FARM EMPLOYMENT TRANSITIONS:
A MARKOV CHAIN ANALYSIS WITH SELF-SELECTIVITY

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Introduction

The U.S. agricultural labor market is heavily dependent on foreign-born workers. According to the 2002 National Agricultural Workers Survey (NAWS) report, 77 percent of agricultural workers were foreign-born for the years 2001-02 (Carroll et al. 2005). Approximately 69 percent of these foreign-born workers lacked authorization to work in the U.S. Hence, 53 percent of all farm workers were undocumented for the same period (Carroll et al. 2005), making U.S. agriculture one of the most undocumented-worker-intensive industries.

Political and national interest in immigration reform rose sharply over the last few years, resulting in the introduction of two bills – somewhat diametrically opposed – in the 109th U.S. Congress. For example, in December 2005 the U.S. House of Representatives passed H.R. 4437 which is considerably stricter on enforcement than the recent Senate immigration bill (S. 2611) which favors legalization and guest worker programs for undocumented immigrant workers[1]. Given the high proportion of unauthorized workers in the agricultural labor force, farm employers are concerned that labor availability and

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[1] HR. 4437 (the Border Protection, Antiterrorism & Illegal Immigration Act of 2005) and the S. 2611 (Comprehensive Immigration Reform Act of 2006) disagree sharply on how undocumented immigrants should be dealt with by law.

cost may be adversely affected if certain reforms are passed, and specifically if they are more stringently applied across the board (Walters et al. 2006).

Not surprisingly, the debate that has ensued on immigration reform and its implications for agriculture is quite similar to that which preceded the passage of the Immigration Reform and Control Act (IRCA) in 1986. In order to discourage the employment of unauthorized immigrant labor in the U.S, several measures were implemented. These included employer sanctions, a supplemental guest worker program, modification of the H-2 program, and legalization of unauthorized workers. Approximately 1.3 million unauthorized farm workers were granted legal status and many farmers and politicians were concerned about the effect on U.S. agriculture. Their prediction was that undocumented agricultural workers who received amnesty would leave agriculture for other employment opportunities, and this would lead to serious labor shortages and wage increases in US agriculture (Tran and Perloff 2002). These predictions did not materialize since the employment of unauthorized workers in U.S. agriculture has increased over time. This increase in undocumented workers seems to suggest that IRCA has not been as effective as lawmakers had intended[2].

However, there is no generally-accepted interpretation on why this considerable increase in composition of unauthorized workers occurred in U.S. agriculture after the IRCA. This phenomenon is even puzzling since existing literature generally concludes that legal status tends to lengthen the duration of a worker staying in farm work. There are two representative methods in the empirical study of the relationship between legal

[2] The proportion of unauthorized workers in U.S. agriculture has risen from 7% in 1989 to 32% for the years 1994-95, and 53% in 2001-02 (Mines et al. 1997, Carroll et al. 2005).

status and likelihood of a worker staying in U.S. agriculture in the post IRCA period: duration model and Markov chain model.

Hashida and Perloff (1996), Emerson and Napasintuwong (2002), and Iwai et al. (2005) use duration model to estimate the length of a farm work spell for given characteristics of a farm worker. Although the duration model may yield a rather accurate estimate for the length of each farm work spell, the problem of the methodology, however, is that it does not deal with the frequency of farm work spells.[3] Since farm workers are generally migratory and frequently move in and out of U.S. agriculture (Emerson 1989, Perloff et al. 1998, Tran and Perloff 2002), in order to adequately estimate the likelihood of a worker staying in U.S. agriculture, the estimation method should take into consideration the frequency of each type of spell (typically, farm work, non-farm work, and other activity) as well as the length of each spell. Tran and Perloff (2002) estimate a stationary, first-order Markov chain model of employment turnover (Amemiya 1985), and calculate the steady-state probability for each demographic group to work in US agriculture. The Tran and Perloff implementation of the Markov chain model has an obvious advantage over the duration model since the former considers frequency of farm work spells as well as length of each spell.

This paper extends the Tran and Perloff Markov chain model to incorporate sample selectivity issues. Each type of spell for a worker with a legal status is observed only if the worker is in that legal status. Each foreign-born worker chooses his/her legal status, considering conditions such as observable and unobservable individual characteristics, cost of application, and benefit of the status. If the legal-status and

[3] Estimated duration may reflect the length of contract for each legal status worker rather than likelihood of staying in US agriculture.

employment-status selection are correlated, the Markov chain model may yield biased estimators without correcting for the legal-status selection process. Regarding this, both Hashida and Perloff (1996) and Iwai et al. (2005) point out the serious sample selection bias problem in their duration models.[4] In order to compensate for the problems in the two representative methods above, it may be necessary to develop and estimate a Markov chain model with correction for sample selection bias.

We have the following three objectives in the current study. We propose a stationary, first-order Markov chain model with selection bias correction to adequately estimate the likelihood of each legal status worker staying in U.S. agriculture. Second, we extend our sample of the NAWS data up to 2004. The data sample (1989-91) used by Tran and Perloff is in a transitional period in the sense that newly legalized workers under IRCA may not have had enough time to move to other industries. Third, we implement a simulation to investigate how the likelihood of a typical unauthorized worker would be expected to change with a change in legal status.

Methodology

In this section we present the estimation method for legal status selection and turnover between employment statuses for workers. First, we introduce the probit model to explain legal status selection for workers, and then first-order Markov chain model to explain the turnover between employment statuses for each legal status workers. Next, we present an estimation method to deal with the possible sample selection bias in the

[4] Hashida and Perloff (1996) correct selection bias using Lee's extension of Heckman's two-stage sample selection method (Lee 1983). Iwai et al. (2005) use a Heckman type two-stage method with the ordered probit model in the first stage.

Markov model. Finally, we introduce several statistical tests which investigate whether there is a sample selection bias or not.

There are three legal statuses for a farm worker: 0=foreign-born unauthorized, 1=foreign-born authorized, and 2=US-born citizen worker. A foreign-born worker's legal status (J_i) takes on two values, 0 or 1, while a US-born worker's legal status is fixed at 2 so that there is no selection problem for the latter. The probit model is used to explain the legal status of a foreign-born worker as a function of the individuals' demographic and policy variables.[5] With the familiar argument of latent regression (Greene 2003), we can assume that an unobserved variable J_i^* is censored as follows:

$$\begin{aligned} J_i &= 0 \quad \text{if } J_i^* \le 0, \\ J_i &= 1 \quad \text{if } 0 < J_i^*. \end{aligned}$$

where $J_i^* = \alpha' x_i + \varepsilon_i$; x_i is a vector of exogenous characteristics of individual i; and ε_i is a disturbance term. The characteristics include gender, marital status, English speaking ability, race (black, white, or other), ethnicity (Hispanic or other), age, age squared, education, education squared, US farm experience, US farm experience squared, presence of relatives or close friends in US non-farm work, and the year of interview (before 1993, after 2001, or in-between).[6] Following the probit model assumption, ε_i is normally distributed with a mean of zero and a standard deviation of σ_ε. Then the likelihood function can be expressed as

[5] Isé and Perloff (1995) use multinomial logit, while Iwai et al. (2005) use ordered probit for legal status selection model. We use the standard probit model assuming there are only two statuses (unauthorized or authroized) for foreign-born workers, so that we can correct selection bias in the Markov model.
[6] The intent of these dummy variables is to test the effects of immigration policy change. The Before 1993 dummy corresponds to the period just after IRCA; the After 2001 dummy corresponds to the period following September 11, 2001.

$$L(\alpha,\sigma_\varepsilon,\mu_j \mid data)=\left\{\prod_{J_i=0}\left[\Phi\left(\frac{-\alpha' x_i}{\sigma_\varepsilon}\right)\right]\prod_{J_i=1}\left[1-\Phi\left(\frac{-\alpha' x_i}{\sigma_\varepsilon}\right)\right]\right\}, \tag{1}$$

where $\Phi(\cdot)$ indicates the cumulative distribution for the standard normal. Note one restriction in the above model that legal status for a worker is not transitional. This is because NAWS data do not track the legal status change for each worker; it only records legal status at the time of interview. However, the only period in which there is likely to have been a change in legal status during the recorded work history is following IRCA. But since the NAWS data start in 1989, most applications and decisions had been made by then. Consequently, we would expect very few legal status transitions by workers over the sample period.

Next, we present the first-order Markov chain model to explain the migration of a worker between activities. Suppose that $y_i(t)$ is the indicator of employment state for worker *i* in period *t* such that $y_i(t)=1$ if person *i* is actively working in US agriculture in period *t*,[7] and $y_i(t)=0$ if the person *i* is in other activities in period *t*.[8] We assume that the employment state of a person follows a stationary, first-order Markov process. Following the standard Markov chain model (Amemiya 1985), the transition of employment state is expressed as

$$\begin{cases}\left(y_i(t) \mid y_i(t-1)\right)=1 \text{ if } \left(y_i^*(t) \mid y_i(t-1)\right)\geq 0\\ \left(y_i(t) \mid y_i(t-1)\right)=0 \text{ otherwise}\end{cases}$$

where $\left(y_i^*(t) \mid y_i(t-1)\right)=\beta' z_i+\gamma' z_i\, y_i(t-1)+u_i(t)$, $E(u_i(t))=0$, $E(u_i^2(t))=\sigma^2$, and

[7] In our estimation one period is two months so that each worker's status is recorded every other month.

[8] We use the two-state model (in U.S. agriculture or in other activities) for the following reasons. First, our focus of the current study is U.S. agriculture. Second, there are many spells without specific activities for which all we know is that the worker is not in U.S. agriculture. Other activities include working in non-agricultural industries, unemployed, and out of the country.

$E(u_i(t)u_i(s)) = 0$ for $t \neq s$. Independent variables z_i include gender, marital status, English speaking ability, ethnicity (Hispanic, or other), age, age squared, education, education squared, US farm experience, US farm experience squared, region (California, Florida, or other), availability of free housing, contract type (seasonal, or year-around basis), task (skilled, or unskilled task), payment type (piece rate payment, or other), employer type (labor contractor, or grower), presence of relatives or close friends in US non-farm work, and the year of the spell (before 1993, after 2001, or in-between). Then the conditional probability of the state variable being one for worker i in period t is given as

$$P\left(y_i(t) \mid y_i(t-1)\right) = 1 - F\left(-\frac{\beta' z_i + \gamma' z_i y_i(t-1)}{\sigma}\right).$$

Further, assuming $u_i(t)$ is normally distributed, we have $P\left(y_i(t) \mid y_i(t-1)\right) = \Phi\left(\frac{\beta' z_i + \gamma' z_i y_i(t-1)}{\sigma}\right)$. Then the likelihood function for the Markov chain model is

$$L\left(\beta, \gamma, \sigma \mid data\right) = \prod_i \prod_t \left[P\left(y_i(t) \mid y_i(t-1)\right)\right]^{y_i(t)} \left[1 - P\left(y_i(t) \mid y_i(t-1)\right)\right]^{1-y_i(t)}. \qquad (2)$$

Next we investigate the possible correlation between legal-status and employment-status selection. Since correlation between ε_i and $u_i(t)$ may lead to biased and inconsistent estimates in equation (2), we should at least test the possible correlation between them. Assuming they are bivariately normally distributed with correlation coefficient ρ, the joint probability of the state variable being 1 and legal status 0 in period t is given as

$$P\left(y_i(t)=1, j=0 \mid y_i(t-1)\right)=\int_{-\frac{\beta' z_i+\gamma' z_i y_i(t-1)}{\sigma}}^{\infty}\int_{-\infty}^{\frac{-\alpha' x_i}{\sigma_\varepsilon}}\phi_2\left(\varepsilon_i, u_i(t), \rho\right) d\varepsilon_i du_i(t).$$

Further assuming that β, γ, ρ and σ depend on j, the above probability may be written as

$$P\left(y_i(t)=1, j=0 \mid y_i(t-1)\right)=\Phi_2\left(\frac{\beta_0' z_i+\gamma_0' z_i y_i(t-1)}{\sigma_0}, \frac{-\alpha' x_i}{\sigma_\varepsilon}, -\rho_0\right). \tag{3}$$

where $\Phi_2(\cdot)$ indicates the cumulative distribution for the bivariate standard normal. Since NAWS data record only one legal status for each worker, the equation above assumes that there is no transition between legal statuses for a worker. Hence, the above equation is similar to the case of the worker-specific unobserved heterogeneity which is constant over time (Fougere and Kamionka 2005). We denote $P\left(y_i(t)=1, j \mid y_i(t-1)\right)=P_{ij}(t)$, $P\left(y_i(t)=0, j \mid y_i(t-1)\right)=\tilde{P}_{ij}(t)$ hereafter. Using these notations, three other joint probabilities are given as

$$\tilde{P}_{i0}(t)=\Phi_2\left(-\frac{\beta_0' z_i+\gamma_0' z_i y_i(t-1)}{\sigma_0}, \frac{-\alpha' x_i}{\sigma_\varepsilon}, \rho_0\right), \tag{4}$$

$$P_{i1}(t)=\Phi_2\left(\frac{\beta_1' z_i+\gamma_1' z_i y_i(t-1)}{\sigma_1}, \frac{\alpha' x_i}{\sigma_\varepsilon}, \rho_1\right), \tag{5}$$

$$\tilde{P}_{i1}(t)=\Phi_2\left(-\frac{\beta_1' z_i+\gamma_1' z_i y_i(t-1)}{\sigma_1}, \frac{\alpha' x_i}{\sigma_\varepsilon}, -\rho_1\right). \tag{6}$$

Using these probabilities, the likelihood function which considers possible selection bias is given as

$$L(\alpha, \sigma_\varepsilon, \mu_j, \beta_j, \gamma_j, \rho_j, \sigma_j \mid data)=\prod_i \prod_{j=0,1} \prod_t \left(P_{ij}(t)\right)^{y_i(t)} \left(\tilde{P}_{ij}(t)\right)^{1-y_i(t)}. \tag{7}$$

Note that the likelihood function for US-born citizen workers is simply given as equation (2) since they do not have the legal-status-selection problem. Next, we introduce tests for existence of sample selection bias in the above estimation. That is, we test whether the ρ_j's are significantly different from zero. The simplest test is checking t-statistics for each ρ_j. The problem with this method is that there are many inconclusive cases since it is possible to have a different test result for each ρ_j. More systematic test methods are the likelihood ratio (LR) test and Wald test. It can be shown that maximizing equation (7) is the identical problem as maximizing equation (1) for legal status 0 and 1, and equation (2) separately for each legal status, if there is no sample selection bias (ρ_j=0 for j=0 and 1). Then the large sample distribution of -2*$ln\lambda$, where λ is the likelihood ratio of restricted over unrestricted maximum likelihood, follows a chi-square distribution with degrees of freedom of 2. While the LR test requires both unrestricted and restricted maximum likelihood estimators, the Wald test requires only the unrestricted estimator. These tests are standard, and we follow the formulas in Greene (2003).

Data

The data used in this study are obtained from the National Agricultural Workers Survey (NAWS) (U.S. Department of Labor 2006). The survey reports each worker's work-history for three years at maximum preceding the date of interview. We used the study period from 1989, when the NAWS was first available, to the most recent year available, 2004, with sample size of 40,650 workers.[9] We record the employment status (in US agriculture or in other activities) of each worker every other month for three years at maximum. Next we describe the definitions of each variable used in the model below.

Legal status is a discrete variable ranging from 0 to 2. A foreign born worker must fall

[9] This sample size is much larger than 1,538 in Tran and Perloff (2002).

into status 0 or 1. Status 0 = “unauthorized” worker means that the worker is undocumented (did not apply to any legal status or application was denied) and also includes one who had no work authorization even if he is documented. Status 1 = “authorized” worker includes naturalized citizen, green card holder and work authorization holder; the work authorization may fall into any of the following: border crossing card/commuter card, pending status, or temporary resident status with a non-immigrant visa. The US-born citizen has status 2 = “citizen” by birth.

The variable *English* measures the capability to speak English. The variable is a discrete variable ranging from 1 to 4, where 1 = not speaking English at all, 2 = speak a little English, 3 = somewhat able to speak English, and 4 = speaking English well. *Hispanic* is a dummy variable for Hispanic which includes Mexican-American, Mexican, Chicano, Puerto Rican, and other Hispanic ethnic groups. *Black* (or African American) and *White* are also dummy variables derived from a question regarding their race which may also be American Indian/Alaka Native, Indigenous, Asian, Native Hawaiian or Pacific Islander, or others. *Age* was calculated from the difference between the beginning date of spell and the date of birth. *Education* is the highest grade level for education, and it ranges from 0 to 20. *Experience* is the number of years of doing farm work in the US (not including farm work experience abroad). *Skilled Task* is a dummy for workers who engage in semi-skilled or supervisory tasks. Although the original questions have over 100 task codes, tasks are grouped into six categories as follows: 1 = pre-harvest, 2 = harvest, 3 = post-harvest, 4 = semi-skilled, 5 = supervisor, and 6 = other.

Seasonal Worker is a dummy for workers who were working on a seasonal basis for the employer. *Piece rate* is a dummy for workers who are paid by piece rate instead of being paid by the hour or a salary. *Labor contractor* is a dummy variable for workers who are employed by labor contractors rather than the grower. *Free housing* is a dummy variable for workers (or workers and their family) who receive free housing from their employer. It does not include those who own their house or live for free with friends or relatives. It also excludes those who pay for housing provided by employers or by the government or charity. *Relative* is a dummy for workers who have relatives or close friends in US non-farm work.

The dummies for *Florida* and *California* are the location of the employment. *Before 1993* dummy variable is for all the years prior to 1993 when the majority of IRCA legalization was granted, and *After 2001* is the years post-September 11, 2001 event.

Empirical Results

For legal status 0 and 1 workers, we estimated the Markov chain model with self-selectivity using the Newton-Raphson method with the maximum likelihood function given as equation (7).[10] Since status 2 workers (citizens by birth), do not have the legal-status-selection problem, we simply estimated equation (2) for this group using the same method.

Legal status selection

The estimates for legal-status-selection parameters in equation (7) and their asymptotic standard errors are reported in table 1. Using a 0.05 significance criterion, we find that all coefficients are statistically significant. The third column of Table 1 shows the marginal effect of each variable on the probability of a worker being legal. The probability of worker *i* being legal is given by $\Pr ob(J_i^* > 0) = 1 - \Phi(-x_i'\alpha)$. Then the marginal effect of variable *k* evaluated at the mean $\bar{x}$ is $\phi(-\bar{x}'\alpha)\alpha_k$ for the continuous variables and $\Phi(-\bar{x}'_{-k}\alpha_{-k}) - \Phi(-\bar{x}'_{-k}\alpha_{-k} - \alpha_k)$ for the dummy variables, where $\bar{x}'_{-k}$ and α_{-k} are variables and coefficients excluding the k^{th}. Females, married, workers with higher English speaking ability, black, white, non-hispanic, with a relative in the US non-

[10] We calculated gradient vector and Hessian matrix for logarithm of equation (7).

agricultural sector are statistically significantly more likely to have legal status all else being the same. We also find that age, education and US farm experience have a significant nonlinear effect on legal status. All three are positive almost throughout the relevant range: US farm experience has a positive effect on legal status up to 34 years; education has a positive effect on legal status up to 18 years, and age has a positive effect on legal status up to 55 years. We find that the greatest positive marginal effect is from the Before 1993 dummy followed by Female dummy and English speaking ability. The greatest negative marginal effect is from the Hispanic dummy followed by the After 2001 dummy. Note that, holding all other characteristics the same, the workers employed before 1993 are 34% more likely and those interviewed after 2001 are 9% less likely to be legal compared to those employed between these periods.

Finally, Table 2 shows the actual-predicted legal status table. A worker is predicted to be status 0 (unauthorized) if $\hat{\alpha}' x_i < 0$, and is predicted to be status 1 (authorized) worker if $\hat{\alpha}' x_i > 0$. Table 2 shows that 76% of unauthorized, and 84% of authorized workers are correctly predicted in their legal status.

Employment state transition

The estimates for employment-state-transition parameters in equation (7) and their asymptotic standard errors (given in the parentheses) are reported in tables 3 and 4. Status 0 (unauthorized) workers have 85,556 spells; status 1 (authorized) workers have 101,132 spells. Based on asymptotic standard errors using a 0.05 significance criterion, the coefficients on the selectivity variables ρ_0 and ρ_1 are both highly significantly negative.[11] We have the same conclusion using LR test and Wald test. We have the computed log likelihood ratio of 16.642 and Wald statistics of 34.443 both of which are larger than the critical value of 5.991 with 2 degree of freedom at 5 % level of significance. That is, using maximum likelihood estimator for equation (2) for each legal status without correcting for self-selectivity would lead to bias in estimates for both unauthorized and authorized workers.

Table 3 presents the employment transition parameters and asymptotic standard errors for legal status 0 (unauthorized) and legal status 1 (authorized) worker given previous state is "not in US agriculture". This corresponds to estimate of β_0 in equation (3) and (4) for status 0 and β_1 in equation (5) and (6) for status 1 worker. A positive estimate means that it has a positive effect on the probability of being in US agriculture given the previous state is not in US agriculture. We find that most of the estimates are statistically significant and have the same sign for both legal statuses, except for a few variables such as seasonal worker dummy and Before 1993 dummy. The former has negative effect for authorized worker, but no significant effect for unauthorized worker, while Before 1993 dummy has negative effect for unauthorized worker but no significant effect for authorized worker. Females, married, workers with higher English speaking ability, with free-housing, employed by labor contractors are statistically significantly less likely to be into agriculture from other employment state, all else being the same. On the other hand, California, Florida, Skilled task worker (in agriculture) and After 2001

[11] The negative correlation between ε_i and $u_i(t)$ does not mean that selection bias has negative effect on probability of being in US agriculture. This is especially true for the case of legal status 0 worker for whom being in US agriculture means that $u_i(t) > -(\beta_0' z_i + \gamma_0' z_i y_i(t-1))/\sigma_0$ and $\varepsilon_i < -\alpha' x_i / \sigma_\varepsilon$.

dummy have significantly positive effect on probability of being into agriculture, all else being the same.

The third and fifth columns in table 3 show the marginal effects of each variable on the joint probability of being in the respective legal status and in US agriculture. This joint probability is given as equation (3) for unauthorized worker and equation (5) for authorized worker. Marginal effects are evaluated at the mean of independent variables for each legal status worker. Note that the marginal effects of some variables have opposite signs to the partial effect on being in US agriculture, which is given as the estimated coefficient. These variables are Marital status, Relative dummy and English speaking ability for authorized workers, and Hispanic dummy for unauthorized workers. All these variables have a very strong effect on being in the respective legal status, especially the Marital status dummy and English speaking ability on being authorized, and the Hispanic dummy on being an unauthorized worker. Although these variables have a negative effect on being in US agriculture, the positive effect on the legal status must dominate. As for the magnitude of the marginal effect for unauthorized workers, the negative effect is largest for Before 1993 dummy followed by the Marital status dummy, while the positive effect is largest for the California dummy followed by the After 2001 dummy. For authorized workers, the negative effect is largest for the Hispanic dummy followed by the Labor contractor dummy, while the positive effect is largest for the Before 1993 dummy followed by the California dummy.

Table 4 shows the employment transition parameters and asymptotic standard errors for each legal status worker given the previous state is “in US agriculture”. This is calculated from $(\hat{\beta}_0 + \hat{\gamma}_0)$ in equations (3) and (4) for status 0 and $(\hat{\beta}_1 + \hat{\gamma}_1)$ in equations

(5) and (6) for status 1 workers.[12] A positive estimate means that it has a positive effect on the probability of being in US agriculture given the previous state is in US agriculture. We find that most of the estimates are statistically significant and have the same sign for both legal statuses, except for a few variables. For example, English speaking ability has no significant effect for either legal status worker, while Marital status dummy has a negative effect for unauthorized, and the Hispanic dummy has a positive effect for authorized workers, but no significant effect on the other. Both Labor contractor and the Piece rate payment dummies have negative effects for authorized workers, but no significant effect for unauthorized workers.

Other than these variables, females, seasonal workers with a relative in US non-agriculture sector, with free-housing, in California, before 1993 are statistically significantly less likely to stay in US agriculture, all else being the same. Note also that education has a negative effect on staying in US agriculture at the mean for both legal statuses.[13] On the other hand, Florida, After 2001, and Skilled task worker (in agriculture) dummies have significantly positive effects, all else being the same.

The third and fifth columns in table 4 show the marginal effects of each variable on the joint probability of being in the respective legal status and remaining in US agriculture. This joint probability is given as equation (3) for the unauthorized worker and equation (5) for the authorized worker. Again, marginal effects of some variables have opposite signs to the partial effect on being in US agriculture, given as the estimated coefficient. This happens only for authorized workers. These variables are Female,

[12] We also used the following formula to calculate estimate for variance and standard errors:
$Est.\,\mathrm{var}(\hat{\beta}_j + \hat{\gamma}_j) = Est.\mathrm{var}(\hat{\beta}_j) + Est.\mathrm{var}(\hat{\gamma}_j) + 2{*}Est.\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j)$.

Marital status, Relative and Before 1993 dummy and Education, all of which have very strong positive effects on being in an authorized legal status. Although these variables have negative effects on staying in US agriculture, the positive effects on the legal status must dominate. Also, strong negative effects on legal status of Hispanic and After 2001 dummies dominate the positive effect on staying in US agriculture.

As for the magnitude of the marginal effect for unauthorized workers, the negative effect is largest from the Before1993 dummy followed by the Female dummy, while the positive effect is largest from the Hispanic dummy followed by the Florida dummy. For authorized workers, the negative effect is largest from the Seasonal worker dummy followed by the Hispanic dummy, while the positive effect is largest from the Before1993 dummy followed by the Florida dummy. Before 1993, it is almost 30% less likely to remain in US agriculture with an unauthorized worker status, and 23% more likely to remain in US agriculture with an authorized worker status, all else being the same.

Finally table 5 shows the estimates and their asymptotic standard errors for the Markov chain model for US-born citizen workers. Here we estimated equation (2) using the maximum likelihood method. We also calculated the marginal effect on the probability of being in US agriculture at the mean of independent variables. We find the strongest negative effect on moving into agriculture is from the Labor contractor and Before 1993 dummies, and the strongest positive effect is from the After 2001 dummy followed by the California dummy. The strongest negative effect on staying in US agriculture is from the Seasonal worker dummy followed by Free housing and Relative

[13] Education has negative effect up to 8.6 years for unauthorized workers and 6.5 years for authorized

dummy, and the strongest positive effect is from the Florida dummy followed by the Skilled task worker (in agriculture) dummy.

Transition and Steady State Probability

In this section we estimate the transition and steady state probability of employment state given the legal status of workers. The probability of being in US agriculture conditional on unauthorized status is given as

$$P\left(y_i\ (t)=1\,|\ j=0, y_i\ (t-1)\right)=\Phi_2\left(\frac{\beta_0^{'}z_i\ +\gamma_0^{'}z_i\ y_i\ (t-1)}{\sigma_0},\frac{-\alpha^{'}x_i}{\sigma_\varepsilon},-\rho_0\right)\Big/\Phi\left(\frac{-\alpha^{'}x_i}{\sigma_\varepsilon}\right). \quad (8)$$

Then, the conditional transition matrix, we denote P_j, for unauthorized workers has the following form:

$$P_0=\begin{bmatrix}\Phi_2\left(\frac{\beta_0^{'}z_i\ +\gamma_0^{'}z_i}{\sigma_0},\frac{-\alpha^{'}x_i}{\sigma_\varepsilon},-\rho_0\right)\Big/\Phi\left(\frac{-\alpha^{'}x_i}{\sigma_\varepsilon}\right) & \Phi_2\left(-\frac{\beta_0^{'}z_i\ +\gamma_0^{'}z_i}{\sigma_0},\frac{-\alpha^{'}x_i}{\sigma_\varepsilon},\rho_0\right)\Big/\Phi\left(\frac{-\alpha^{'}x_i}{\sigma_\varepsilon}\right) \\ \Phi_2\left(\frac{\beta_0^{'}z_i}{\sigma_0},\frac{-\alpha^{'}x_i}{\sigma_\varepsilon},-\rho_0\right)\Big/\Phi\left(\frac{-\alpha^{'}x_i}{\sigma_\varepsilon}\right) & \Phi_2\left(\frac{-\beta_0^{'}z_i}{\sigma_0},\frac{-\alpha^{'}x_i}{\sigma_\varepsilon},\rho_0\right)\Big/\Phi\left(\frac{-\alpha^{'}x_i}{\sigma_\varepsilon}\right)\end{bmatrix}.$$

In this matrix the upper left element is the probability of being "in US agriculture" given that his/her legal status is unauthorized and previous employment state is "in US agriculture". The upper right element is the probability of being "not in US agriculture" given that his/her legal status is unauthorized and previous employment state is "in US agriculture". Also note that sum of these equals one. The second row corresponds to the case that the previous employment state is "not in US agriculture". So, other than the

workers, while their mean education length is 6.02 and 5.64 years respectively.

condition on legal status, this is the same as the standard transition matrix for Markov processes. We can calculate the conditional transition matrix for authorized workers the same way, but the transition matrix for the US-born citizen worker is not conditioned on legal status and has the following simple form:

$$P_2 = \begin{bmatrix} \Phi\left(\dfrac{\beta_2' z_i + \gamma_2' z_i}{\sigma_0}\right) & \Phi\left(-\dfrac{\beta_2' z_i + \gamma_2' z_i}{\sigma_0}\right) \\ \Phi\left(\dfrac{\beta_2' z_i}{\sigma_2}\right) & \Phi\left(-\dfrac{\beta_2' z_i}{\sigma_2}\right) \end{bmatrix}.$$

Table 6 presents the transition matrix of employment turnover, P_0, P_1 and P_2, estimated at the mean of the independent variables for each legal status worker. For the first two legal status workers, the transitional probabilities are conditional on legal status. We find that there is not much difference between legal statuses for the probability of staying in US agriculture, although unauthorized workers have the highest probability of 90%. However, legal status 1 (authorized) workers have a substantially lower probability of staying in the "not in US agriculture" state with a probability of 59%. In addition, authorized (legal status 1) workers have greater transition mobility between agricultural employment and being out of agriculture than do unauthorized (legal status 0) workers.

Using these transition matrices we calculate the steady state probability of employment status for each legal status worker. Following Amemiya (1985), the steady state probability vector for each worker (denoted $p_j(\infty)$) is calculated as $p_j(\infty)[1 \quad 1] = (P_j')^{\infty}$ for each j. Table 7 shows the steady state probability of each worker in two employment states. According to this, unauthorized workers have the highest steady state probability of "being in US agriculture" with 77%, followed by authorized workers with 75% and by US-born citizen workers with 73%. However, the difference between legal statuses is very small.

Simulation Study

In this section we implement simulations to examine how the steady state probability of a typical unauthorized worker staying in US agriculture would be expected to change with a change in legal status. This approach isolates the effect of legal status of the worker from differing observable characteristics of workers by holding the characteristics constant across varying legal status. In addition, we vary the time period (before or after 2001[14]), the type of worker (seasonal or non-seasonal), the skill level (skilled or non-skilled), the type of employer (grower or labor contractor), and the location (California or other states of the U.S.[15]). We fix each continuous variable at the mean of unauthorized worker observations, and fix each remaining discrete variable at the category with the maximum number of observations of unauthorized workers. The profile of the "typical" unauthorized worker is illustrated in Table 8.

As before, the conditional probability of being in US agriculture for unauthorized status workers is given as equation (8). When the legal status of unauthorized worker *i* is converted to status 1, the conditional probability would be

$$P\left(y_i(t)=1 \mid \varepsilon_i < \frac{-\alpha' x_i}{\sigma_\varepsilon}, y_i(t-1) \right) = \Phi_2\left(\frac{\beta_1' z_i + \gamma_1' z_i\, y_i(t-1)}{\sigma_1}, \frac{-\alpha' x_i}{\sigma_\varepsilon}, -\rho_1 \right) \Big/ \Phi\left(\frac{-\alpha' x_i}{\sigma_\varepsilon} \right).$$

Note that the condition in the square brackets is retained, since it formulates the

[14] Before 2001 means years from 1993 to 2001.
[15] Other states of the U.S. does not include Florida.

unobservable characteristics for legal status selection of the worker i.[16] In the same way we calculate the conditional probabilities for the other three elements in the transition matrix, then calculate the steady state probability in US agriculture. Finally, we calculate the change in the steady state probability from this legal status conversion.

The results are shown in Table 9. For 27 out of 32 cases, unauthorized workers working as "legal" workers would have a higher steady state probability in US agriculture than when working as unauthorized workers. If we focus on before 1993 cases, in all 16 cases, legal status would increase the steady state probability in US agriculture, but the magnitude of the change is not large. The highest increase is for seasonal, unskilled workers employed by growers not in California with a 7.3% point increase. There are only four cases with changes greater than 5% points, all of which occur for workers employed by growers. These five cases tend to be unskilled (with one exception) and seasonal workers (with one exception).

There are five cases after 2001 in which legal status would decrease the steady state probability in US agriculture. Interestingly, all of these cases are for workers employed by labor contractors. However, the largest decrease is only 1.1% point for seasonal, skilled workers employed by labor contractors in California. Overall, we could say that the change in the steady state probability from legal status conversion is very small after 2001; none of the 16 cases is over 5% points in absolute value.

Conclusion

We have proposed and estimated a stationary, first-order Markov chain model with selection bias correction to adequately estimate the likelihood of each legal status

[16] See Maddala (1983) for the detailed argument.

worker staying in U.S. agriculture. We used the NAWS data from 1989, when the NAWS was first available, to the most recent year available, 2004, with a sample size of 40,650 workers, and recorded the employment status (in US agriculture or in other activities) of each worker every other month for three years at maximum.

Our maximum likelihood estimation shows statistically significant coefficients on the selection bias terms for both authorized and unauthorized workers. Then we corrected selection bias in the calculation of transition and steady state probabilities of employment turnover. The conditional steady state probability in US agriculture is highest for unauthorized workers, but there is not much difference between legal statuses. Also, the simulation study shows that a legal status change for unauthorized worker would result in only small changes in the steady state probability of being in US agriculture, especially after 2001. The dramatic increase in composition of unauthorized workers in US agriculture during 1990s remains unexplained since our results find too small a difference in employment turnover between legal statuses to explain that phenomenon. The next issue is to study the entry into and exit out of US agriculture: what type of worker entered and left US agriculture.

Appendix

Table 1. Legal-status-selection parameters

	Parameter Estimate	Marginal Effect
Female	0.368*	0.146
	(0.009)	
Married	0.157*	0.062
	(0.008)	
English Speaking	0.277*	0.110
	(0.005)	
Black	0.081*	0.032
	(0.036)	
White	0.204*	0.081
	(0.007)	
Hispanic	-0.272*	-0.108
	(0.021)	
Age	0.054*	0.009
	(0.001)	
Age^2	-0.0005*	
	(0.00002)	
Education	0.048*	0.013
	(0.003)	
$Education^2$	-0.001*	
	(0.0002)	
Experience	0.152*	0.043
	(0.001)	
$Experience^2$	-0.002*	
	(0.00003)	
Relative	0.193*	0.077
	(0.008)	
Before 1993	0.901*	0.343
	(0.008)	
After 2001	-0.239*	-0.094
	(0.012)	
Constant	-3.260*	
	(0.035)	

* indicates that the estimated coefficient is statistically significant at 5 percent level of significance.

Table 2. Actual-predicted legal status table

	Predicted Legal Status		Total
Actual Legal Status	0	1	
0	76%	24%	100%
1	16%	84%	100%

Table 3. Employment transition parameters when the previous state is "not in US agriculture".

	Unauthorized	Marginal Effect	Authorized	Marginal Effect
Female	-0.123*	-0.060	-0.197*	-0.004
	(0.021)		(0.018)	
Married	-0.281*	-0.092	-0.055*	0.007
	(0.017)		(0.018)	
English Speaking	-0.040*	-0.030	-0.027*	0.032
	(0.013)		(0.010)	
Hispanic	-0.060	0.001	-0.166*	-0.088
	(0.059)		(0.037)	
Age	0.079*	0.004	0.029*	0.003
	(0.003)		(0.004)	
Age^2	-0.001*		-0.0003*	
	(0.00004)		(0.00004)	
Education	0.024*	-0.002	0.013	0.004
	(0.008)		(0.007)	
$Education^2$	-0.002*		-0.001*	
	(0.001)		(0.0005)	
Experience	-0.010*	-0.011	0.018*	0.015
	(0.004)		(0.004)	
$Experience^2$	0.0002*		-0.0003*	
	(0.00007)		(0.00008)	
California	0.298*	0.086	0.274*	0.080
	(0.019)		(0.017)	
Florida	0.081*	0.024	0.250*	0.073
	(0.026)		(0.030)	
Free Housing	-0.050*	-0.014	-0.058*	-0.017
	(0.020)		(0.020)	
Seasonal Worker	0.020	0.006	-0.131*	-0.039
	(0.017)		(0.015)	
Skilled Task	0.109*	0.032	0.132*	0.039
	(0.024)		(0.019)	
Piece Rate	0.010	0.003	0.040*	0.012
	(0.019)		(0.017)	
Labor Contractor	-0.074*	-0.022	-0.154*	-0.045
	(0.019)		(0.018)	
Relative	-0.064*	-0.031	-0.022	0.022
	(0.018)		(0.016)	
Before 1993	-0.183*	-0.112	0.043	0.143
	(0.025)		(0.022)	
After 2001	0.228*	0.082	0.150*	0.010
	(0.026)		(0.031)	
Constant	-1.685*		-0.759*	
	(0.085)		(0.123)	
Rho	-0.199*		-0.110*	
	(0.039)		(0.038)	

* indicates that the estimated coefficient is statistically significant at 5 percent level of significance.

Table 4. Employment transition parameters when the previous state is "in US agriculture".

	Unauthorized	Marginal Effect	Authorized	Marginal Effect
Female	-0.276*	-0.128	-0.250*	0.062
	(0.022)		(0.016)	
Married	-0.037*	-0.043	-0.017	0.041
	(0.017)		(0.015)	
English Speaking	-0.023	-0.071	0.011	0.080
	(0.013)		(0.009)	
Hispanic	0.084	0.078	0.129*	-0.055
	(0.057)		(0.030)	
Age	-0.018*	-0.008	-0.006	0.004
	(0.004)		(0.004)	
Age^2	0.0002*		0.0000004	
	(0.00005)		(0.00004)	
Education	-0.017*	-0.009	-0.020*	0.0089
	(0.008)		(0.006)	
Education^2	0.001		0.002*	
	(0.001)		(0.0004)	
Experience	-0.013*	-0.033	0.004	0.025
	(0.005)		(0.004)	
Experience^2	0.0001		0.0000005	
	(0.00009)		(0.00007)	
California	-0.084*	-0.012	-0.078*	-0.013
	(0.018)		(0.014)	
Florida	0.518*	0.071	0.515*	0.086
	(0.024)		(0.022)	
Free Housing	-0.080*	-0.011	-0.144*	-0.024
	(0.021)		(0.018)	
Seasonal Worker	-0.437*	-0.060	-0.407*	-0.068
	(0.016)		(0.012)	
Skilled Task	0.172*	0.024	0.146*	0.024
	(0.022)		(0.036)	
Piece Rate	-0.011	-0.001	-0.042*	-0.007
	(0.019)		(0.015)	
Labor Contractor	0.026	0.004	-0.069*	-0.012
	(0.019)		(0.016)	
Relative	-0.124*	-0.064	-0.078*	0.041
	(0.019)		(0.013)	
Before 1993	-0.299*	-0.261	-0.234*	0.214
	(0.028)		(0.018)	
After 2001	0.080*	0.069	0.073*	-0.055
	(0.022)		(0.023)	
Constant	1.872*		1.533*	
	(0.091)		(0.108)	
Rho	-0.199*		-0.110*	
	(0.039)		(0.038)	

* indicates that the estimated coefficient is statistically significant at 5 percent level of significance.

Table 5. Markov chain model estimates for US-born citizen workers.

	Previous state is "not in US agriculture"	Marginal Effect	Previous state is "in US agriculture"	Marginal Effect
Female	-0.071*	-0.025	-0.116*	-0.022
	(0.021)		(0.022)	
Married	-0.001	-0.0005	-0.003	-0.0005
	(0.021)		(0.020)	
Hispanic	-0.022	-0.008	-0.085*	-0.016
	(0.023)		(0.023)	
Age	0.037*	0.004	0.027*	0.0003
	(0.003)		(0.004)	
Age^2	-0.0004*		-0.0004*	
	(0.00005)		(0.00005)	
Education	0.003	-0.0005	-0.006	0.003
	(0.013)		(0.011)	
$Education^2$	-0.0002		0.001	
	(0.0007)		(0.001)	
Experience	0.027*	0.005	-0.001	0.0003
	(0.003)		(0.003)	
$Experience^2$	-0.0004*		0.0001	
	(0.00006)		(0.00006)	
California	0.216*	0.075	-0.036	-0.007
	(0.039)		(0.035)	
Florida	0.093*	0.033	0.300*	0.057
	(0.035)		(0.03)	
Free Housing	-0.020	-0.007	-0.245*	-0.046
	(0.026)		(0.025)	
Seasonal Worker	-0.081*	-0.028	-0.641*	-0.121
	(0.019)		(0.020)	
Skilled Task	0.058*	0.020	0.198*	0.037
	(0.028)		(0.025)	
Piece Rate	0.013	0.004	-0.115*	-0.022
	(0.034)		(0.036)	
Labor Contractor	-0.127*	-0.044	-0.152*	-0.029
	(0.037)		(0.041)	
Relative	0.160*	0.056	-0.221*	-0.042
	(0.023)		(0.022)	
Before 1993	-0.103*	-0.036	-0.156*	-0.029
	(0.021)		(0.021)	
After 2001	0.433*	0.151	-0.106*	-0.020
	(0.034)		(0.031)	
Constant	-1.678*		1.183*	
	(0.086)		(0.090)	

* indicates that the estimated coefficient is statistically significant at 5 percent level of significance.

Table 6. Transition matrix for each legal status worker.

	Employments state=1	Employments state=0
Legal status 0		
Previous employment state=1	0.904	0.096
Previous employment state=0	0.321	0.679
Legal status 1		
Previous employment state=1	0.860	0.140
Previous employment state=0	0.410	0.590
Legal status 2		
Previous employment state=1	0.890	0.110
Previous employment state=0	0.303	0.697

Employment state 1 is “in US agriculture” and Employment state 0 is “not in US agriculture”. One period is two months. Status 0 and status 1 worker probabilities are conditional on legal status.

Table 7. Steady state probability of employment state.

Legal status 0	
Employment state=1	0.770
Employment state=0	0.230
Legal status 1	
Employment state=1	0.746
Employment state=0	0.254
Legal status 2	
Employment state=1	0.733
Employment state=0	0.267

Table 8. Profile of the “Typical” Unauthorized Worker

Female	0
Married	0
English Speaking	1.506
Black	0
White	0
Hispanic	1
Age	27.880
Education	6.020
Experience	5.436
Florida	0
Free Housing	0
Piece Rate	0
Before 1993	0
Relative	0
Constant	1

Table 9. Simulated change in steady state probability in US agriculture by Legal Status

After 2001	Seasonal	Skilled Task	Labor Contractor	California	Legal Status: Unauthorized	Legal Status: Authorized	Change
No	No	No	No	No	0.773	0.842	0.069
No	No	No	No	Yes	0.807	0.857	0.050
No	No	No	Yes	No	0.764	0.798	0.033
No	No	No	Yes	Yes	0.801	0.821	0.020
No	No	Yes	No	No	0.848	0.891	0.044
No	No	Yes	No	Yes	0.868	0.899	0.031
No	No	Yes	Yes	No	0.842	0.859	0.017
No	No	Yes	Yes	Yes	0.865	0.872	0.007
No	Yes	No	No	No	0.618	0.691	0.073
No	Yes	No	No	Yes	0.670	0.726	0.055
No	Yes	No	Yes	No	0.604	0.625	0.021
No	Yes	No	Yes	Yes	0.660	0.671	0.010
No	Yes	Yes	No	No	0.712	0.768	0.056
No	Yes	Yes	No	Yes	0.750	0.791	0.041
No	Yes	Yes	Yes	No	0.702	0.712	0.011
No	Yes	Yes	Yes	Yes	0.743	0.745	0.002
Yes	No	No	No	No	0.834	0.875	0.041
Yes	No	No	No	Yes	0.854	0.884	0.030
Yes	No	No	Yes	No	0.829	0.839	0.011
Yes	No	No	Yes	Yes	0.851	0.855	0.004
Yes	No	Yes	No	No	0.890	0.914	0.024
Yes	No	Yes	No	Yes	0.901	0.918	0.017
Yes	No	Yes	Yes	No	0.888	0.889	0.001
Yes	No	Yes	Yes	Yes	0.900	0.897	-0.003
Yes	Yes	No	No	No	0.699	0.744	0.045
Yes	Yes	No	No	Yes	0.735	0.769	0.034
Yes	Yes	No	Yes	No	0.689	0.686	-0.003
Yes	Yes	No	Yes	Yes	0.729	0.722	-0.007
Yes	Yes	Yes	No	No	0.779	0.810	0.032
Yes	Yes	Yes	No	Yes	0.802	0.825	0.023
Yes	Yes	Yes	Yes	No	0.772	0.764	-0.008
Yes	Yes	Yes	Yes	Yes	0.799	0.787	-0.011

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