.078**	0.925**	0.033	1.033
	(0.027)	(0.025)	(0.031)	(0.029)	(0.026)	(0.027)
education (yrs)	-0.082***	0.921***	-0.096***	0.908***	0.014***	1.014***
	(0.015)	(0.014)	(0.009)	(0.008)	(0.005)	(0.005)
U.S. farmwork experience (yrs)	-0.065***	0.937***	-0.062***	0.940***	-0.019***	0.981***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.001)	(0.001)
used work network	0.216***	1.241***	-1.033***	0.356***	-0.347***	0.707***
	(0.083)	(0.103)	(0.015)	(0.005)	(0.110)	(0.078)
summer	0.413***	1.512***	-0.567***	0.567***	-0.271***	0.762***
	(0.088)	(0.134)	(0.034)	(0.019)	(0.049)	(0.038)
fall	0.268**	1.307**	-0.753***	0.471***	0.239**	1.269**
	(0.118)	(0.154)	(0.126)	(0.059)	(0.120)	(0.152)
time trend	-0.159***	0.853***	-0.178***	0.837***	-0.168***	0.845***
	(0.053)	(0.045)	(0.063)	(0.053)	(0.037)	(0.031)
constant	-2.356		7.164***		-0.625	
	(2.129)		(2.737)		(1.493)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.041	1.042		
			(0.063)	(0.065)		
farm employment (10,000s)			-0.062*	0.940*		
			(0.033)	(0.031)		
state population percent Hispanic			0.547***	1.729***		
			(0.091)	(0.158)		
mean hired farmworker wage			-0.162	0.851		
			(0.381)	(0.324)		
minimum wage			-0.413	0.662		
			(0.631)	(0.418)		
monthly welfare value (100s USD)			-0.002	0.998		
			(0.024)	(0.023)		
annual education value (1,000s USD)			-0.006	0.994		
			(0.017)	(0.017)		
linewatch hours per mile (1,000s)			-0.111***	0.895***		
			(0.020)	(0.018)		
Observations			32564			

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

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

Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

is consistent with Arizona becoming a "high-growth" region for illegal immigrants in recent years. Johnson (2006) writes: "Arizona has become the primary crossing location into the U.S. This shift may have affected final destinations as well. In fact, Arizona now has a higher percentage than California of illegal immigrants per capita: One of every 11 Arizona residents is an illegal immigrant; in California it is one of every 15." The results of this regression are consistent with this story.

Some of the state attribute results for the illegal migrant sample in Table 9 are unexpected. While the coefficients on state population Hispanic share and on linewatch hours per mile are in the expected directions, neither is statistically significant at conventional levels. In addition, there is a suggestion of welfare migration from the significant coefficient on maximum monthly welfare value. All else equal, illegal migrants are 3.9 percent more likely to go to a state offering an additional $100 per month in welfare benefits for his or her family size. The positive rural unemployment rate effect is significant and the level of this effect is magnified for the illegal subsample. Farm employment is also a significant predictor for this subpopulation.

Comparing the results for the legal migrant subsample presented in Table 10, state population Hispanic share is highly significant and border patrol is negatively so. This is unexpected given that these workers are authorized to be and work within the U.S. Farm employment is significant in the legal sample regression in the negative direction. Legal workers are more likely to choose to work in lower agricultural employment states.

The individual characteristic results in Table 10 are similar to those with the full sample. A notable difference is that the work network indicator is positively significant for Texas over California for legal workers. In addition, legal workers are more likely to choose Texas over California in the summer or fall. All time trend variables are significant for the legal sample indicating that legal workers have been more likely to choose California over each alternative destination over time.

6.5 Extension: New versus Experienced Mexican Farmworkers

A second extension is the separate characterization of new and experienced migrants. Migrants may change destinations as their U.S. experience elapses. New migrants are defined as those with zero or one year of U.S. farmwork experience when surveyed. Experienced migrants are those with two or more years of experience.

Results for new and experienced migrant samples are presented in Tables 11 and 12 respectively. Many of the significant individual characteristics in the full sample regression are not significant for new migrants alone. Specifically, the strong patterns by gender, age, and education do not appear. Instead, family structure characteristics appear to be of greater importance. The presence of a spouse increases the probability of choosing Texas or Arizona over California, and the presence of more children decreases the probability of

Table 11: Conditional Logit Model – New Farmworkers from Mexico

Reference Category: California	Texas		Florida		Arizona	
	coef	odds	coef	odds	coef	odds
female	-0.396**	0.673**	0.120	1.127	-0.001	0.999
	(0.169)	(0.114)	(0.219)	(0.246)	(0.292)	(0.292)
age	0.011	1.011	-0.012	0.988	0.023	1.024
	(0.020)	(0.020)	(0.016)	(0.016)	(0.017)	(0.018)
spouse	0.548*	1.731*	-0.186	0.830	0.559***	1.749***
	(0.303)	(0.525)	(0.156)	(0.130)	(0.133)	(0.232)
children (#)	-0.617***	0.540***	0.025	1.025	-0.201	0.818
	(0.124)	(0.067)	(0.090)	(0.092)	(0.129)	(0.106)
education (yrs)	0.017	1.018	-0.027	0.973	0.127**	1.135**
	(0.022)	(0.022)	(0.023)	(0.023)	(0.053)	(0.060)
U.S. farmwork experience (yrs)	0.356**	1.428**	0.481***	1.618***	-0.831***	0.436***
	(0.145)	(0.207)	(0.181)	(0.293)	(0.039)	(0.017)
illegal	-2.035***	0.131***	0.373**	1.452**	-0.197	0.821
	(0.302)	(0.039)	(0.166)	(0.241)	(0.445)	(0.365)
used work network	-1.354***	0.258***	-2.407***	0.090***	-0.945***	0.389***
	(0.338)	(0.087)	(0.478)	(0.043)	(0.116)	(0.045)
summer	-0.290	0.748	-1.076***	0.341***	-1.134***	0.322***
	(0.234)	(0.175)	(0.201)	(0.069)	(0.273)	(0.088)
fall	-0.818***	0.441***	-0.799***	0.450***	-0.890***	0.411***
	(0.134)	(0.059)	(0.156)	(0.070)	(0.174)	(0.072)
time trend	0.366**	1.442**	0.253	1.288	0.113	1.120
	(0.166)	(0.239)	(0.229)	(0.295)	(0.126)	(0.141)
constant	-0.454		12.577		4.317	
	(0.666)		(10.254)		(5.628)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.279**	1.321**		
			(0.129)	(0.170)		
farm employment (10,000s)			0.151	1.163		
			(0.105)	(0.122)		
state population percent Hispanic			0.808	2.243		
			(0.661)	(1.483)		
mean hired farmworker wage			-1.021***	0.360***		
			(0.243)	(0.087)		
minimum wage			1.943*	6.982*		
			(1.009)	(7.044)		
monthly welfare value (100s USD)			-0.063*	0.939*		
			(0.036)	(0.034)		
annual education value (1,000s USD)			-0.302	0.740		
			(0.259)	(0.192)		
linewatch hours per mile (1,000s)			-0.096	0.908		
			(0.076)	(0.069)		
Observations			11532			

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

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

Table 12: Conditional Logit Model – Return Farmworkers from Mexico

Reference Category: California	**Texas**		**Florida**		**Arizona**	
	coef	odds	coef	odds	coef	odds
female	-0.659***	0.517***	0.409***	1.505***	-0.621***	0.538***
	(0.126)	(0.065)	(0.094)	(0.142)	(0.177)	(0.095)
age	0.020***	1.020***	-0.008**	0.992**	0.035***	1.035***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)
spouse	0.267**	1.306**	0.016	1.016	0.114	1.121
	(0.118)	(0.154)	(0.086)	(0.087)	(0.088)	(0.098)
children (#)	0.001	1.001	-0.058**	0.944**	-0.016	0.984
	(0.029)	(0.029)	(0.028)	(0.026)	(0.025)	(0.025)
education (yrs)	-0.084***	0.919***	-0.069***	0.934***	0.019***	1.019***
	(0.015)	(0.014)	(0.007)	(0.007)	(0.003)	(0.003)
U.S. farmwork experience (yrs)	-0.041***	0.960***	-0.041***	0.960***	-0.016***	0.984***
	(0.009)	(0.009)	(0.002)	(0.002)	(0.003)	(0.003)
illegal	-0.235***	0.790***	0.249***	1.283***	0.202**	1.224**
	(0.050)	(0.040)	(0.058)	(0.074)	(0.083)	(0.102)
used work network	0.096**	1.101**	-1.207***	0.299***	-0.390***	0.677***
	(0.047)	(0.052)	(0.045)	(0.014)	(0.077)	(0.052)
summer	0.301**	1.351**	-0.708***	0.493***	-0.433***	0.649***
	(0.149)	(0.202)	(0.036)	(0.018)	(0.050)	(0.032)
fall	0.096	1.101	-0.777***	0.460***	-0.054	0.947
	(0.149)	(0.165)	(0.101)	(0.047)	(0.090)	(0.085)
time trend	-0.149***	0.862***	-0.112	0.894	-0.132***	0.876***
	(0.052)	(0.045)	(0.076)	(0.068)	(0.051)	(0.044)
constant	-1.300		7.391**		-0.268	
	(1.382)		(2.934)		(1.090)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.132***	1.141***		
			(0.035)	(0.040)		
farm employment (10,000s)			-0.003	0.997		
			(0.022)	(0.022)		
state population percent Hispanic			0.422***	1.525***		
			(0.158)	(0.242)		
mean hired farmworker wage			-0.194	0.824		
			(0.405)	(0.333)		
minimum wage			-0.067	0.935		
			(0.425)	(0.397)		
monthly welfare value (100s USD)			0.019	1.019		
			(0.026)	(0.027)		
annual education value (1,000s USD)			0.006	1.006		
			(0.035)	(0.036)		
linewatch hours per mile (1,000s)			-0.079***	0.924***		
			(0.013)	(0.012)		
Observations			53276			

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

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Mexican state of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

Table 13: Conditional Logit Model – Illegal Returning versus Legal Returning

Reference Category: California				
	Illegal		**Legal**	
	coef	odds	coef	odds
rural unemployment rate	0.377***	1.458***	0.016	1.016
	(0.038)	(0.056)	(0.046)	(0.047)
farm employment (10,000s)	0.140***	1.151***	-0.083**	0.920**
	(0.028)	(0.032)	(0.034)	(0.031)
state population percent Hispanic	0.729*	2.073*	0.361***	1.435***
	(0.423)	(0.877)	(0.108)	(0.155)
mean hired farmworker wage	-0.507***	0.602***	-0.003	0.997
	(0.171)	(0.103)	(0.485)	(0.484)
minimum wage	1.021	2.776	-0.524	0.592
	(0.656)	(1.822)	(0.419)	(0.248)
monthly welfare value (100s USD)	0.063**	1.065**	0.020	1.021
	(0.030)	(0.032)	(0.026)	(0.026)
annual education value (1,000s USD)	0.051	1.052	0.016*	1.016*
	(0.087)	(0.091)	(0.009)	(0.009)
linewatch hours per mile (1,000s)	-0.081***	0.922***	-0.091***	0.913***
	(0.031)	(0.029)	(0.023)	(0.021)
Observations	21276		32000	
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$				

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include controls for gender, age, marital status, number of children, education, U.S. farmwork experience, legal status, work networks, seasons, time trends, Mexican state of origin dummies and state fixed effects. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

choosing these states. New migrants in the fall are less likely to choose Texas but over time, new migrants have been more likely to choose Texas over California all else equal. As experience increases from zero to one year, migrants are more likely to choose Texas or Florida over California and are less likely to choose Arizona over California. Illegal new workers are 87 percent less likely to choose Texas over California than are legal new workers.

In terms of the state attributes, similar to the illegal subsample, coefficients on state population Hispanic share and linewatch hours per mile take the predicted directions but are insignificant at conventional levels. The rural unemployment rate shows a positive effect and mean hired farmworker wage a negative effect. Minimum wage is statistically significant for this group in the positive direction. Holding other factors constant, new migrants would be almost seven times more likely to choose a state with a one dollar higher minimum wage. The maximum welfare value variable is significant in the negative direction.

Results for more experienced migrants are presented in Table 12. These results approximate the full sample results. One difference is that among the more experienced population, workers were more likely to use a work network when migrating to Texas over California. Hispanic share and linewatch hours are strong predictors of locational choice.

Table 13 shows the state attribute results restricting the sample first to illegal return migrants and then to legal return migrants. Rural unemployment rates and farm employment totals are positive predictors of the locational choices of illegal return migrants. Farm employment totals are negative predictors, however, for legal return migrants. State Hispanic share is a positive predictor for both groups. The magnitude of

Table 14: Conditional Logit Model – Mexican Farmworkers, by Family Structure

Reference Category: California	Alone		With Family	
	coef	odds	coef	odds
rural unemployment rate	0.206***	1.229***	0.084	1.087
	(0.036)	(0.044)	(0.072)	(0.079)
farm employment (10,000s)	0.078*	1.081*	-0.054	0.947
	(0.044)	(0.048)	(0.039)	(0.037)
state population percent Hispanic	0.723***	2.061***	0.161	1.175
	(0.265)	(0.545)	(0.108)	(0.126)
mean hired farmworker wage	-0.582**	0.559**	0.012	1.012
	(0.243)	(0.136)	(0.410)	(0.415)
minimum wage	0.668	1.951	0.012	1.012
	(0.446)	(0.871)	(0.583)	(0.590)
monthly welfare value (100s USD)	0.002	1.002	-0.229**	0.795**
	(0.046)	(0.046)	(0.100)	(0.079)
annual education value (1,000s USD)			-0.096**	0.908**
			(0.043)	(0.039)
linewatch hours per mile (1,000s)	-0.097***	0.908***	-0.066***	0.936***
	(0.024)	(0.022)	(0.013)	(0.012)
Observations	39776		25032	
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$				

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include controls for gender, age, marital status, number of children, education, U.S. farmwork experience, legal status, work networks, seasons, time trends, Mexican state of origin dummies and state fixed effects. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

the effect, however, is stronger for illegal return migrants than for legal ones. The magnitude of the negative linewatch effect is also stronger for the illegal return migrants than for the legal return migrant population.

6.6 Extension: Mexican Farmworkers Alone versus With Family

Migrants with children with them in the U.S. might be hypothesized to choose states with high welfare and education values. The opposite result, however, is documented in Table 14. Migrants traveling with children are less likely to choose states with high welfare and education values. Single migrants are more likely to treat state Hispanic share as an important determinant of destination than are those with family. Linewatch hours per mile is a significant negative predictor of locational choice for both migrants traveling alone and those arriving in the U.S. with their children.

6.7 Extension: Spatial Lags

Table 15 considers the case that characteristics of the destination's neighboring state in addition to characteristics of the destination state itself influence the propensity to migrate to certain locations. Neighbor's welfare values are associated with decreased probability of locating in a destination. These effects, however, are small. In the full sample, migrants are found to be less than one percent less likely to locate in a given state when that state's spatial neighbor increases welfare values \$100 per month. Overall, support for welfare migration by those in the agricultural population is limited.

Table 15: Conditional Logit Model – Neighboring States' Attributes

Reference Category: California						
	All		**Illegal**		**Legal**	
Own Attributes	coef	odds	coef	odds	coef	odds
rural unemployment rate	0.170**	1.185**	0.260	1.296	0.178*	1.194*
	(0.085)	(0.101)	(0.200)	(0.259)	(0.107)	(0.127)
farm employment (10,000s)	0.025	1.025	0.109	1.115	-0.024	0.976
	(0.062)	(0.064)	(0.115)	(0.128)	(0.032)	(0.032)
state population percent Hispanic	0.870**	2.386**	1.346*	3.843*	0.632**	1.882**
	(0.423)	(1.008)	(0.747)	(2.871)	(0.309)	(0.582)
mean hired farmworker wage	-0.498	0.608	-0.851***	0.427***	-0.134	0.875
	(0.345)	(0.210)	(0.260)	(0.111)	(0.513)	(0.449)
minimum wage	0.766	2.152	1.321	3.746	0.484	1.623
	(0.555)	(1.194)	(1.271)	(4.763)	(0.402)	(0.652)
monthly welfare value (100s USD)	-0.013	0.988	-0.025	0.975	-0.005	0.995
	(0.035)	(0.035)	(0.033)	(0.032)	(0.037)	(0.036)
annual education value (1,000s USD)	-0.161*	0.852*	-0.305**	0.737**	-0.079	0.924
	(0.085)	(0.072)	(0.131)	(0.097)	(0.059)	(0.054)
linewatch hours per mile (1,000s)	-0.085***	0.919***	-0.102*	0.903*	-0.114***	0.892***
	(0.028)	(0.026)	(0.054)	(0.049)	(0.012)	(0.011)
Neighbor's Attributes						
rural unemployment rate	0.040	1.041	-0.005	0.995	0.056**	1.057**
	(0.115)	(0.119)	(0.244)	(0.242)	(0.023)	(0.024)
farm employment (10,000s)	-0.000	1.000	-0.000**	1.000**	0.000*	1.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
state population percent Hispanic	0.345	1.412	0.263	1.300	0.500	1.648
	(0.402)	(0.567)	(0.578)	(0.751)	(0.365)	(0.601)
mean hired farmworker wage	0.138	1.148	0.430	1.537	-0.288	0.750
	(0.654)	(0.750)	(0.905)	(1.391)	(0.437)	(0.327)
minimum wage	0.684	1.982	-0.105	0.901	1.673***	5.328***
	(0.566)	(1.122)	(1.456)	(1.311)	(0.359)	(1.914)
monthly welfare value (100s USD)	-0.001**	0.999**	-0.001**	0.999**	-0.001***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
annual education value (1,000s USD)	-0.000	1.000	-0.000***	1.000***	-0.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
linewatch hours per mile (1,000s)	0.000	1.000	0.000***	1.000***	-0.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	64808		32244		32564	
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$						

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include controls for gender, age, marital status, number of children, education, U.S. farmwork experience, legal status, work networks, seasons, time trends, Mexican state of origin dummies and state fixed effects. Labor market variables (unemployment rate, employment totals and average wages) are lagged one year. Robust standard errors in parentheses.

Table 16: Conditional Logit Model – Central American Farmworkers

Reference Category: California	Texas		Florida		Arizona	
	coef	odds	coef	odds	coef	odds
female	1.249***	3.486***	1.500***	4.482***	-0.685***	0.504***
	(0.247)	(0.861)	(0.116)	(0.522)	(0.045)	(0.023)
age	0.045***	1.046***	0.002	1.002	0.062***	1.064***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)
spouse	0.960***	2.612***	0.644***	1.904***	1.528***	4.608***
	(0.053)	(0.139)	(0.091)	(0.173)	(0.319)	(1.469)
children (#)	0.280***	1.324***	-0.093***	0.911***	0.116	1.123
	(0.040)	(0.052)	(0.031)	(0.028)	(0.171)	(0.192)
education (yrs)	0.135***	1.144***	-0.178***	0.837***	-0.015	0.986
	(0.034)	(0.039)	(0.034)	(0.029)	(0.060)	(0.059)
U.S. farmwork experience (yrs)	-0.056**	0.945**	-0.012	0.988	-0.063***	0.939***
	(0.024)	(0.023)	(0.010)	(0.010)	(0.022)	(0.021)
illegal	-0.042	0.959	0.987***	2.684***	-0.280	0.756
	(0.292)	(0.280)	(0.243)	(0.653)	(0.523)	(0.395)
used work network	1.471***	4.355***	0.846***	2.331***	0.030	1.030
	(0.265)	(1.153)	(0.311)	(0.725)	(0.249)	(0.257)
summer	-1.304***	0.272***	-1.304***	0.271***	0.297	1.346
	(0.351)	(0.095)	(0.020)	(0.005)	(0.398)	(0.535)
fall	-14.987***	0.000***	-1.129***	0.323***	0.104	1.110
	(1.131)	(0.000)	(0.087)	(0.028)	(0.181)	(0.201)
time trend	0.434***	1.544***	0.823***	2.277***	0.521***	1.683***
	(0.135)	(0.208)	(0.177)	(0.403)	(0.090)	(0.152)
constant	-1.393		27.116***		11.175*	
	(2.075)		(8.356)		(6.396)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.423***	1.527***		
			(0.106)	(0.162)		
farm employment (10,000s)			0.474***	1.606***		
			(0.053)	(0.086)		
state population percent Hispanic			1.568***	4.796***		
			(0.531)	(2.548)		
mean hired farmworker wage			-1.350***	0.259***		
			(0.325)	(0.084)		
minimum wage			4.458***	86.343***		
			(0.770)	(66.443)		
monthly welfare value (100s USD)			0.119**	1.127**		
			(0.048)	(0.054)		
annual education value (1,000s USD)			0.126*	1.134*		
			(0.072)	(0.082)		
linewatch hours per mile (1,000s)			-0.152***	0.859***		
			(0.032)	(0.027)		
Observations			3268			
$***p < 0.01$, $**p < 0.05$, $*p < 0.1$						

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Regressions include Central American country of origin dummies. Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

6.8 Extension: Central American Farmworkers

A primary descriptive result is that state population Hispanic share is significant in a positive direction across specifications. This is consistent with social capital theory literature in which migrants respond to networks. Because the majority of these persons are of Mexican origin, it is uncertain whether the identified effect in this paper is a response to populations from the specific source country of Mexico or instead is a response to linguistic networks for example. Table 16 therefore considers Central American migrants as a comparison group.

Most variables with this alternate group are strongly statistically significant. Time trends for Texas, Florida, and Arizona are all statistically significant and positive. Those with work networks are more likely to choose both Texas and Florida over California. The opposite is true for the Mexican population. The Arizona coefficient for work network is also positive, although not statistically significant.

All state attributes are significant. The unemployment rate effect is positive and mean hired farmworker wage effect negative as in several of the Mexico regression. Workers are more likely to choose higher farm employment states and higher minimum wage states. Central American migrants, unlike their Mexican counterparts, do show evidence consistent with welfare migration. One reason for this might be that Central American migrants have higher migration costs due to their longer travel distances but face the same benefits once within the U.S. as do Mexican migrants. Due to the small sample size of Central American migrants represented in the NAWS, the robustness of this finding is unclear.

6.9 Extension: U.S. Born Farmworkers

Table 17 considers the locational choices of U.S. born farmworkers. Welfare values and minimum and average wages are positive significant predictors of locational choice. U.S. Born farmworkers are 19.8 percent more likely to be observed in a state offering $100 more in welfare monthly welfare benefits for his or her family size and are more than 250 percent more likely to be observed in a state with a dollar higher minimum wage. As with the immigrant population, rural unemployment rates positively predict locational choice.

7 Conclusions

In a recent report, the Federation for American Immigration Reform found that the illegal immigrant population in California in 2004 cost the state $10.5 billion for education, uncompensated medical care, and incarceration of illegal immigrants and their children. After accounting for tax payments made by illegal immigrants to the state, the total net cost for this population was estimated to be $8.8 billion. In similar reports, net outlays were $3.7 billion per year in Texas, $1.3 billion per year in Arizona, and one billion per year in Florida. Given these estimated magnitudes of fiscal costs associated with illegal migration, an understanding of the relationship between the key illegal immigrant receiving states and migrant flows themselves is important for policy-making.

This paper contributes to that effort by examining the determinants of locational choice of illegal and legal Mexican migrants to the U.S. This is important for public policy, especially regional planning. Identified locational choice determinants may be useful predictors of future migrant flows to be used in more sophisticated policy analysis.

Results suggest that migrants choose their destinations based on networks (seen via the significance of Hispanic share of a state's population, personal network variables, and Mexican sending state controls (not

Table 17: Conditional Logit Model – U.S. Born Farmworkers

Reference Category: California	Texas		Florida		Arizona	
	coef	odds	coef	odds	coef	odds
female	-0.109	0.896	0.250**	1.284**	0.019	1.020
	(0.083)	(0.074)	(0.102)	(0.132)	(0.130)	(0.132)
age	0.011*	1.011*	0.031***	1.032***	-0.018**	0.982**
	(0.006)	(0.006)	(0.003)	(0.003)	(0.007)	(0.007)
spouse	0.713***	2.040***	0.381	1.464	0.398***	1.489***
	(0.199)	(0.405)	(0.300)	(0.439)	(0.133)	(0.199)
children (#)	0.282***	1.326***	0.452***	1.571***	0.100	1.105
	(0.100)	(0.133)	(0.140)	(0.220)	(0.094)	(0.104)
education (yrs)	-0.148***	0.862***	-0.074***	0.928***	-0.109***	0.897***
	(0.006)	(0.005)	(0.011)	(0.010)	(0.011)	(0.010)
U.S. farmwork experience (yrs)	-0.036***	0.965***	-0.028***	0.972***	-0.005	0.995
	(0.007)	(0.006)	(0.003)	(0.003)	(0.011)	(0.011)
used work network	-0.288***	0.750***	-1.235***	0.291***	-0.306***	0.736***
	(0.015)	(0.011)	(0.067)	(0.019)	(0.046)	(0.034)
summer	0.450***	1.569***	-0.384***	0.681***	-0.329*	0.720*
	(0.062)	(0.097)	(0.045)	(0.031)	(0.189)	(0.136)
fall	1.042***	2.835***	0.001	1.001	0.884***	2.420***
	(0.050)	(0.143)	(0.052)	(0.052)	(0.093)	(0.226)
time trend	0.171***	1.187***	0.258***	1.295***	0.260***	1.297***
	(0.025)	(0.030)	(0.069)	(0.089)	(0.033)	(0.043)
constant	4.467**		14.628***		8.748***	
	(2.039)		(3.229)		(1.877)	
			State	**Attrib.**		
			coef	odds		
rural unemployment rate			0.074*	1.077*		
			(0.041)	(0.044)		
farm employment (10,000s)			0.141***	1.152***		
			(0.024)	(0.028)		
state population percent Hispanic			0.931***	2.537***		
			(0.301)	(0.763)		
mean hired farmworker wage			1.018*	2.768*		
			(0.575)	(1.593)		
minimum wage			0.939***	2.558***		
			(0.156)	(0.398)		
monthly welfare value (100s USD)			0.180**	1.198**		
			(0.083)	(0.100)		
annual education value (1,000s USD)			-0.070	0.933		
			(0.067)	(0.062)		
Observations			6700			

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

Source: National Agricultural Workers Survey, pooled cross sections 1989-2004.
Notes: Labor market variables (unemployment rate, employment totals, and average wages) are lagged one year. Robust standard errors in parentheses.

shown)). Linewatch hours are important determinants of state choice in many of the regressions. These variables are shown to be more important to experienced migrants than to first-time migrants. This suggests that informational networks may be imperfect, and information may be conveyed at a lag. One explanation for this might be that illegal migrants are more likely to continue moving after crossing the border. Because the data used here only provide information on final destinations, as opposed to initial crossing locations, these stories cannot be distinguished empirically.

Overall, results suggest that state-level characteristics that might be adjusted in attempts to persuade or dissuade migration are scarce. Border enforcement may seem to be one of the most adjustable margins to impact illegal immigration. However, there may be decreasing returns to scale. Figure 8 showed increases in linewatch hours, for example, over the same years that Figure 9 showed decreases in apprehensions. The high significance of linewatch variables across specifications, however, suggests that border enforcement does influence migration decisions of illegal and legal Mexican workers. Whether the effect is to dissuade migration in general or simply to reroute trips is not identified in this study.

The empirical estimates presented in this paper are conditional on selection into the surveyed population. While the conditional logistic model is attractive for studies analyzing multiple discrete choices, there are currently few established methods for jointly modeling selection propensities and outcomes in the presence of choices over more than two options.[29]

This paper is a first step at looking at where people go and why. Immigrant workers have historically been important to the competitiveness of the labor-intensive industry of agriculture. Further work is warranted to learn more about the economic consequences (costs and benefits) of international migration to regional economies.

[29]Note, however, that recent work by Bourguignon, Fournier, and Gurgand (2004) presents methods for dealing with selection within the standard multinomial logit framework.

References

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 (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.

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

Bourguignon, F., M. Fournier, and M. Gurgand (2004): "Selection Bias Corrections Based on the Multinomial Logit Model: Monte-Carlo Comparisons," Discussion paper.

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

Dávila, A., J. A. Pagán, and G. Soydemir (2002): "The Short-term and Long-term Deterrence Effects of INS Border and Interior Enforcement on Undocumented Immigration," *Journal of Economic Behavior and Organization*, 49(4), 459–472.

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.

Gabbard, S. M., and J. M. Perloff (1996): "All it Takes is Confidence: Job Search Confidence and Farm Workers' Wages, Benefits, and Working Conditions," Department of Agricultural and Resource Economics, Division of Agriculture and Natural Resources, University of California at Berkeley, Working Paper 777.

——— (1997): "The Effects of Pay and Work Conditions on Farmworker Retention," *Industrial Relations*, 36(4), 474–488.

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.

Greene, W. H. (2000): *Econometric Analysis*. Prentice-Hall International Inc., Upper Saddle River, New Jersey.

Hanson, G. H., R. Robertson, and A. Spilimbergo (2002): "Does Border Enforcement Protect U.S. Workers from Illegal Immigration?," *The Review of Economics and Statistics*, 84(1), 73–92.

Hanson, G. H., and A. Spilimbergo (1999): "Illegal Immigration, Border Enforcement, and Relative Wages: Evidence from Apprehensions at the U.S.-Mexico Border," *The American Economic Review*, 89(5), 1337–1357.

——— (2001): "Political Economy, Sectoral Shocks, and Border Enforcement," *Canadian Journal of Economics*, 34(3), 612–638.

INS (2003): "Estimates of the Unauthorized Immigrant Population Residing in the United States: 1990 to 2000," Discussion paper.

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

Johnson, H. P. (2006): "At Issue: Critical Facts on Critical Issues, Illegal Immigration," Public Policy Institute of California.

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

Maddala, G. (1986): *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press, Cambridge.

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

Massey, D. S., J. Arango, G. Hugo, A. Kouaouci, A. Pellegrino, and J. E. Taylor (1998): *Worlds in Motion: Understanding International Migration at the End of the Millennium*. Clarendon Press, Oxford.

Massey, D. S., J. Durand, and N. J. Malone (2002): *Beyond Smoke and Mirrors: Mexican Immigration in an Era of Economic Integration*. Russell Sage Foundation, New York.

Massey, D. S., and K. E. Espinosa (1997): "What's Driving Mexico-U.S. Migration? A Theoretical, Empirical, and Policy Analysis," *The American Journal of Sociology*, 102, 939–999.

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.

——— (1984): "Econometric Analysis of Qualitative Response Models," in *Handbook of Econometrics Volume II*, ed. by Z. Zvi Griliches, and M. D. Intriligator.

Mckenzie, D., and H. Rapoport (2004): "Network Effects and the Dynamics of Migration and Inequality: Theory and Evidence from Mexico," Stanford Center for International Development, Working Paper No. 201.

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

Munshi, K. (2003): "Networks in the Modern Economy: Mexican Migrants in the U.S. Labor Market," *The Quarterly Journal of Economics*, 118(2), 549–599.

Orrenius, P. M. (2004): "The Effect of U.S. Border Enforcement on the Crossing Behavior of Mexican Migrants," in *Crossing the Border: Research from the Mexican Migration Project*, ed. by J. Durand, and D. S. Massey. Russel Sage Foundation, New York.

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

Passel, J. S. (2004): "Undocumented Immigrants: Facts and Figures," Discussion paper, Urban Institute, Immigration Studies Program.

——— (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.

Passel, J. S., R. Capps, and M. Fix (2005): "Estimates of the Size and Characteristics of the Undocumented Population," Discussion paper, Pew Hispanic Center.

Pellegrini, P. A., and S. A. (2002): "Modelling Spatial Choice: A Review and Synthesis in a Migration Context," *Human Geography*, 26(4), 487–510.

Prengaman, P. (2005): "Groups Target Bosses to Deter Illegal Hiring," *The Washington Times*.

Seghetti, L. M., S. R. Viña, and K. Ester (2004): "Enforcing Immigration Law: The Role of State and Local Law Enforcement," Discussion paper, CPS Report for Congress, Order Code RL32270.

Tran, L. H., and J. M. Perloff (2002): "Turnover in U.S. Agricultural Labor Markets," *American Journal of Agricultural Economics*, 84(2), 427–437.

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 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.

B State Agricultural Characteristics

B.1 State Agricultural Production Values

The nature of agricultural markets and intensities of agricultural activity vary by state. In terms of the total value of agricultural products sold, California ranks first in the nation. By the 2002 Census of Agriculture, the market value of agricultural products sold in California in 2002 was $25.7 billion.[30] California ranked first for value of crops including nursery and greenhouse ($19.1 billion) and second for value of livestock, poultry, and their products ($6.6 billion).[31] California produces more than 50 percent of the nation's fruits, nuts, and vegetables and 99 percent or more of at least 12 crops.

Texas ranked second in the 2002 Census of Agriculture in terms of total agricultural product value with $14.1 billion in sales. While the state was first in terms of livestock and poultry value ($10.4 billion), it was sixth by crop value ($3.7 billion).[32] Texas accumulates 51.3 percent of total agricultural cash receipts in cattle and calves, followed by cotton (8.7 percent) and greenhouse and nursery (8.6 percent).

Florida and Arizona place lower in agricultural production rankings. Florida ranked ninth ($6.2 billion) in value of agricultural products in 2002.[33] Five billion of this value was in crops, and $1.2 billion was in livestock, poultry, and their products. Arizona ranked only 29th in value of agricultural products sold in 2002 ($2.4 billion) where $1.6 billion of this value was in crops and the remaining $0.8 billion was in livestock and poultry.[34]

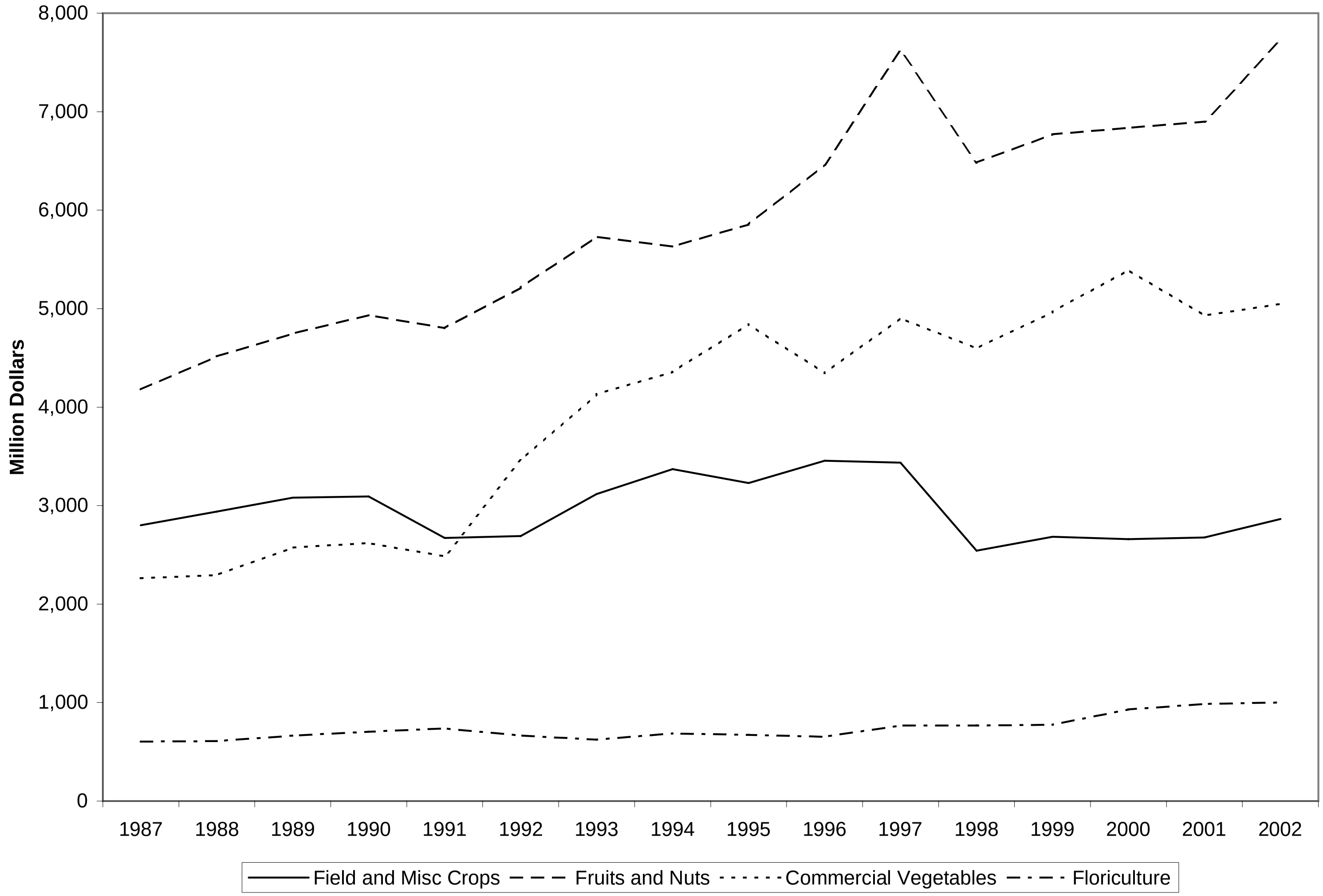
Workers in the NAWS are in crop agriculture only. USDA classifies crops into the commodity groups of field crops, fruit and nut crops, vegetable crops, and floriculture crops. An additional commodity category is livestock and dairy. This group is not considered here. Figures B-1 to B-4 present total values by state and crop category over time. The relative importance of the groups varies across states. While California is a key producer of all categories, Texas specializes in field crops and Florida (to a lesser degree) in fruits and nuts. Arizona has relatively lower values in all crop categories although vegetable values are increasing over time. Crop definitions for Figures B-1 to B-4 are presented in Table B-1.

B.2 State Farm Characteristics

Farm size and acreage also varies across states. California is home to 76.5 thousand farms on 26.4 million acres with an average farm size of 345 acres. Texas, on the other hand, houses 230 thousand farms on 129.8 million acres with an average farm size of 564 acres. Florida has 42.5 thousand farms on 10 million acres

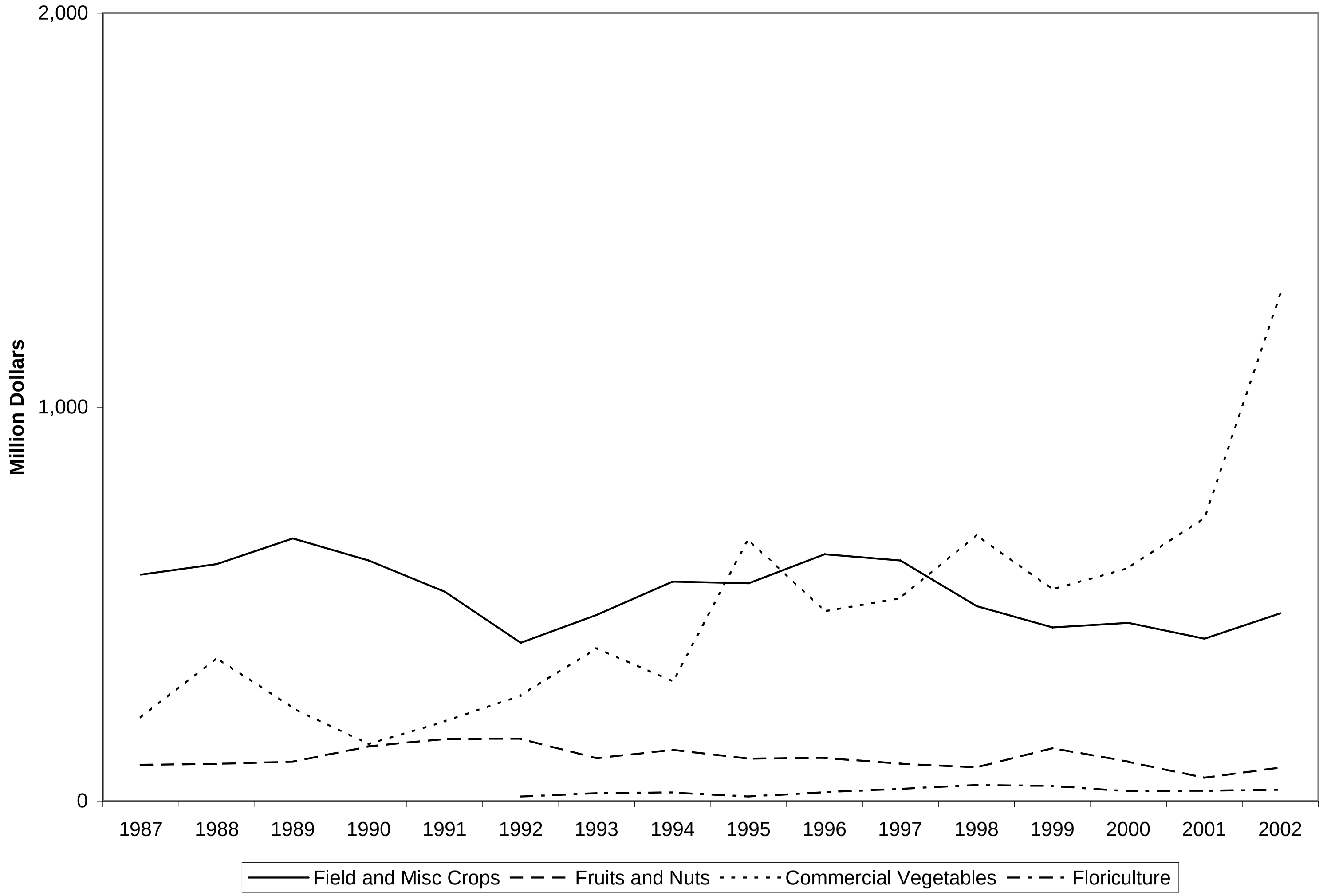
[30] The 2007 Census of Agriculture data were not available at the time of this writing.
[31] California Agricultural Statistics Service.
[32] Texas Agricultural Statistics Service.
[33] Florida Agricultural Statistics Service.
[34] Arizona Agricultural Statistics Service.

Figure B-1: California Crop Values



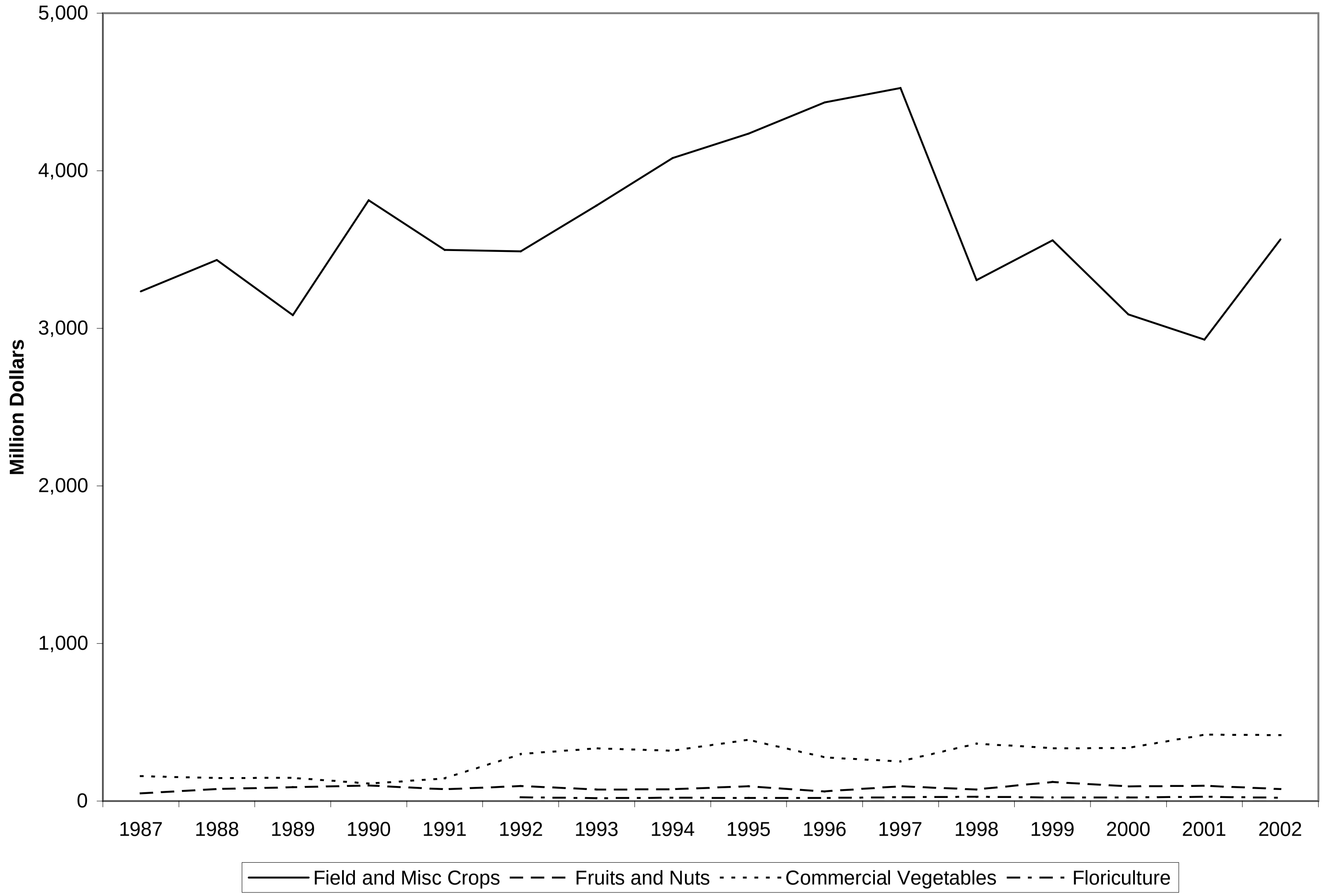
Source: U.S. Department of Agriculture, *Crop Values Final Estimates* and *Floriculture Crops Annual Summary*, selected years

Figure B-2: Arizona Crop Values



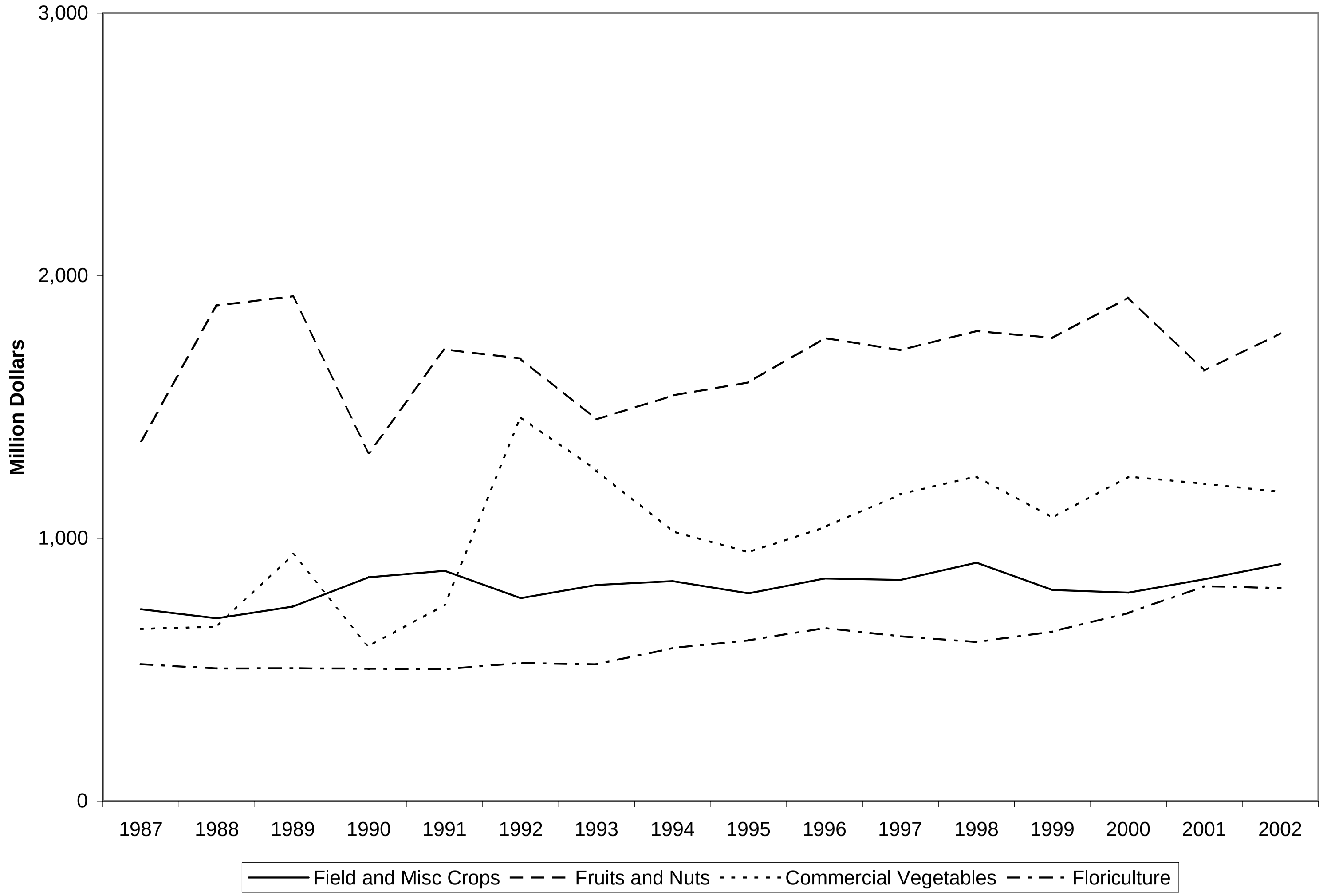
Source: U.S. Department of Agriculture, *Crop Values Final Estimates* and *Floriculture Crops Annual Summary*, selected years

Figure B-3: Texas Crop Values



Source: U.S. Department of Agriculture, *Crop Values Final Estimates* and *Floriculture Crops Annual Summary*, selected years

Figure B-4: Florida Crop Values



Source: U.S. Department of Agriculture, *Crop Values Final Estimates* and *Floriculture Crops Annual Summary*, selected years

Table B-1: Crop Classification Definitions

Field crops	barley, beans (all dry), corn (grain and silage), cotton, cottonseed, hay, oats, Irish potatoes, sweet potatoes, rice, sorghum (grain and silage), sugar beets, and wheat
Fruit and nut crops	almonds, apples, apricots, avocados, berries (boysenberries, raspberries, strawberries (fresh and processing), sweet cherries, dates, figs, grapefruit, grapes, kiwifruit, lemons, nectarines, olives, oranges, peaches, pears, pecans, pistachios, plums (fresh market and dried), tangerines (including Mandarins and hybrids, tangelos, and tangors), and walnuts
Vegetable crops	artichokes, asparagus, fresh snap beans, broccoli, brussel sprouts, cabbage, carrots), cauliflower, celery, sweet corn, cucumbers (fresh market and for pickles), eggplant, escarole/endive, garlic, greens (collard, kale, and mustard), lettuce, melons (cantaloupe, honeydew, watermelon), mushrooms, onions, peppers (bell and chili), pumpkins, radishes, fresh market spinach, squash, and tomatoes (fresh market and processing)
Floriculture crops	cut flowers, potted flowering plants, foliage plants, potted herbaceous perennials, annual bedding/garden plants, cut cultivated greens, propagative floriculture material, and special Hawaiian crops

with an average size of 235 acres, and Arizona has 10.1 thousand on 26.2 acres with the larger average size of 2,594 acres.