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Abstract

This study investigates convergence in hired farm wages in U.S. counties over the period 1978-92. The time-invariant distribution of wages is characterized using Markov chains. This study is concerned with two questions: Are regional hired farm wages moving in the same direction? If so, are they consistent with the direction of the entire U.S. farm wages? Concerning with efficiency in agricultural labor markets, the study approximates it to the extent that it is reflected in farm wages. Time-invariant distributions of wages are calculated for the Northeast, Midwest, South, and West region, and for the entire U.S. The results support the hypothesis of convergence at regional level to lower-than-respective regional average wage. Convergence is the strongest in the Northeast and the weakest in the South. Likewise, convergence to lower-than-average wage is present at the U.S. level, but it is stronger than that at the regional level.

JEL Codes: Q01, Q12, Q15, Q18, C21, R14

Key words: Farm wage movements, labor markets, convergence, Markov chains, U.S. agriculture

1. Introduction

It is a law of nature that under uniform conditions, the hot weather moves toward cold or vice versa; and as a result, after a sufficient period of time temperature across locations becomes the same. The very same law makes itself known in the context of international trade, labor market efficiency, and institutional changes: wages as the temperature in labor markets tend to equalize across economies as trade is promoted, efficiency-oriented policies are implemented, and similar labor market institutions across economies are developed.[1]

Research often focuses on three main factors behind wage movements. Institutional changes, such as decline in minimum wages and unionization rate, and increase in economic deregulation, usually occupy the first seat in debates, while skill-biased technological change and international trade appear in the second and third places, respectively. For example, deunionization studied by Chaykowski and Slotsve (1996) and Fortin and Lemieux (1997), skill-biased technological change by Bound and Johnson (1992), Juhn, Murphy, and Pierce (1993), Bhagwati and Kosters (1994), and Berman, Bound, and Griliches (1994), and barriers to international trade by Murphy and Welch (1991) were rather often found behind wage inequalities. However, these studies commonly neglect factor price movements in a specific sector within-country. With the present study investigating convergence of the U.S. real farm wages, we add a unique observation to the literature that low-wage counties experience faster growth of wages than do high-wage counties.

This study concentrates on the period 1978-92 because it is this period that the U.S. agricultural sector witnessed significant changes with respect to organizational structure and labor markets. With 17 percent decline in the number of family and partnership farms and with 45 and 36 percent increases in corporate and co-operative farms, respectively, the U.S. agriculture experienced a significant shift from family to corporate farming (USDC, 1992). This path-breaking organizational change would favor large farms in that they would increase their market power and induce consumer welfare loss. With respect to labor and land markets, labor cost increased as much as 90 percent, while land prices increased

[1] In the context of trade and wage relationship, see Dixit and Norman (1980), Coe (1985), Decressin and Fatas (1993), Button and Pentecost (1993), Mallick and Carayannis (1994), Abraham and Van Rompuy (1995), Abraham (1996), Carayannis and Mallick (1996); in the context of labor market efficiency and uniform wages, see Schweitzer and Dupuy (1996) and Bernard and Jones (1996); in the context of institutional changes and factor price formation, see Ruttan and Hayami (1978), DiNardo, Fortin, and Lemieux (1996), and Card (1996).

by only 28 percent (USDC, 1992). Finally, a significant proportion of farms exited or merged, with 17 percent decline in the number of farms, and acres of farmland was reduced by 7 percent (4 percent of which is cropland). What is obvious is that rising cost of labor concurrent with corporate farming characterizes the current status of the U.S. farming: one which makes the emergence of new labor market institutions and labor-saving technological change unavoidable.

Despite the theoretical expectations for convergence, whether such a process occurs in the U.S. agricultural sector remains unclear. Agricultural producers generally suffer from the lack of sufficient local workers to harvest their crops during the key production periods, and thus rely on large numbers of seasonal workers. Migrant workers, comprising 42 percent of the farm labor force over the period 1989-91, performed over half of the agricultural activities. The seasonal pattern in labor demand together with the scarcity of farm workers led to highly competitive subcontracting arrangements that push wages upward (USDL, 1994; Thilmany and Martin, 1995; Perloff, Lynch, and Gabbard, 1998). However, non-overlapping harvest periods across regions help suppress wages that would otherwise be rising. Labor demand in the South, for example, is generally at a low in August, when the Northeast is near its peak in September, giving migrant workers a chance to move into regions where labor is scarce. Of the migrants in the Northeast in September, five percent come from California, 13 percent from within the region, 16 percent from the South, and 66 percent from outside the U.S. (USDL, 1994).

In the period 1978-92 the share of labor cost in production expenses increased by 25 percent, while the shares of livestock-poultry and feed for livestock remained almost unchanged (USDC, 1992), manifesting significant changes in agricultural labor and other related markets to come. This study investigates the dynamics behind this rising labor cost and hypothesizes that the cross-county dispersion of hired farm wages in the U.S. narrowed down during 1978-92 - the so-called convergence hypothesis. The study indirectly tests whether labor in low-productivity counties has become more productive, while at the same time labor in high-productivity counties remained as productive as it used to be. The estimations are carried out at regional and at the U.S. levels, using county-level data on hired farm wages. Consistent with theoretical expectations, convergence in wages would suggest that low-productivity counties became more productive, while high-productivity counties remained the same. The essence of the convergence argument lies in free flow of factors from one place where productivity is low to another where it is relatively high. If convergence is plausible at all, it surely is more likely to be true across regions within a country where labor markets are subject to similar constraints and where there is no barrier to technology transfer.

This study applies a Markov chain model to allow for the integration of the transition information in the cross-section approach with the steady state information in the time series approach.[2] This is accomplished by estimating a Markov transition function for the data and then by inferring the time-invariant distribution of the cross-section. The contributions of the study to the literature are twofold. First, to the best of our knowledge, the study is the first of its kind, investigating convergence of hired farm wages in the US. Second, it brings to the fore a nonparametric method which is very useful to project future distributions, whose knowledge is highly desirable by policy makers.

The remainder of this paper is organized as follows. Section 2 describes how to apply Markov chains to investigate convergence, and states a theorem that guarantees the existence and uniqueness of time-invariant probability distribution. Data, variables, and grouping of counties on the basis of their geographical proximity are all described in Section 3. Discussed in Section 4 are the main findings from the Markov chain analysis. Finally, Section 5 elaborates on policy implications of the findings for the U.S. agriculture. Furthermore, Appendix outlines χ^2 test statistics for the two assumptions of Markov chains.

2. Markov Chains

Consider a stochastic process $\{X_t, t = 0, 1, 2, ...\}$ that takes on a finite or countable number of possible values. Unless otherwise mentioned, this set of possible values of the process will be denoted by the set of nonnegative integers $\{0, 1, 2, ...\}$. If $X_t = i$, then the process is said to be in state i at time t.

Assumption 1 (Time-stationary transition probabilities). Whenever the process is in state i, there is a fixed probability p_{ij} that it will next be in state j : that is,

$$p\{X_{t+1} = j \mid X_t = i,\ X_{t-1} = i_{t-1},\ \dots\ , X_1 = i_1,\ X_0 = i_0\} = p_{ij} \qquad (2.1)$$

for all states $i_0,\ i_1,\ \dots\ , i_{t-1},\ i, j$ and $t \geq 0$. Such a stochastic process is known as a *Markov chain.* Eq. (2.1) may be interpreted as stating that, for a Markov chain, the conditional distribution of any future state X_{t+1} given the past states $X_0, X_1, ..., X_{t-1}$ and the present state X_t, is independent of the past states and

[2] Markov chains were applied by Quah (1993) to analyze convergence of cross-country growth rates and by Robertson (1995) to investigate convergence of bank size.

depends only on the present state. The value p_{ij} stands for the probability that the process will, when in state i, next make a transition into state j. Since the probabilities are nonnegative and since the process must make a transition into some state, we have $\Sigma_{j=0}^{\infty} p_{ij} = 1$ for $i = 0, 1, ...$ and $p_{ij} \geq 0$ for $i, j \geq 0$.

Assumption 2 (A first-order Markov chain). The stochastic process follows a first-order chain written as

$$X_{t+1} = PX_t \text{ where } P = (p_{ij}). \tag{2.2}$$

That is, the probability of a county being in a particular state at time $(t+1)$ is solely a function of its state at time t. A second-order chain can similarly be defined as one in which the probability of a county being in a particular state at time $(t+1)$ only depends on that county's states at times $(t-1)$ and t.[3]

If Assumptions 1 and 2 are satisfied, then one can calculate the time-stationary transition probabilities as $p_{ij} = (\frac{n_{ij}}{n_i})$, which is the solution to the following maximization problem,

$$Max \prod_{i,j} p_{ij}^{n_{ij}} \text{ subject to } \Sigma_{j=1}^{m} p_{ij} = 1 \text{ for } i = 0, 1, 2, ..., m \text{ and } p_{ij} \geq 0.$$

The term n_{ij}^t is the number of counties moving from state i at time $(t-1)$ to state j at time t; $n_{ij} = \Sigma_{t=1}^{T} n_{ij}^t$ is the total number of counties moving from state i to state j over $t = 1, 2, ..., T$; and $n_i = \Sigma_{j=1}^{m} n_{ij}$ is the total number of counties that were in state i over $t = 0, 1, ..., T$ and $i = j = 1, ..., m$. The $s - step - ahead$ distribution should evolve as

$$X_{t+s} = [P]^s X_t. \tag{2.3}$$

The time-invariant distribution π of the stochastic process is obtained as $[P]^s \to \pi$ when $s \to \infty$. This distribution is one in which the elements of P no longer change from one period to the next, although counties may continue to alter their states over time.

Existence and uniqueness of the time-invariant distribution, π. The presence of the invariant distribution guarantees that the process is independent of initial classification of observations. Provided below are several definitions and a theorem, adopted from Hoel, Port, and Stone (1987), which are used to prove the existence and uniqueness of π.

[3] See Appendix for testing procedures for the two assumptions.

Definition 2.1. *Class i is said to have period d if $p_{ij}^n = 0$ whenever n is not divisible by d, and d is the largest integer with this property. For instance, starting in i, it may be possible for the process to enter class i only at times $2, 4, 6, 8, ...$, in which case class i has period 2.*

Definition 2.2. *A class with period 1 is said to be aperiodic.*

Definition 2.3. *Class j is said to be accessible from class i if $p_{ij}^n > 0$ for some $n \geq 0$.*

Definition 2.4. *Two classes i and j that are accessible to each other are said to communicate.*

Definition 2.5. *For any class i we let f_i denote the probability that, starting in class i, the process will ever reenter class i. Class i is said to be recurrent if $f_i = 1$, and transient if $f_i < 1$. Class i is recurrent if $\sum_{n=1}^{\infty} p_{ii}^n = \infty$ and transient if $\sum_{n=1}^{\infty} p_{ii}^n < \infty$.*

Definition 2.6. *A Markov chain is said to be irreducible if there is only one grouping of classes; that is, if all classes communicate with each other.*

Definition 2.7. *If a class i is recurrent, then it is said to be* positive *recurrent if, starting in i, the expected time until the process returns to class i is finite. Positive recurrent, aperiodic classes are called ergodic.*

Theorem 2.8. *For an irreducible ergodic Markov chain, $\lim_{n\to\infty} p_{ij}^n$ exists and is independent of i. Furthermore, letting $\pi_j = \lim_{n\to\infty} p_{ij}^n$, $j \geq 0$ then π_j is the unique non-negative solution of*

$$\pi_j = \sum_{i=0}^{\infty} \pi_i p_{ij}, \ j \geq 0 \text{ and } \sum_{j=0}^{\infty} \pi_j = 1. \tag{2.4}$$

3. Data and variables

Data used in this study were obtained from the Census of Agriculture (USDC, 1992), with a separate cross-section of 3,130 counties for each year: 1978, 1982, 1987, and 1992. Each county is represented by an average farm in that county. The variable of interest, which is real farm wages per worker in county c at time

t, is calculated as $w_{c,t} = \frac{(C_{c,t}/N_{c,t})}{p_t}$. The cost of hired farm/ranch labor $C_{c,t}$ includes gross salaries and wages, commissions, dismissal pay, vacation pay, and paid bonuses paid to hired workers, family members, hired managers, administrative and clerical employees, salaried corporate officers, and supplemental cost for benefits such as employer's social security contributions, unemployment compensation, workman's compensation insurance, life and medical insurance, and pension plans. The number of hired farm/ranch workers $N_{c,t}$ includes paid family members, hired bookkeepers, office workers, and maintenance workers, if their work is primarily associated with agricultural production. This variable also includes any short term or temporary workers who may have worked only a few days, but does not include contract labor or custom workers. Owing to the lack of county-level price index, we deflated the nominal wages by the consumer price index p_t (1990=100, period averages): $p_{1978} = 49.9$, $p_{1982} = 73.9$, $p_{1987} = 87$, and $p_{1992} = 107.4$ (IMF, 1998).

Denote by $w^r_{c,t}$ the time t real farm wage prevailing in county $c-$ region r and calculate the regional average wage as $\overline{w}^r_t = (1/n_r)\Sigma^{n_r}_{c=1} w^r_{c,t}$ where n_r is the number of counties in region r. Define county c's odds ratio at time t as $F^r_{c,t} = (w^r_{c,t}/\overline{w}^r_t)$. When the analysis is carried out for the entire U.S., however, county c's odds ratio at time t becomes $F_{c,t} = (w_{c,t}/\overline{w}_t)$ where $\overline{w}_t = (1/n)\Sigma^n_{c=1} w_{c,t}$ with n being the number of counties in the entire U.S.

In order to determine the number of states in the transition matrix, we apply Cochran's (1966) variance minimization rule. First, $F^r_{c,t}$ is calculated for the initial period 1978, sorted in an ascending order, and finally divided into intervals (which correspond to states in our context) in such a way that each interval has minimum variance. For the determination of cut off points we simply look at the sorted data $F^r_{c,1978}$, and jump points in this monotonically increasing variable are accepted as possible cut off points. The application of this procedure produced the following 5 intervals or states: for given r, State 1 = $\#\{F^r_{c,t} \in [0, 0.49]\}$, State 2 = $\#\{F^r_{c,t} \in [0.50, 0.99]\}$, State 3 = $\#\{F^r_{c,t} \in [1.00, 1.49]\}$, State 4 = $\#\{F^r_{c,t} \in [1.50, 1.99]\}$, and State 5 = $\#\{F^r_{c,t} > 1.99\}$ where the sign # denotes the number of counties in the respective set.

4. Description of transition matrices

To have a better understanding of a transition probability matrix, the conditions under which this matrix for the Northeast region represents an irreducible, ergodic Markov chain are discussed in detail, and the meanings of the formal definitions provided in Section 2 are explained with examples. A Markov chain characterizes the long run movements in real hired farm wages and provides a description of future changes in these wages. More specifically, using Markov chains, an attempt is made to answer three questions: Do wages tend to be equal across counties? If so, how fast do they converge? and how does the long run distribution look like?

The transition matrix for Northeast (P)							
		(t+1)					
	States	1	2	3	4	5	N
	1	$\boxed{0.50}$	0.46	0.04			20
	2	0.05	$\boxed{0.74}$	0.20	0.01		214
(t)	3		0.37	$\boxed{0.51}$	0.10	0.02	115
	4		0.10	0.30	$\boxed{0.40}$	0.20	29
	5		0.06	0.28	0.33	$\boxed{0.33}$	12
T-invariant		0.06	0.55	0.29	0.07	0.03	390
Eigenvalues		1.00	$\boxed{0.66}$	0.46	0.26	0.10	

Elements p_{ij}*'s in* P. An element p_{ij} represents the probability that a farm will, when in State i at time t, next make a transition into state j at time $(t+1)$ where $i = j = 1, ..., 5$. The elements in the first row of P are denoted by p_{1j}, $j = 1, ..., 5$, where $p_{11} = 0.50$, $p_{12} = 0.46$, and $p_{13} = 0.04$. Of the entire sample of 390, a total of 20 farms over the period 1978-92 fell in State 1. Of these 20 farms, 50 percent (p_{11}) remained in that same state; 46 percent (p_{12}) moved into State 2; and four percent (p_{13}) moved into State 3 in the following period. Similarly, of 390 farms, a total of 214 farms fell in State 2 (i.e., the second row in P). Of 214 farms, 74 percent (p_{22}) remained in that same state, 20 percent (p_{23}) moved into State 3, one percent (p_{24}) into State 4, five percent (p_{21}) into State 1 in the following period.

State 2 is *accessible* from State 1 since p_{12} is positive (0.46). States 1 and 2 are accessible to each other, hence they are said to *communicate*, and it is denoted by $1 \longleftrightarrow 2$. In fact, all of the five states are communicating, implying that all of the states are in the same class. The Markov chain is then *irreducible* since there is only one class. It is easy to verify that the chain P is irreducible. For example, it is possible to go from State 1 to State 5 through the path $1 \longleftrightarrow 2 \longleftrightarrow 3 \longleftrightarrow 4 \longleftrightarrow 5$. That is, one way of getting from State 1 to State 5 is to go from State 1 to State 2 (with probability $p_{12} = 0.46$), then go from State 2 to State 3 (with probability $p_{23} = 0.20$),..., finally go from State 4 to State 5 (with probability $p_{45} = 0.20$).

Persistence, direction of movements, and mobility. Persistence is measured with the probabilities in the diagonal elements of P; large values for high persistence, low values for low persistence. Over this one-period horizon, the predominant feature in P is high persistence among those farms in State 2 and low persistence in States 5 and 4, implied by the diagonal entries 0.74, 0.33, and 0.40, respectively. This is interpreted as wages tending to move away from the regional average corresponding to State 3. A close look at the off-diagonal elements also shows a pattern of movements, one in which farms tend to move towards States 2 and 3. This is a pattern where a large majority of farms moves towards a level little less than the regional average wage. Consider, for example, 20 farms in State 1. Of these, 46 percent tend to move into State 2 and only four percent into State 3 in the following period; likewise, of 29 farms in State 4, 30 percent tend to move into State 3, while only 20 percent moving into State 5. An examination of all the off-diagonal elements indicates that farms move towards States 2 and 3, which is also justified by the time-invariant distribution with 55 percent of being in State 2 and 29 percent of being in State 3. One can further calculate a measure of mobility μ as $\mu(P) = (m - Trace(P))/(m-1) = (5-2.48)/4 = 0.63$ where P is of dimension $m = 5$.[4] The lower is μ, the lower mobility there is in county-level wages (or higher persistence there is in the kernel P) (Quah, 1993).

Time-invariant distribution, peaks, and polarization. The invariant distribution characterizes the limiting behavior of farms as the number of iterations of P goes to ∞. Nothing enforces existence or uniqueness of this distribution. That precisely one such distribution was found is a consequence of P at hand. Note that the invariant distribution is a projection of what is likely to happen in the future, provided that policies remain unchanged for a sufficiently long period of time and that no unforeseen events occur. The invariant distribution for the Northeast is ($\pi_1 = 0.06$, $\pi_2 = 0.55$, $\pi_3 = 0.29$, $\pi_4 = 0.07$, $\pi_5 = 0.03$) (see Figure 1). Everything else constant, this distribution states that in the final period, States 2 and 3 should include 84 percent ($= \pi_2 + \pi_3$) of 390 farms in the Northeast. This establishes a right skewed distribution in which there is a peak at State 2, suggesting that at the limit the majority of farms would move away from the regional average wage, and that wages would converge to a level lower than the regional average. Since there is only one peak to emerge, polarization does not take place in the Northeast. If, however, there had been two peaks, one on the lower tail and the other on the upper tail of the invariant distribution, then one would have claimed two peaks, implying polarization or coexistence of high and low-wage counties.

[4] $Trace(P)$ is defined as the sum of diagonal elements in P.

Convergence and its speed. A bell-shaped distribution π should imply convergence to the regional average, a left (right) skewed distribution convergence to a level higher (lower) than the regional average, and a bi-modal distribution (or two peaks) should imply polarization. The speed of convergence, denoted by λ and measured by the second largest eigenvalue of the kernel P, is the rate at which the kernel converges to the time-invariant distribution. The speed for the Northeast is 0.66.[5] (This concept is different from the one used in the convergence studies applying parametric regression method. Passing time in our context corresponds to the speed of convergence in the parametric regression.)

χ^2 statistics for time stationarity of P. Assumption 1 is tested by using χ^2 statistic under the null hypothesis that the kernel is time stationary. The null is accepted at the 0.05 level, since the calculated-χ^2 statistic < the table-$\chi^2_{m(m-1)(T-1)}$ where $m = 5$ and $T = 3$. Had it been nonstationary, the transition probability matrix for each period would have been examined separately.

The Midwest, South, West regions, and the entire U.S. The above interpretations also apply to transition matrices for the Midwest, South, and West regions (see Tables 1-4). Estimation results for the Midwest are similar to those for Northeast, implying that counties tend to cluster around States 2 and 3. That is, low-wage (high-wage) counties tend to experience rising (declining) wage. The time-invariant probabilities for the Midwest region indicate that, in the final period, States 2 and 3 are likely to include 76 percent ($= \pi_2 + \pi_3$) of total counties with wages around the regional average. In the South, wages are expected to be even smaller than that those in the Northeast and Midwest, with 58 percent ($= \pi_1 + \pi_2$) of the counties in South that cluster around States 1 and 2, and this percentage point rises to 80 percent when State 3 is added. In the West, in the final period, States 2 and 3 are likely to include 73 percent ($= \pi_2 + \pi_3$) of the counties in West. To provide an economywide picture of convergence, we calculated the transition matrix for the entire U.S. The time-invariant distribution for the whole U.S. suggests even more concentration around States 1 and 2, since in its calculation the U.S. average farm wage was taken as the reference point. The time-invariant distribution for the entire U.S. is ($\pi_1 = 0.22$, $\pi_2 = 0.46$, $\pi_3 = 0.20$, $\pi_4 = 0.08$, $\pi_5 = 0.04$) (see Figure 1).

Chi-square tests for Assumption 1 suggest that the process is time-invariant for the Midwest, South, and West as well. Furthermore, owing to a few periods

[5] Since the time-invariant distribution is computed as the left eigenvector corresponding to the (isolated) unit eigenvalue, which is the largest eigenvalue of the kernel P, the second largest eigenvalue should measure the speed of convergence.

of time over which the analysis is performed, we are left with the assumption, without testing it, that the process is of first-order. Put differently, the time horizon of the actual data is not long enough to formulate a second-order chain. Furthermore, the mobility measure μ is equal to 0.60 for the Midwest, 0.58 for the South, 0.60 for the West, and 0.61 for the entire U.S. This indicates that counties in the South that are represented by their average farm wages move from one state to another at a relatively slower speed than the other regions. The South has the highest persistence relative to the other regions and the entire U.S. Consistent with high persistence, the South has the highest rate of convergence $\lambda = 0.79$; and for the Midwest $\lambda = 0.71$, for the West $\lambda = 0.69$, and for the entire U.S. $\lambda = 0.70$.

5. Key findings and policy implications

This study is concerned with two questions: Are regional hired farm wages moving in the same direction? If so, are they consistent with the direction of the entire U.S. farm wages? Concerning with efficiency in agricultural labor markets, the study approximates it to the extent that it is reflected in farm wages. Time-invariant distributions of wages are calculated at region level, including the Northeast, Midwest, South, and West regions, and at the U.S. level, and then compared with respect to the speed of convergence and the shape of future regional wage distributions.

The key findings are threefold. First, in the future, wages in all the regions are expected to decline relative to the respective, current regional average wage. The same trend is anticipated for the entire U.S., too. This conjecture is drawn from the shape of regional and the U.S. time-invariant distributions, all of which are skewed right (see Figure 1).

Second, the lowest ($\mu = 58$) and highest ($\mu = 63$) mobility takes place in the South and Northeast, respectively. In conformity with this, the South and Northeast has the fastest ($\lambda = 0.79$) and lowest ($\lambda = 0.66$) speed of convergence. The same figures for the entire U.S. are in between the figures for the South and Northeast (i.e., $\mu = 61$ and $\lambda = 0.70$). Taken together, these indicators provide evidence for the predicted relative stability in agricultural markets in the South.

Third, convergence to lower-than-regional average wage is the strongest in the Northeast, reflected by the highest time-invariant probability corresponding to State 2, while it is the weakest in the South and modest at the U.S. level (see Figure 1). This can be, in part, attributed to sharply differing regional labor demands. In the North, where the convergence of farm wage is the highest, the absence of a significant supply of migrant labor creates competition for workers from California (5 percent), the South (16 percent), outside the US (66 percent), and within the region (13 percent) during peak labor requirements in September. Unlike the Northeast, however, 35 percent of the migrant labor force in the South comes from within the region, 57 percent from outside the US, 6 percent from the Northeast, and 2 percent from California. Even at off-peak periods, migrants consist of 46 percent of the South's farm labor force. This ready supply of labor decreases the pressure on wages, supporting the finding of weak convergence in the South. For the US, on the other hand, the results indicate that in the long run the average US farm wage is more likely to decline.

These findings do hold implications for migration of labor and technological change. With respect to migration, a significant number of migrant labor moves into areas of vegetables and fruits/nuts farming, while at the same time a relatively less significant amount goes into areas of horticulture and crop farming. For example, the proportion of farm worker who migrated to vegetables, fruits/nuts, horticulture, and crop farming areas was 52, 51, 29, and 20 percent, respectively, for the period 1989-91 (USDL, 1994). But, it is fortunate that weak regional competition for migrant labor owing to non-overlapping harvest periods keeps wages lower than they would be otherwise. The flip side of the coin is that wages are forced upward by within-region competition for migrant labor. Thus, because of the significant proportion of vegetables, fruits, and horticultural products in the Northeast and the absence of large migrant labor force, mobility of county-level wages would be expectably higher in that region compared to the South.

As regards technological change, there is a puzzle to solve. Considerable microevidence finds a positive relationship between the introduction of new technologies and rising wage inequality (i.e., divergence of wages) because, as Berman, Bound, and Griliches (1994) document, industries that invest more in R&D tend to pay a higher premium for skill. On the contrary, recent macroeconomic evidence suggests that technological change and wage inequality have been negatively correlated over time (see Blackburn, et al. (1990-91)). In the context of our study, conjecturing a decline in future farm wages relative to the current average wage, this puzzle raises few questions. In particular, does convergence of farm wages to lower-than-current average suggest that the future technological change will be of labor-saving (or labor augmenting) type? If so, what should the essential components of new farm bill be? A better characterization of institutions that provide technical skills is a requirement for a new farm bill, and the government should take the lead in the supply of such institutions not so much that the financing of such skill acquisition is beyond individual farmers' capacity but rather that labor-augmenting technical skills are also more likely to lead to land saving through intensive farming capabilities of farmers equipped with new skills. Namely, labor and land saving technological changes should go hand in hand, making labor abundant and thus cheaper.

A new farm bill may help raise productive efficiency, shift production to more productive regions, and boost aggregate output, provided that the farm legislation frees farmers to think about the optimal mix of crops without being constrained by government payments, and that it allows them to operate as profit maximizing agents. The government can accelerate this process by reducing farm subsidies and subsidies that are tied to farmers' production decisions. Firstly, the new farm bill should reduce the degree of government support to the farm sector and phase down subsidies in the coming years. The phase-out of direct government payments has two important implications for farm wages. Everything else equal, a decline in farm subsidies results in a decline in farm income. To the extent that farmers have perceived farm commodity payments as a permanent part of farm income, this decline will be indirectly reflected in farm labor demand and wages. Moreover, the loss of farm subsidies could increase the variability in farm income, making agricultural production more risky. Secondly, the new farm bill should no longer use commodity programs to control output. Under previous farm legistlations, annual set-aside programs were an important policy tool for controlling U.S. production of major program crops. To receive federal subsidies, farmers had to agree to set-asides of a portion of their acres. Under the new regime, such programs should be cautiously formulated so that producers freely respond to market prices.

This study offers two challenges for further research. The first is an extension of the current methodology to incorporate policy variables to allow for the quantification of specific impacts. Having developed that methodology, a second challenge is the application of the model to income from specific farming activities so that one can compare the distribution of income across farming types. This will help examine the trade-off among alternative income sources in the agricultural sector.

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A. Hypothesis testing

Here we present hypothesis testing procedures, adopted from Anderson and Goodman (1957) and Goodman (1962), to investigate whether or not the transition probability matrices at hand are time-stationary and follow a first-order process. For illustrative purposes, the following contingency table will be referred to throughout this Appendix:

$$A(t) = \begin{array}{|l|ll|l|} \hline \text{States} & 1 & 2 & \text{Total} \\ \hline 1 & n_{11}^t & n_{12}^t & n_{1.}^t \\ 2 & n_{21}^t & n_{22}^t & n_{2.}^t \\ \hline \text{Total} & n_{.1}^t & n_{.2}^t & n^t \\ \hline \end{array} \quad \text{and} \quad Z_i = \begin{array}{|l|ll|} \hline t/j & j=1 & j=2 \\ \hline t=1 & \hat{p}_{i1}^1 & \hat{p}_{i2}^1 \\ t=2 & \hat{p}_{i1}^2 & \hat{p}_{i2}^2 \\ t=3 & \hat{p}_{i1}^3 & \hat{p}_{i2}^3 \\ \hline \end{array}.$$

If $T = 3$, then we will have 3 contingency tables, $A(t)$ for $t = 1, 2, 3$, given two states $i = j = 1, 2$. In this example, $n_{ij} = \Sigma_{t=1}^3 n_{ij}^t$ and $n_i = \Sigma_{j=1}^2 n_{ij} = \Sigma_{t=1}^3 n_{i.}^t$

Assumption 1. The transition probabilities are time-stationary. Here the null hypothesis is $H_0 : p_{ij}^t = \hat{p}_{ij}$ for all t, and an alternative to this assumption is that the transition probability depends on t, $H_1 : p_{ij}^t = \hat{p}_{ij}^t$ where $\hat{p}_{ij}^t = \left(\frac{n_{ij}^t}{n_i^{t-1}}\right)$ is the estimate of the transition probability for time t. Under these hypotheses, the likelihood ratio is of the form, $\lambda = \Pi_t \Pi_{i,j} \left[\frac{\hat{p}_{ij}}{\hat{p}_{ij}^t}\right]^{n_{ij}^t}$, where $\Pi_{t=1}^T \Pi_{i,j} \hat{p}_{ij}^{n_{ij}^t}$ hold under H_0 and $\Pi_{t=1}^T \Pi_{i,j} (\hat{p}_{ij}^t)^{n_{ij}^t}$ holds under H_1. And $-2\log\lambda$ is distributed as $\chi^2_{(T-1)[m(m-1)]}$ when H_0 is true. It should be noted that the likelihood ratio resembles likelihood ratios obtained for standard tests of homogeneity in contingency table $A(t)$. The null hypothesis states that the random variables represented by the T rows in Z_i have the same distribution. In order to test it, we calculate $\chi_i^2 = \Sigma_{i,j} n_i^{t-1} (\hat{p}_{ij}^t - \hat{p}_{ij})^2 / \hat{p}_{ij}$. If H_0 is true, χ_i^2 has the limiting distribution with $(m-1)(T-1)$ degrees of freedom, and the set of χ_i^2 's is asymptotically independent, and the sum, $\chi^2 = \Sigma_{i=1}^2 \chi_i^2 = \Sigma_i \Sigma_{t,j} n_i^{t-1} (\hat{p}_{ij}^t - \hat{p}_{ij})^2 / \hat{p}_{ij}$, has the usual limiting distribution with $(T-1)[m(m-1)]$ degrees of freedom.

Another way of testing the same hypothesis is to calculate $\lambda_i = \Pi_{t,j} \left[\frac{\hat{p}_{ij}}{\hat{p}_{ij}^t}\right]^{n_{ij}^t}$ for $i = 1, 2$ by using Z_i. The asymptotic distribution of $-2\log\lambda_i$ is χ_i^2 with $(m-1)(T-1)$ degrees of freedom. The test criterion based on λ can then be written as $\Sigma_{i=1}^m - 2\log\lambda_i = -2\log\lambda$.

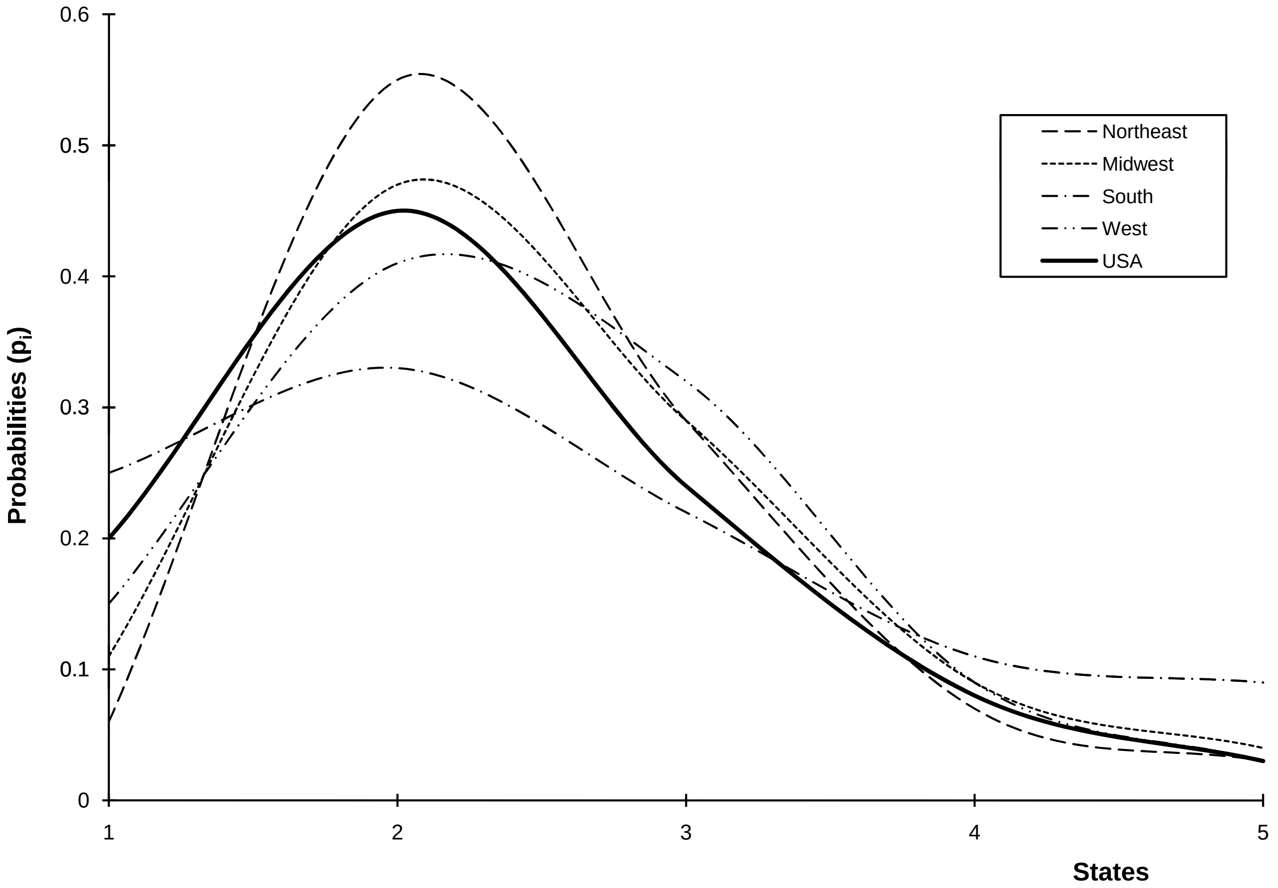
Assumption 2. The Markov chain is of a given order. Intuitively speaking, this assumption states that the location of a county at time $(t+1)$ is independent of its location at time t. A Markov chain is second-order if a county is in class

i at time $(t-2)$, in j at time $(t-1)$, and in k at time t. Let p^t_{ijk} denote the probability that a county follows a second-order chain. Time stationarity then implies $p^t_{ijk} = p_{ijk}$ for all $t = 2, \ldots, T$. A first-order stationary chain is a special case of second-order chain, one for which p^t_{ijk} does not depend on i.

Now let n^t_{ijk} be the number of counties in class i at $(t-2)$, in class j at $(t-1)$, and in class k at t. Let $n^{t-1}_{ij} = \Sigma_k n^t_{ijk}$ and $n_{ijk} = \Sigma^T_{t=2} n^t_{ijk}$. The maximum likelihood estimate of p_{ijk} for stationary chains is $\hat{p}_{ijk} = (n_{ijk}/\Sigma^m_{l=1} n_{ijl}) = \left(\Sigma^T_{t=2} n^t_{ijk}/\Sigma^T_{t=2} n^{t-1}_{ij}\right)$. The null hypothesis in this case is $H_0 : p_{1jk} = p_{2jk} = \ldots = p_{mjk} = p_{jk}$ for $j, k = 1, \ldots, m$. The likelihood ratio test criterion is $\lambda = \Pi^m_{i,j,k=1} \left[\frac{\hat{p}_{jk}}{\hat{p}_{ijk}}\right]^{n_{ijk}}$ where $\hat{p}_{jk} = (\Sigma^m_{i=1} n_{ijk}/\Sigma^m_{i=1}\Sigma^m_{l=1} n_{ijl}) = \left(\Sigma^T_{t=2} n^t_{jk}/\Sigma^{T-1}_{t=1} n^t_j\right)$ is the maximum likelihood estimate of p_{jk}. Under the null hypothesis, $-2\log\lambda$ has an asymptotic- $\chi^2_{m(m-1)^2}$ distribution where $\chi^2_j = \Sigma_{i,k} n^*_{ij}(\hat{p}_{ijk} - \hat{p}_{jk})^2/\hat{p}_{jk}$ and $n^*_{ij} = \Sigma_k n_{ijk} = \Sigma_k \Sigma^T_{t=2} n^t_{ijk} = \Sigma^T_{t=2} n^{t-1}_{ij} = \Sigma^{T-1}_{t=1} n^t_{ij}$ with $(m-1)^2$ degrees of freedom. The corresponding test using the likelihood ratio is $\lambda_j = \Pi^m_{i,k=1}\left[\frac{\hat{p}_{jk}}{\hat{p}_{ijk}}\right]^{n_{ijk}}$. The asymptotic distribution of $-2\log\lambda_j$ is chi-square with $(m-1)^2$ degrees of freedom.

To test the joint hypothesis $H_0 : p_{ijk} = p_{jk}$ for all $i, j, k = 1, 2, \ldots, m$, we calculate $\chi^2 = \Sigma^m_{j=1}\chi^2_j = \Sigma_{j,i,k} n^*_{ij}(\hat{p}_{ijk} - \hat{p}_{jk})^2/\hat{p}_{jk}$ which has the limiting distribution with $m(m-1)^2$. Similarly, the joint test criterion is $\Sigma^m_{j=1} - 2\log\lambda_j = -2\log\lambda = 2\Sigma_{j,i,k} n_{ijk}[\log\hat{p}_{ijk} - \log\hat{p}_{jk}]$.

Figure 1. Regional versus National Distribution of Farm Wages



The transition matrix for the Midwest region						
States	1	2	3	4	5	N
1	$\boxed{0.56}$	0.41	0.03			243
2	0.10	$\boxed{0.67}$	0.21	0.02		1009
3	0.01	0.35	$\boxed{0.49}$	0.13	0.02	607
4		0.11	0.44	$\boxed{0.31}$	0.14	178
5			0.14	0.30	$\boxed{0.56}$	97
T-invariant	0.11	0.47	0.29	0.09	0.04	2134
Eigenvalues	1.0	$\boxed{0.71}$	0.51	0.30	0.09	

The transition matrix for the South region						
States	1	2	3	4	5	N
1	$\boxed{0.77}$	0.20	0.03			685
2	0.15	$\boxed{0.59}$	0.21	0.03	0.02	892
3	0.04	0.30	$\boxed{0.44}$	0.17	0.05	509
4	0.01	0.13	0.33	$\boxed{0.33}$	0.20	298
5		0.03	0.12	0.28	$\boxed{0.57}$	238
T-invariant	0.25	0.33	0.22	0.11	0.09	2622
Eigenvalues	1.0	$\boxed{0.79}$	0.55	0.29	0.08	

The transition matrix for the West region						
States	1	2	3	4	5	N
1	$\boxed{0.60}$	0.37	0.02	0.01		121
2	0.13	$\boxed{0.60}$	0.25	0.02		328
3	0.02	0.30	$\boxed{0.52}$	0.14	0.02	257
4	0.03	0.09	0.43	$\boxed{0.36}$	0.09	74
5		0.04	0.25	0.17	$\boxed{0.54}$	26
T-invariant	0.15	0.41	0.32	0.09	0.03	806
Eigenvalues	1.0	$\boxed{0.67}$	0.49	0.32	0.12	

The transition matrix for the entire U.S.						
States	1	2	3	4	5	N
1	$\boxed{0.66}$	0.30	0.03	0.01		1069
2	0.14	$\boxed{0.65}$	0.19	0.02		1443
3	0.02	0.35	$\boxed{0.47}$	0.14	0.02	1488
4		0.13	0.41	$\boxed{0.32}$	0.14	579
5		0.03	0.20	0.29	$\boxed{0.48}$	373
T-invariant	0.20	0.45	0.24	0.08	0.03	4952
Eigenvalues	1.0	$\boxed{0.70}$	0.51	0.28	0.08	