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DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS
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THE IMPACT OF WAGE DIFFERENTIALS ON CHOOSING TO WORK IN AGRICULTURE

by

Jeffrey M. Perloff

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Jeffrey M. Perloff

August 1990

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The Impact of Wage Differentials on Choosing to Work in Agriculture

The likelihood of nonagricultural workers joining the agricultural work force in response to an increase in the agricultural wage is estimated in this study. Knowing the responsiveness of the labor supply to wage differentials is important for evaluating many public policies. For example, if the Immigration Reform and Control Act of 1986 (IRCA) eventually restricts the supply of ineligible immigrant labor in the United States, many farmers and legislators fear large wage increases, which will lead to significant crop losses (at least in the short run) or mass noncompliance with the law. How realistic are the fears that large wage adjustments will be required to equilibrate the hired farm worker labor market is assessed in this study.

The study is based on 1988 data from the U. S. Department of Labor, Bureau of Labor Statistics Current Population Survey (CPS), which is a random sample covering all sectors of the economy. The decision to work in the agricultural or the nonagricultural sectors and wages in each sector, controlling for choice of sector, are simultaneously determined. Then the empirically estimated model is used to simulate the increase in the share of agricultural workers from a given increase in the relative agricultural wage.

In the first section, the basic modeling methodology is developed. The data set is described and summary statistics for the key variables are presented in the second section. The empirical results are discussed in the third section. Simulations are used in the next section to show the likely response of workers to higher wages in the agricultural sector. In the final section, inferences and conclusions are drawn from the analyses.

Methodology

A model of industry choice and wages by industry is used to examine the effect of relative wages and nonwage factors on industry choice. The model is a variant of those of Lee, Willis and Rosen, Nakosteen and Zimmer, and Robinson and Tomes. In this model, the natural logarithms of the hourly earnings ("wages") in the agricultural (w_a) and nonagricultural (w_n) sectors are a function of demographic and individual characteristics (X_a and X_n) and unmeasured sources of individual differences (ε_a and ε_n), and the impact of individual characteristics on wages may vary across the sectors:

$$w_a = X_a'\beta_a + \varepsilon_a, \tag{1}$$

and

$$w_n = X_n'\beta_n + \varepsilon_n. \tag{2}$$

An individual's wage in a given sector is observed only if the individual is working in that sector at the time of the CPS interview.

An individual's choice of sector may depend on nonwage factors as well as the relative wage in the two sectors. Agricultural work is more physically taxing and dangerous than many other types of work. However, many people prefer working outside in agriculture to an indoor job. Let c be the cost or benefit (disutility or utility) of working in agriculture relative to working in another industry. This (unobserved) variable is a function of a worker's characteristics, Z:

$$c = Z'\delta + \varepsilon_c. \qquad (3)$$

The worker compares this cost or benefit to the relative wage in agriculture. The wage ratio (R) between agricultural and nonagricultural sectors is approximated by the difference in the natural logarithms of these wages:

$$R \approx w_a - w_n. \qquad (4)$$

The difference in the logs is a close approximation of the ratio for small differences. Alternatively, one can define R as the log wage difference so that equation (4) holds exactly.

The worker chooses to work in agriculture (industry choice, i, equals 1) only if the total benefit to working in agriculture, R - c, is positive:

$$i = 1 \quad \text{if } R - c > 0$$

and (5)

$$i = 0 \quad \text{if } R - c \leq 0.$$

If $i = 1$, then the observed wage is w_a; otherwise, the observed wage is w_n.

The disturbance terms (ε_a, ε_n, and ε_c) in equations (1), (2), and (3) are assumed to be jointly normally distributed. As a result, a probit estimation technique can be used to estimate the choice of industry equation (5). Substituting for R in equation (5) using equations (4), (1), and (2) and for c using (3), we obtain a reduced-form industry choice equation,

$$i = 1 \quad \text{if } X_a'\beta_a - X_n'\beta_n - Z'\delta - \varepsilon_c > 0$$

and (6)

$$i = 0 \quad \text{if } X_a'\beta_a - X_n'\beta_n - Z'\delta - \varepsilon_c \leq 0.$$

which can be estimated using probit with the exogenous variables (X_a, X_n, and Z) in equations (1), (2), and (3) on the right-hand side. Conditional on industry choice, as determined by equation (6), the hourly earnings equations (1) and (2) can be estimated using Heckman's (1979) technique to compensate for sample selection bias. Were we to estimate equations (1) and (2) using ordinary least-squares techniques, the estimates would be biased because workers are not randomly assigned to the agricultural and nonagricultural sectors. That is, the unobserved individual difference or disturbance terms (ε_a and ε_n) would not be normally distributed if we examine data for only those workers observed in each sector.

Based on the consistently estimated wage equations, (1) and (2), the estimated wage differential is $\hat{R} = X_a'\hat{\beta}_a - X_n'\hat{\beta}_n$. That is, although we observe a worker's wage in one sector only, these equations can be used to determined the relative wage. Substituting this estimated value for R in equation (5), the structural probit for industry choice can then be estimated.

The key exogenous variables represent regions and demographic characteristics. Because agricultural and nonagricultural wages differ geographically (reflecting differences in labor demand and supply and the type of work), regional dummies are included in X_a and X_n. Years of schooling and years of experience are also hypothesized to influence wages and are included in X_a and X_n. Wages and the costs of working in agriculture may be affected by workers' racial and ethnic characteristics because of discrimination or because they reflect language skills and legal status. They may, for similar reasons, also affect the costs of working in agriculture; hence they are included in X_a, X_n, and Z.

Also included is a dummy variable for "married, living with spouse," which has an ambiguous effect because married couples make joint employment and housing decisions. Given the relatively high variance in agricultural wage, one may be more willing to work in agriculture if one's spouse has a steady income; however, offsetting that effect, to the degree that migration is required in agricultural jobs, living with a spouse may be difficult. Similarly, having children may make migratory living relatively unattractive; however, whole families may work together in agriculture. Thus, marital status and children are included in Z, but their signs are also uncertain.

The reduced-form probit and the wage equations can be estimated without any further restrictions. The identifying restrictions that allow us to estimate the structural probit equation are that education and experience variables affect wages but do not affect the choice of sector except indirectly through their effects on the wage differential. Thus, in the structural probit, only other demographic characteristics and the wage differential are included. It is hard to tell a story why a year or two more of primary education would affect one's utility from working in agriculture rather than nonagriculture except indirectly through its effect on relative wages. It is similarly difficult to see why experience would affect utility directly; however, a case might be made that age (the experience variable is a linear function of age) affects utility differently in the two sectors. Not using the experience variables as identifying restrictions, however, has only a minor quantitative (and not a qualitative) effect on the results reported below.

The Data

Data used in this study are from the CPS for the 1988 calendar year, which is a random sample of individuals by housing units throughout the United States conducted monthly over the year.[1] Because selection is based on location, agricultural workers, nonagricultural workers, the unemployed, and documented and undocumented immigrants are surveyed.

The inhabitants of any given housing unit are asked questions about economic issues at two times, separated by a four-month interval. To prevent double counting some workers (people initially interviewed in the first eight months of the year have a second interview in the same calendar year), only the first of these interviews is used. Only individuals at least 16 years old, with no missing variables, who usually work at least 15 hours per week (i.e., the employed), and earned at least $2 an hour (to eliminate observations with implausible hourly earnings) were included.

Sample Restrictions

In the following analysis, the sample is restricted to only a subset of males who are relatively likely to consider agricultural employment: workers with no more than a ninth-grade education who live outside of major cities. Because less than 2 percent of all CPS workers are in agriculture, the industry choice equation for the entire sample involves the tail of the sector-choice equation's error distribution; so the results are more sensitive to the choice of the error distribution (e.g., normal versus logistic) than if the mean were closer to the center of the distribution as reported below. Estimating a probit for all workers indicates that the only important determinant of agricultural employment is gender, and the estimated equation predicts (with nearly 99 percent accuracy) that everyone works in nonagriculture. The wage equations are not substantially different, however, if a larger sample is used.

Education was restricted because it would be a nonproductive exercise to calculate the wage differential necessary to induce a brain surgeon or other skilled worker to start working as an agricultural field hand. Although there are some hired farm workers who are highly educated (about one in 20 are college educated), the majority of agricultural workers have less than a high school education. The average number of years of education of seasonal agricultural workers is 10 according to the CPS and 7 according to the Department of Labor's National Agricultural Workers Survey for the same time period. The results reported below are not sensitive to the arbitrary ninth-grade cutoff. Similar qualitative results are obtained for thresholds at eighth grade, tenth grade, eleventh grade, and the twelfth grade (short of a diploma).[2]

Similarly, it is unlikely that workers in the middle of Manhattan are likely to switch to farm work with any plausible agricultural wage increase; so, because we are concerned with the short-run effect of a wage differential on choice of working in agriculture, the sample has been further restricted to those hired workers who live outside of major metropolitan areas with more than 100,000 people ("nonurban" areas). Although some agricultural workers with limited education live in cities, especially in California (e.g., Fresno), over two-thirds do not. Of workers with nine years or less of schooling, only one in ten work in agriculture of all workers compared to one in five of our nonurban sample.

Females were dropped because there are not enough women in the sample to estimate an agricultural wage equation for females. There are only 396 females with 12 in agriculture (and more than 12 variables in the wage equations) in the sample. The effects of also including city-dwellers and females are briefly discussed below.

Means and Standard Deviations

Presented in Table 1 are the means and standard deviations (for continuous variables) of several key variables for our sample of 931 men, of whom 19.4 percent identified themselves as hired agricultural workers (including managers and foremen). It is also shown in the table that more than a quarter (26.2 percent) of those in our sample live in the South Atlantic region, whereas only slightly more than a fifth (21.0 percent) of the agricultural workers live in that region. Similarly, where only 7.7 percent of the sampled live in the West (Pacific region), over a quarter (27.5 percent) of the agricultural workers live there. Moreover, only 5.7 percent of those in the total sample, but 27.1 percent of the agricultural workers, live in California.

There are relatively more blacks and other nonwhites in the agricultural subsample than in the overall sample. Agricultural workers are less likely to be married and living with their spouses than nonagricultural workers (52.5 versus 77.9 percent), perhaps reflecting the migratory nature of many agricultural jobs and the relative youth of agricultural workers.

Nonagricultural workers are, on average, seven years older than agricultural workers. Because the average level of education in the United States has risen over time, non-Hispanics with relatively little formal education tend to be older than the rest of the population. The average age of workers in agriculture is 42; the average age of non-Hispanics is 49 (and the median is 50), however the average age of Hispanics is only 35 (and the median is 32).

Although 17.9 percent of the nonagricultural workers are union members, only 1.7 percent of the agricultural workers are union members (all of whom are in California). In this sample, agricultural workers average one fewer year of school than nonagricultural workers. Agricultural workers also have 6 years less work experience (calculated as age minus 6 minus years of formal school).

Many agricultural workers receive piece-rate payments (35 percent receive only piece rate compared to 11 percent of nonagricultural workers). In this study, hourly earnings are calculated by dividing the reported weekly earnings by the reported usual weekly hours. For workers who receive time rate pay, this calculated hourly earnings number is usually identical or very close to the reported wage. The average hourly earnings of agricultural workers ($4.80) is only 62 percent of those of nonagricultural workers ($7.69). They work, on average, 2.2 more hours a week, however, so that the average weekly earnings of agricultural workers are 66 percent of that of nonagricultural workers ($203 versus $308).

The Empirical Results

The first step of the analysis is to estimate a reduced-form probit equation describing how choice of industry depends on exogenous geographic and demographic variables. Then, conditional on industry choice, wage (hourly earnings) equations are estimated for each sector. Finally, a structural probit equation is estimated.

Reduced-Form Probit Equation

The reduced-form probit (working in agriculture = 1 and working in non-agriculture = 0) coefficient and asymptotic standard error estimates are shown in the second and third columns of Table 2. Because it is a reduced-form equation, the coefficients reflect both wage differential and cost factors as described above.

Compared to the West, living in the West North Central region makes one more likely to be in agriculture (all else the same). Similarly, Californians in the sample are much more likely to work in agriculture than others in the West.

An extra year of experience makes a worker more likely to work in agriculture if the individual has at least 32 years of experience (and less likely otherwise). In contrast, one more year of formal schooling makes one less likely to work in agriculture if one has had at least 5 years of schooling. Married men living with their spouses are less likely to be agricultural workers; however, the more children one has, the more likely one works in agriculture.

Workers who report their ethnicity as Mexican (as opposed to Mexican-American, Chicano, or other non-Mexican Hispanic or non-Hispanics) are much more likely to work in agriculture than other groups. Workers who report that they are non-Mexican Hispanics (including Mexican-Americans) are also more likely to work in agriculture than other groups but not as likely as the Mexicans.

The equation correctly predicts 87.3 percent of the observations. The various standard probit R^2 measures (Maddala, Hensher and Johnson, and Chow) range from 0.29 to 0.46.[3] A log-likelihood test strongly rejects the hypothesis that only the constant term matters.

Wage Equations

The wage equations (the regression of the natural logarithm of hourly earnings on demographic and geographic variables) in Table 3 were estimated using Heckman's two-stage technique to control for nonrandom industry choice. The correlation between the disturbance in the regression and the selection criteria is very high (nearly one), and the estimates of the correlation are virtually the same for the two equations. On the basis of a Heckman t-test on the selectivity parameter, we can reject the hypothesis that ordinary-least squares estimates have no sample selectivity bias in both the wage equations.

The equations show that there is a different relationship in the two sectors with respect to geographic and demographic variables. In the nonagricultural sector, controlling for demographic characteristics, wages do not differ statistically significantly across regions or states with the sole exception that wages are higher in California. In contrast, there are pronounced regional differences in agricultural wages. Compared to the West, wages are significantly lower in the New England, mid-Atlantic, East North Central, South Atlantic, East and West South Central, and Mountain regions. Surprisingly, in this sample, agricultural wages are lower in California than in the rest of the West, controlling for other factors. The wages in Texas are significantly lower than in the West.

At least for this relatively uneducated group, extra education does not statistically significantly increase one's nonagricultural wage. In agriculture, however, extra education is positively related to wages up to 5 years of school but negatively for more years.[4] Agricultural wage differences due to extra years of school are small (only a few pennies per hour), however.

At least until one has 33 years of experience, extra experience increases the nonagricultural wage; whereas, extra experience (or age) does not have a statistically significant effect on the agricultural wage. In the nonagricultural sector, having 20 years of experience instead of 10 is worth 18¢ more per hour.

In the nonagricultural sector, controlling for other factors, blacks earn 14 percent less per hour than whites; whereas there is no statistically significant wage differential between whites and other nonwhites or either group of Hispanics. In the agricultural sector, workers who report their ethnicity as Mexican earn 82 percent more an hour than whites; other Hispanics earn 65 percent more; and blacks earn 28 percent more.[5] These cross-sector racial wage differentials may reflect either discrimination or other effects not otherwise captured by the exogenous variables in this equation. For example, nonwhites and Hispanics may be more likely to work in jobs that pay premia, such as dangerous jobs or certain migrant jobs.

The qualitative results from these wage equations are similar to those of earlier studies (e.g., Perloff) that are based on CPS data but did not adjust for the sample selection effect of industry choice. The quantitative effects differ substantially, however. For example, in the wage equations shown above, the estimated ratio of wages in agriculture to those in nonagriculture averaged 31 percent over the sample. Based on estimates of the same equations using ordinary least squares, the comparable average wage ratio is 66 percent, or more than double, reflecting the failure to control for sample selection. Those people for whom the wage ratio is relatively high are more likely to work in agriculture as discussed next.

Structural Probit Equation

The structural probit equation is reported in the last two columns of Table 2. To estimate it, the wage ratio, R, is approximated by the estimated difference in the natural logarithm of the wage one would earn in agriculture and in the nonagricultural sector.

In the structural probit equation, controlling for demographic and wage ratios, workers are more likely to work in agriculture in most other regions of the country than in the West. They are also more likely to work in agriculture in California than in the rest of the West. Of course, given that wage ratios vary geographically, much of the geographic difference in choice of sector is captured by the wage-ratio term.

The structural probit equation does not show a significant difference between choice of sector among whites and other racial or ethnic groups after controlling for wage ratios. That is, the preference of working in agriculture of these groups shown in the reduced-form equation is presumably captured in the structural equation by the wage-ratio term, which reflects relatively high agricultural wages for these groups.

The wage ratio has a large, statistically significant effect. A 1-percent increase in the relative wage in agriculture increases the probability that one works in agriculture by 3.37 percent at the sample mean. On average over the entire sample (Hensher and Johnson), a 1-percent increase in the relative agricultural wage increases the probability of working in agriculture by 1.3 percent.

The ratio of the estimated agricultural wage to the nonagricultural wage is 0.37 for those workers in agriculture and only 0.30 for those who are not in agriculture. That is, the estimated wage ratio of those who choose to work in agriculture is nearly a quarter more than of those who choose not to work in agriculture. Thus, choosing to work in agriculture appears, in large part, to be based on a comparison of wages between the two sectors.

The structural probit has virtually the same explanatory power as the reduced-form equation. The probit R^2 measures range from 0.29 to 0.46; and the prediction success table shows that the correct sector is predicted for 87.5 percent of the sample.

Sensitivity Experiments

Other experiments were used to test the sensitivity of these results to the specifications used. In none of these experiments was the key result (the effect of the wage ratio in the structural probit) substantially affected.

As a sensitivity test on the assumed error structure, the system was estimated using logit rather than probit equations (that is, the disturbances were modeled as logistic rather than normal). Although the key result was virtually the same as with the probit system, the correlation between the reduced-form logit equation and the selectivity equations' disturbance terms were estimated to be greater than one, which is, of course, impossible. For that reason, only the probit equations are reported here.

The system of equations reported above does not have a union variable on the right-hand side of any equation. Expanding this system of equations to include a union equation (with an error term that was correlated with the industry choice equation error term) and including a union dummy as an endogenous right-hand side variable in the wage equations proved impossible to estimate (due to the very small number of union workers in the agricultural sector within this sample). Using the specification above, but including union as an exogenous variable, leaves the race and ethnicity coefficients in the wage equation virtually unaffected. As a result, union status was left to the residual term in the equations reported here. Alternatively this system may be viewed as quasi-reduced form equations where the included demographic and regional (all the union members in the sample are in California) variables also explain union status.

As mentioned above, the results are not sensitive to the educational threshold. In another experiment, seasonal dummy variables (eleven monthly dummies), which were included in all the equations, had coefficients that were not statistically significantly different from zero either individually or collectively in any equation. In yet another experiment, military veteran status was included in the probits. Although its coefficient was significant in the reduced-form probit, it is not included in the equations reported here because of its ambiguous interpretation. On the one hand, virtually all veterans have legal status (although the inverse does not hold); on the other hand, it may be a proxy for other factors such as intelligence or skills. Next, the dummy variable for non-Mexican Hispanic was divided into Mexican-American (or Chicano) and other Hispanics; however, these latter two variables had virtually identical coefficients.

Finally, a model was estimated using a larger sample that included city dwellers and females but was still restricted to those with no more than nine years of education. Agricultural workers are only 6.6 percent of this larger sample. The same system was used except that a dummy variable for city and another for female were included on the right-hand side of all equations. Both these dummies had large, statistically significant effects in all equations; however, the other demographic coefficients were relatively unaffected. In the structural probit equation, the relative wage term remained large and had a t-statistic of 4.7. The predicted 4.4 percent shift into agriculture from a 1-percent increase in the relative wage at the sample mean is larger than in the model above. The original model is stressed in this paper because the estimates in the larger model are based on estimates in the tails of the normal (probit) distribution, which make inferences outside the sample, which we now examine, more speculative.

The Response to Higher Agricultural Wages

The system of equations can be used to simulate the effect of higher wages on the agricultural supply of nonurban, relatively uneducated workers. As shown in Table 4, the estimated agricultural wage is only 29 percent of the estimated nonagricultural wage when averaged across the sample. The simulations reflect the effects of an across-the-board increase in the agricultural wage holding the nonagricultural wage constant. That is, the simulations increase the constant term in the regression on the logarithm of the agricultural wage, which is equivalent to a constant percentage increase in the agricultural wage for all workers.

In Table 4, two methods are used to calculate the effect of the wage increase on the share of workers in agriculture as both are commonly used in probit studies. In the first method, a worker is assigned to the agricultural sector if the probability he works in agriculture (according to the structural probit equation) is at least 50 percent. Using this 50-percent rule, the model predicts that 11 percent of the workers will work in agriculture. In the second method, the probability of working in agriculture that the model predicts for each individual is averaged across all individuals (using equal weights). This average is 19 percent, which is (by the nature of the probit estimation technique) virtually the same as the actual percent in the sample.

If the agricultural wage were increased by 2 percent, the wage ratio would increase by 2.2 percent. Using the 50-percent rule, the share of workers in agriculture would increase by 3.1 percent (or 0.33 percentage points from 10.63 to 10.96 percent); whereas, using the second method, the share would increase by 3.2 percent (or 0.62 percentage points from 19.45 to 20.07 percent). If the agricultural wage were raised by 10 percent (with no response in the nonagricultural wage), the first method indicates a 23-percent increase in the share of agricultural workers; and the second method predicts a 16 percent increase.

Simulations of larger wage increases should, of course, be viewed with substantial caution. If the point estimates are assumed to hold with larger increases, a 50-percent increase in the agricultural wage leads to a 139-percent increase in the share of agricultural workers using the first method (to a quarter of this relatively uneducated labor force), and an 82-percent increase using the second method.

In interpreting these simulations, it should be remembered that they reflect a national average for nonurban, relatively uneducated workers. There may also be (a presumably smaller) response by better educated or urban workers. Thus, the simulations reported here may be lower bounds on the true (larger) response. However, if IRCA were strictly enforced, driving undocumented workers out of agriculture, a substantial number of U. S. citizens and immigrants with legal documentation would have to be hired to replace them. One survey of California employers (Rosenberg and Perloff) indicates that in 1987, after the passage of IRCA, one-third of new hires were illegal aliens.

Conclusions

This paper presents a model of industry choice and wage determination. The chief result of this analysis is that inducing more workers to switch to agriculture may not require large wage increases. Indeed, a 10-percent increase in wages may increase the share in agriculture of nonurban male workers with no more than a ninth-grade education by nearly a quarter. Nonetheless, in some states and in certain crops, half or two-thirds of the agricultural work force has been undocumented aliens so that larger wage increases may be required. Because this study has focused on only supply-side effects, a full analysis of the wage effects of a government policy that prevented undocumented workers from working requires a comparable demand-side analysis.

Further work on agricultural labor supply remains to be done as well. For example, this report has focused on the role of higher wages in attracting agricultural labor. In general, however, better working conditions and other benefits (such as health insurance and housing) could also attract extra workers, holding wages constant.

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Footnotes

[1] Some critics argue that the BLS undersamples migrant and illegal agricultural workers. Although this complaint may be valid, the CPS data set is used for four reasons. First, the CPS is the only random sample that includes both agricultural and nonagricultural workers in sufficient quantities to conduct a study of individual supply responses to wage differentials. Second, the included variable "Mexican" (as opposed to Mexican American, Chicano, or other Hispanic or non-Hispanic workers) is a proxy for legal status. This proxy is imperfect, however, because some of these Mexican workers may have legal status and others may misreport whether they are Mexicans. Third, if IRCA or other programs prevent undocumented aliens from working in agriculture, one would want be primarily interested in the determinants of industry choices of workers with legal status. Fourth, the empirical study reported below was also estimated using only non-Hispanic workers, and the qualitative results for all equations and the quantitative results for the wage equations are virtually the same as those reported below. Thus, it seems unlikely that including more workers without legal status in the sample or including a variable for legal status would greatly change the results.

[2] It is unlikely that restricting our sample to relatively uneducated workers creates a sample selection bias for two reasons. First, in the short run, education must be viewed as a predetermined variable, and selecting on a prede-

termined variable does not cause a sample selection bias. Second, a Heckman sample selection test (based on a sample of all workers) does not indicate a sample-selection bias.

[3] The probit equations and summary statistics were estimated using Kenneth J. White's Shazam program, version 6.1. The sample-selection adjusted wage equations reported below were estimated using William H. Greene's Limdep program, version 5.1.

[4] Most previous studies based on the CPS (without educational limits on the sample) find that education does not have a statistically significant effect in the agricultural sector (e.g., Perloff) but does in the nonagricultural sector.

[5] The unconditional mean hourly earnings by demographic group in agriculture are: all $4.87 (with a standard error of 2.16), white 5.00 (2.14), black $4.14 (2.13), Hispanic $4.97 (1.70), and Mexican $5.07 (1.68).

Table 1

Means and Standard Deviations

Variable	All	Agriculture	Non-Agriculture
Number of Observations	931	181	750
Binary (0-1) variables (percent)			
Region			
New England (CT,MA,ME,NH,RI,VT)	8.8	2.8	10.3
Mid-Atlantic (NJ,NY,PA)	4.4	0.6	5.3
East North Central (IL,IN,MI,OH,WI)	7.7	3.3	8.8
West North Central (IA,KS,MN,MO,ND,NE,SD)	10.2	14.4	9.2
South Atlantic (DC,DE,FL,GA,MD,NC,SC,VA,WV)	26.2	21.0	27.5
East South Central (AL,KY,MI,TN)	13.2	7.2	14.7
West South Central (AR,LA,OK,TX)	12.6	12.7	12.5
Mountain (AZ,CO,ID,MT,NM,NV,UT,WY)	9.2	10.5	8.9
Pacific (AK,CA,HI,OR,WA)	7.7	27.5	2.8
States			
California	5.7	27.1	0.5
Texas	6.2	8.3	5.7
Florida	3.7	3.9	3.6
Demographic characteristics			
Black	13.1	14.4	12.8
Other Nonwhites	2.1	1.7	2.3
Mexican (ethnicity)	13.2	43.1	6.0
Mexican-American (ethnicity)	4.9	7.7	4.3
Other Hispanics (ethnicity)	1.4	2.2	1.2

Married, Living Together	72.9	52.5	77.9
Job Characteristics			
Union Member	14.7	1.7	17.9
Paid by the Hour	75.8	64.6	78.5
Agricultural Manager or Foreman	1.1	5.5	0.0
Agriculture (Hired Farm Worker)	19.4	100.0	0.0
Continuous variables (mean (s.d.))			
Number of Children	.7	1.07	.6
	(1.2)	(1.5)	(1.1)
Years of Schooling	7.5	6.6	7.7
	(2.1)	(2.2)	(2.0)
Years of Experience	34.3	29.3	35.6
	(13.9)	(16.9)	(12.8)
Earnings per hour ("wage")	7.13	4.80	7.69
	(3.7)	(2.2)	(3.7)
Usual weekly hours	40.5	42.3	40.1
	(8.6)	(10.8)	(7.9)

Table 2

Probit Equation: Probability of Working in Agriculture

	Reduced-Form Equation		Structural Equation	
	Coefficient	Asymptotic S.E.	Coefficient	Asymptotic S.E.
Constant	-1.6850	0.7919	-0.8320	0.6336
New England	0.8507	0.6578	1.7278	0.6718
Mid-Atlantic	0.2749	0.7558	1.8039	0.8124
East North Central	0.7512	0.6572	1.9637	0.7020
West North Central	1.6973	0.6319	2.1878	0.6269
South Atlantic	0.7273	0.6270	2.2353	0.6831
East South Central	0.8943	0.6425	2.3763	0.7039
West South Central	0.7172	0.6432	2.2399	0.7095
Mountain	0.5270	0.6298	1.9857	0.6958
California	2.5634	0.6735	4.2979	0.7616
Texas	-0.3190	0.3340	0.1003	0.3459
Florida	0.1140	0.3002	-0.1936	0.2986
Mexican	1.3387	0.2331	0.4290	0.3167
Non-Mexican Hispanic	0.9263	0.2601	0.0284	0.3384
Black	0.5120	0.1741	-0.1448	0.2335
Other Nonwhite	0.3833	0.4249	-0.7369	0.4859
Married, Living with Spouse	-0.6666	0.1385	-0.6085	0.1298
Number of Children	0.0899	0.0537	0.0825	0.0495
Years of School	0.3610	0.1400	-	-
Years of School Squared	-0.0358	0.0120	-	-
Experience	-0.0561	0.0160	-	-
Experience Squared	0.0009	0.0002	-	-

$R = \ln(w_o) - \ln(w_n)$	-	-	1.7273	0.3742
Number of Observations	931		931	
Log-Likelihood (Constant only)	-458.57		-458.57	
Log-Likelihood	-300.27		-301.65	
Likelihood ratio test	316.61 (21 d.f.)		313.85 (18 d.f.)	
R^2 Measures:				
Maddala R^2	0.29		0.29	
Cragg-Uhler R^2	0.46		0.46	
McFadden R^2	0.35		0.34	
Chow R^2	0.38		0.37	
Percentage of Correct Predictions	87.3		87.5	

Prediction Success Table

		actual 0	actual 1
	0	731	99
Predicted	1	19	82

Prediction Success Table

		actual 0	actual 1
	0	733	99
Predicted	1	17	82

Table 3

Logarithmic Wage Equations Adjusting for Sample Selectivity

	Agriculture		Non-Agriculture	
	Coefficient	Asymptotic S.E.	Coefficient	Asymptotic S.E.
Constant	1.3161	0.3586	1.4641	0.1777
New England	-0.5338	0.2736	0.0637	0.1235
Mid-Atlantic	-0.9429	0.3073	-0.0006	0.1322
East North Central	-0.7060	0.2761	0.0578	0.1245
West North Central	-0.3139	0.2846	0.0540	0.1326
South Atlantic	-0.9556	0.2555	-0.0343	0.1184
East South Central	-1.0005	0.2658	-0.0745	0.1211
West South Central	-0.9481	0.2734	-0.0169	0.1248
Mountain	-0.8560	0.2648	0.0473	0.1211
California	-0.5710	0.2771	0.4837	0.2378
Texas	-0.3038	0.1215	-0.0474	0.0932
Florida	0.1633	0.1099	0.0314	0.0807
Years of School	0.1535	0.0555	0.0339	0.0395
Years of School Squared	-0.0149	0.0050	-0.0023	0.0034
Experience	-0.0061	0.0069	0.0325	0.0057
Experience Squared	0.0001	0.0001	-0.0005	0.0001
Mexican	0.6067	0.1136	0.0820	0.1004
Non-Mexican Hispanic	0.5082	0.1129	-0.0225	0.0840
Black	0.2511	0.0762	-0.1543	0.0521
Other Nonwhite	0.7284	0.1866	0.0755	0.1061
Selectivity Parameter	0.3867	0.0936	0.4607	0.1348

Number of Observations	181	750
Mean of ln(wage)	1.50	1.94
Standard Deviation of ln(wage)	0.35	0.44
Standard Error of the Regression	0.27	0.40
Standard Error Corrected for Selection	0.40	0.47
Sum of Squared Residuals	13.62	119.85
R^2	0.39	0.17
F(20, 729)	5.15	7.71
Log-Likelihood	-22.70	-376.50
Log-Likelihood (Constant only)	-67.70	-448.41
$\chi^2(20)$	90.00	143.82
Squared Correlation of Disturbance in Regression and Selection Criterion	0.937	0.979

Table 4

Effect of an Increase in the Agricultural Wage

Increase in the Agricultural Wage (%)	w_a/w_n (%)	Percent Agricultural Workers	
		50 % Rule	Average
0.00	29.38	10.63	19.45
2.00	30.04	10.96	20.07
4.00	30.63	11.82	20.69
6.00	31.21	12.35	21.31
8.00	31.80	12.78	21.94
10.00	32.39	13.10	22.57
20.00	35.34	15.47	25.76
30.00	38.28	18.69	28.96
40.00	41.23	21.91	32.15
50.00	44.17	25.35	35.30