

# The Effect of Legalization on Wages and Health Insurance of Farm Workers: Evidence from the National Agricultural Workers Survey

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## *Abstract:*

We estimate the effect of legalization and the associated increase in job mobility on the wages and benefits of agricultural workers. Using data from the National Agricultural Workers Survey, we employ propensity-score matching techniques to compare legal permanent residents with an appropriate control group of undocumented workers.

Consistent with previous findings, we document that legalization results in a modest wage gain in the neighborhood of 5 percent. Further, we also show that, in addition to higher wages, legalization leads to a significantly higher likelihood of receiving employer-sponsored health insurance as well as a bonus. Because previous estimates of the impact of legalization do not consider other forms of compensation, they understate the true gains to legalization.

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## **I. Introduction**

Undocumented workers living in the United States are restricted to employment in the informal economy, and thus have limited job mobility. They seek to avoid apprehension; and once employed, they are unlikely to search for higher paying jobs. In contrast, legal permanent residents are authorized to live and work in the United States, and so they are free to accept any job in any sector of the formal economy. If employers want to retain such workers (in the face of labor shortage or product demand pressures, for example), they are forced to offer these workers higher compensation. Given the greater labor market mobility of legal permanent residents, one would expect that there to be significant wage premium associated for legal permanent residents compared to undocumented workers.<sup>1</sup>

Estimating the wage effects of obtaining legal permanent residence can be difficult due to limited data on the undocumented population. One of the best examples in recent literature comes from Kossoudji and Cobb-Clark (2002). Their study uses the Legalized Population Surveys (LPS), a panel dataset consisting of a sample of the undocumented population who received amnesty and legal permanent residence under the 1986 Immigration Reform and Control Act (IRCA), to examine the wage impact of legalization.

The surprising finding in their analysis is the relatively modest wage gain associated with becoming a legal permanent resident. In comparing the population of legalized Latino men from the LPS to a similar population from the 1979 National

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<sup>1</sup> We use the term “undocumented” to describe foreign-born persons living in the United States without legal authorization to do so.

Longitudinal Survey of Youth, Kossoudji and Cobb-Clark (2002) estimate the wage gains to legalization under IRCA to be approximately 6 percent. Hanson (2005) suggests two possible reasons for the relatively small size of the wage premium for legalization. The first is that the panel dataset used in Kossoudji and Cobb-Clark (2002) covered only 3 years following the legalization of the undocumented sample, and therefore might not have been long enough for the individuals to realize the full wage gains to legalization. The second is that the estimated wage premium may be downwardly biased if the formerly undocumented individuals are negatively selected with respect to unobserved skill.

This current paper explores a third possibility as to why the returns to legalization and the associated increase in job mobility estimated in the current literature are fairly low. Estimating changes in wages following legalization may not capture the entire benefits of legalization, due to the fact that wages are not the only form of compensation for labor. In addition to wage gains, legalized workers may experience gains in other forms of compensation, such as employer-sponsored health insurance, employer contributions to a retirement account, or employee bonuses. Becoming a legal permanent resident (and working in the formal sector of the economy) raises job mobility which in turn would increase total compensation, including potentially both wages and benefits.

Specifically, in this paper, we contribute to the literature by estimating not only the wage gains following legalization, but also changes in the likelihood of obtaining employer-sponsored health insurance and changes in the likelihood of receiving a bonus. We use data from the National Agricultural Workers Survey (NAWS) and propensity-score matching techniques to compare legal permanent residents with an appropriate

control group of undocumented workers in order to quantify the effect of legalization on wages and benefits. We find that legalization results in a modest wage gain in the neighborhood of 5 percent, which is comparable to the 6 percent estimate found in Kossoudji and Cobb-Clark (2002). In addition to higher wages, we also find a significantly higher likelihood of receiving both employer-sponsored health insurance and a bonus among the legal permanent resident crop workers as compared to the undocumented crop workers.

If undocumented agricultural workers who transition to legal permanent residence are more likely to leave farm work following their legalization, then there may be negative selection in the population of farm workers who are legal permanent residents. Tran and Perloff (2002) use the National Agricultural Workers Survey to examine the probabilities of leaving farm work for those foreign-born workers who were granted amnesty and legal permanent residence following IRCA in 1986. They find no difference between the workers granted legal permanent residence under IRCA and undocumented workers in their probability of leaving farm work, which suggests that such negative selection is not an issue in practice.

## **II. Data**

We use data from the National Agricultural Workers Survey from 2000 to 2006. NAWS is the only nationally representative survey of demographic, employment, and health characteristics of hired crop workers. The survey was mandated by the Immigration Reform and Control Act of 1986 and was first implemented in 1988; however

information on employer-sponsored health insurance is not available until 2000.<sup>2</sup> NAWS is an employment-based, random survey of the demographic, employment, and health characteristics of the U.S. crop labor force. To reflect the seasonality of agricultural production and employment, the crop workers are surveyed in three cycles each year. The information is obtained directly from farm workers through face-to-face interviews.

To estimate the effect of legalization and the accompanying increase in job mobility on total compensation, which includes wages, employer-sponsored health insurance, and bonuses, we use a sample of full-time, unmarried, male agricultural workers who are either legal permanent residents (foreign-born individuals who are legally authorized to live and work in the U.S.) or undocumented workers. More than 80 percent of all agricultural workers surveyed in NAWS after 2000 are male. By restricting the sample to unmarried males, we isolate the population with only two potential sources of health insurance: their employers or the private health insurance market. Female farm workers, particularly single women with children, could be eligible for means-tested government health insurance through the Medicaid program. Married male farm workers could have access to employer-sponsored health insurance through their spouses' employers. Additionally, we focus on those who are employed full-time in agriculture (at least 35 hours per week), as others are not likely to be eligible for benefits, such as health insurance.

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<sup>2</sup> Initially designed in response to the IRCA, which granted amnesty to substantial fraction of agricultural workers, the purpose of the NAWS was to determine if a shortage of seasonal agricultural workers was to be expected following the passage of IRCA in 1986.

The NAWS data is fairly unique in the amount of information that it provides on the legal status of foreign-born workers; there are few large-scale datasets that include questions about legal status.<sup>3</sup> Another advantage of NAWS is that it only surveys crop workers employed in the agricultural sector. Comparing the wages and benefits of legal permanent residents to undocumented workers could be biased if the legal permanent residents are employed in a different set of industries as compared to the undocumented workers. Using the NAWS sample eliminates this potential source of bias, since all the individuals surveyed are crop workers.

Descriptive sample statistics are presented in Table 1. The average hourly wage for this sample of agricultural workers is \$ 7.79 (constant 2006 dollars). Only 6 percent of workers receive employer-sponsored health insurance, and about 17 percent get additional pay in the form a bonus. The average age in the sample is just over 27 years, and about 15 percent of the population are legal permanent residents, while the rest are undocumented workers. The education level of this population is low, with approximately 6.5 years of schooling at the mean. English proficiency (speaking) is also low, with an average, on a scale of 1 to 4 (with 1 being the lowest proficiency level), of 1.53. A significant percentage (44 percent) of the workers are migrants, that is, they are working on farms that are at least 75 miles from their homes. One out of every five workers (21 percent) is employed by a farm labor contractor and not directly by a grower.

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<sup>3</sup> For example, the Current Population Survey, which is the largest nationally representative labor force survey in the U.S., does not include information on respondent's legal status. For differences between NAWS and the CPS, see Findeis et al. (2002).

The majority of workers are paid by the hours, with only 18 percent who are paid by the piece. The agricultural sector in California employs 45 percent of all workers in the sample, and the largest fraction of the population (41 percent) is employed in fruits and nuts operations at time of the survey.

### **III. Econometric Specification**

To estimate the impact of legalization and the associated increase in job mobility on agricultural workers' wages and benefits, we implement a propensity score matching estimator as originally developed by Rosenbaum and Rubin (1983). Matching techniques have been previously used for estimating the impact of job training programs on wages (Dehejia and Wahba 2002), the effect of foreign technology transfer on plant productivity (Yasar and Paul 2008), and the changes in farmland loss resulting from agricultural preservation programs (Liu and Lynch 2008).

Our objective here is to assess the extent to which legalization affects wages and benefits of foreign-born workers employed in the agricultural sector. Permanent U.S. residents enjoy much greater job mobility than undocumented workers, and subsequently they have greater bargaining power that could result in higher wages and benefits. To empirically evaluate the effect of the higher job mobility associated with legal permanent U.S. residence, one would need data on wages and benefits for workers who are permanent legal residents and data on their wages and benefits had they been undocumented. Because such a counterfactual is not observed, one can compare the wages and benefits of agricultural workers who are legal permanent residents with those of agricultural workers who are undocumented. This approach would ignore the

selection issues that stem from the facts that entering the U.S. illegally and becoming a legal permanent resident are choices that can be affected by personal characteristics, which also determine wages and benefits. To circumvent the potential endogeneity of legal status, we use propensity score matching techniques to compare the wages and benefits of legal permanent residents to those of a select group of undocumented workers who are similar to them.

Let  $LPR_i$  be an indicator variable equal to 1 if individual  $i$  is in the treatment group, i.e., a legal permanent resident, and equal to 0 if  $i$  is in the control group, i.e., an undocumented worker. Let  $\ln W_i^1$  be the natural log of the hourly wage of  $i$ , if  $i$  is a legal permanent resident ( $LPR_i = 1$ ), and let  $\ln W_i^0$  be the natural log of the hourly wage of  $i$ , if  $i$  were instead an undocumented worker ( $LPR_i = 0$ ). One can then define the impact of legalization on wages as  $\ln W_i^1 - \ln W_i^0$ . However, both of these values cannot be observed for the same individual, since one cannot simultaneously be a legal permanent resident and an undocumented worker.

Formally, one of the quantities we want to estimate is the average treatment effect on the treated (*ATT*) for the hourly wage:

$$(1) \quad ATT(\ln W) = E[\ln W_i^1 - \ln W_i^0 \mid LPR_i = 1] = E[\ln W_i^1 \mid LPR_i = 1] - E[\ln W_i^0 \mid LPR_i = 1].$$

Econometrically, the problem is that we do not observe the counterfactual

$E[\ln W_i^0 \mid LPR_i = 1]$ . One approach is to use  $E[\ln W_i^0 \mid LPR_i = 0]$  in place of the unobserved counterfactual  $E[\ln W_i^0 \mid LPR_i = 1]$ , but this may introduce a selection bias if

the differences in characteristics between legal permanent residents and undocumented workers also affect wages.

For example, one obvious choice for a control group for the legal permanent residents in the National Agricultural Workers Survey would be the group of undocumented workers. However, undocumented workers are quite different from the legal permanent residents along many socio-demographic characteristics, which we would expect to have an effect on wages, regardless of legal status. For instance, the legal permanent residents in the NAWS sample are older than the undocumented workers, and they have more years of farm work experience (see Original Sample in Table 3), both of which result in higher wages. Therefore, it is necessary to select a control group of undocumented workers who more closely resemble the legal permanent residents along a vector of covariates  $\mathbf{Z}$ .

The matching estimator will perform well if the following Conditional Mean Independence assumption (see Rosenbaum and Rubin 1983) is satisfied for a given vector of covariates  $\mathbf{Z}$ , which contains all the variables that affect both treatment (legal permanent resident status) and the outcome (hourly wages):

$$(2) \quad E[\ln W_i^0 \mid LPR_i = 1, Z_i] = E[\ln W_i^0 \mid LPR_i = 0, Z_i] = E[\ln W_i^0 \mid Z_i].$$

To avoid dimensionality problems of matching on a large number of covariates, Rosenbaum and Rubin (1983) show that matching on a vector of covariates  $\mathbf{Z}$  is equivalent to matching on a function of the covariates  $P(\mathbf{Z})$ , the propensity score. This score is simply the conditional probability of being treated (being a legal permanent

resident):

$$(3) \quad P_i(Z_i) = \Pr(LPR_i = 1 | Z_i) = E[LPR_i = 1 | Z_i].$$

In our main empirical analysis, we use a logit specification to estimate the propensity score above, but we also employ a probit model to demonstrate robustness.

Using this propensity score, we can then construct an estimate of the average effect of treatment of legal permanent resident status on the wages of the treated as shown below:

$$(4) \quad \begin{aligned} ATT(\ln W) &= E[\ln W_i^1 | LPR_i = 1] - E[\ln W_i^0 | LPR_i = 1] = \\ &= E[\ln W_i^1 | LPR_i = 1] - E[\ln W_i^0 | LPR_i = 0, P_i(Z_i)]. \end{aligned}$$

Similarly, we can estimate the average treatment effect on the treated for the other two outcomes – the likelihood of receiving employer-sponsored health insurance ( $HI_i$ ) and the likelihood of receiving a bonus ( $B_i$ ):

$$(5) \quad \begin{aligned} ATT(HI) &= E[HI_i^1 | LPR_i = 1] - E[HI_i^0 | LPR_i = 1] = \\ &= E[HI_i^1 | LPR_i = 1] - E[HI_i^0 | LPR_i = 0, P_i(Z_i)]. \end{aligned}$$

$$(6) \quad \begin{aligned} ATT(B) &= E[B_i^1 | LPR_i = 1] - E[B_i^0 | LPR_i = 1] = \\ &= E[B_i^1 | LPR_i = 1] - E[B_i^0 | LPR_i = 0, P_i(Z_i)]. \end{aligned}$$

Matching on the propensity score  $P(Z)$  ensures that the distribution of covariates (contained in  $\mathbf{Z}$ ) in the selected control group (of undocumented workers) is the same as the distribution of those covariates in the treatment group (of legal permanent residents).

Matching essentially randomizes the treatment, eliminating the bias by selecting controls with similar characteristics to the treated.

To construct a control group for the legal permanent resident crop workers, we first use nearest-neighbor matching. For each legal permanent resident, nearest-neighbor matching selects one (or more) undocumented crop worker with the closest propensity score to that of the legal permanent resident, and weights the neighbors by the frequency with which they are matched to the observations in the treatment group. Matching is done with replacement, and ties are equally weighted.

For robustness, we also develop a control group for the legal permanent residents using kernel matching, with the normal (Gaussian) kernel. This method constructs the counterfactual wages, employer-sponsored health insurance, and bonuses for the legal permanent residents using a local average of the observations whose propensity scores lie within a certain bandwidth of the propensity scores of the treatment group.<sup>4</sup> For both nearest-neighbor matching and kernel matching, the estimated standard errors do not take into account the fact that the propensity score is estimated. To correct for this, we bootstrap the standard errors.

One advantage to using a matching strategy as opposed to a parametric estimation of the impact of legalization on wages and benefits is that matching does not require

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<sup>4</sup> For the bandwidth parameter  $h$ , we use the value suggested by Silverman (1986), which corresponds to the normal (Gaussian) kernel; this value is  $h = 1.06 * St.Dev.(Y) / N^{0.2}$ , where  $Y$  is the outcome of interest ( $\ln W$ ,  $HI$ , or  $B$ ) and  $N$  is the number of observations in the sample.

functional form or distributional assumptions. Further, finding plausibly exogenous instruments for legal status is a challenge given the nature of U.S. immigration policy.

#### **IV. Results and Discussion**

We start this section with an account of the propensity score model used in the matching algorithm. Once a proper control group is selected, we compare the wages and benefits (health insurance and bonus) of legal permanent residents to those of undocumented workers employed in the agricultural sector. Finally, we conclude this section with a number of robustness checks which further reaffirm our main findings.

##### **IV.1 Propensity Score Estimation**

To circumvent the potential endogeneity of the legal status, we use matching techniques to compare the wages and benefits of legal permanent residents to those of a group of similar undocumented workers. We first specify the vector of covariates  $\mathbf{Z}$  used in the estimation of the propensity score, i.e. the probability of being a permanent legal resident. The vector of controls  $\mathbf{Z}$  should include all characteristics that may affect both treatment (legal permanent resident status) and outcome (wage and benefits). Because we investigate wages and benefits, all standard Mincerian regression variables are included as covariates. Given the sample of unmarried males employed full-time, the following individual controls are included in  $\mathbf{Z}$  – (U.S. farm) experience, (U.S. farm) experience squared, years of schooling, and English proficiency (speaking) in the propensity score estimation. We additionally control for age, which is usually used to proxy for overall experience and in this context also affects the treatment – legal

permanent residents tend to be older than undocumented workers. Further, we include three other covariates that may affect workers' benefits (health insurance and bonus) – (indicators for) being a migrant worker, being employed by a contractor (and not a grower), and being paid by the piece (and by the hour). Because having children imposes extra costs of undocumented migration, we include (an indicator for having) children as well. Finally, we also include year, region, and crop dummies, which affect both the treatment (legal permanent resident status) as well as the outcomes of interest (wages and benefits).

The results of the propensity score estimation are reported in Table 2. The first and second columns of Table 2 report the estimates of the Logit and the Probit models respectively. Both set of results are very similar. As expected, the estimated coefficients confirm that older age, greater experience, more schooling, better command of English, and having children significantly increase the likelihood of being a legal permanent resident. The overall fit of the propensity score model, both the probit and logit specifications, is very good, with pseudo-R square measure of 0.49.

#### **IV.2 Differences in Wages and Benefits between Legal Permanent Residents and Undocumented Workers**

The first half of Table 3 presents the differences in covariates between the legal permanent residents and the undocumented workers in the original unmatched sample. It is immediately clear that the two groups of agricultural workers have quite dissimilar personal characteristics. On average, legal permanent residents are older and have more farm work experience. Undocumented workers are only slightly better educated but have

lower proficiency in (speaking) English; they are more likely to be migrant workers, employed by a contractor, and paid by the piece. All the differences are statistically significant at the 5 percent level, indicating that direct comparison of wages and benefits between the two groups without correcting for selection bias is inappropriate.

Based on this evidence, we develop a matching procedure whose goal is to select an appropriate control group of untreated individuals (undocumented agricultural workers). The matching procedure is successful if members in the selected control group have similar observable characteristics included in the vector of covariates  $Z$  (see Dehejia and Wahba 2002). The second half of Table 3 formally verifies that there are no significant differences in covariates left between legal permanent residents and undocumented agricultural workers in the matched sample. For example, the difference in average age between legal permanent resident agricultural workers and undocumented agricultural workers in the matched sample is only 0.77 years (the average for legal permanent residents is 38.75 years and 37.98 for undocumented workers). The difference in age between the two groups in the original unmatched sample, on the other hand, is 13.54 years ( $= 38.75 - 25.21$ ). The statistical significance in the differences in age between the two groups in the original sample vanishes after matching. Similarly, the differences in the rest of the covariates in  $Z$  in the original sample disappear in the matched sample. Also, the average propensity score difference between the two groups (legal permanent residents and undocumented workers) in the matched sample is very small at 0.002, giving us confidence that the balancing property of the propensity score is ensured.

Another measure of success of the matching procedure is the absolute standardized bias. It is defined as the difference in the means of the control and the treatment group covariates scaled by the square root of the averaged sample variances of the covariates (Rosenbaum and Rubin 1985). Table 3 presents the mean values of the absolute standardized bias before and after matching. While there is no formal absolute standardized bias cut-off below which the matching is considered successful, a value under 20 is considered reasonable (Rosenbaum and Rubin 1985). The mean absolute standardized bias before matching is 31.23 and it drops down to 8.60 after matching. Table 3 additionally reports the reduction of bias attained for each covariate as a result of the matching procedure – the average values of all the covariates are closer for the treated and the matched control group than for the treated the control group in the original unmatched sample.

Based on the evidence presented so far, we can be confident that the matching procedure is effective in eliminating the selection bias that may affect the naïve estimator of the differences in wages and benefits between the treated (legal permanent resident agricultural workers) and the controls (undocumented agricultural workers). As such, we turn our attention to the matching estimator of the differences in wages and benefits between the two groups. We first present the estimates of the effect of legalization and the associated increase in job mobility on the wage, the likelihood of receiving employer-sponsored health insurance, and the likelihood of receiving a bonus using nearest-neighbor matching. The following subsection presents a number of robustness checks including the kernel matching estimator discussed earlier.

Panel A of Table 4 reports the estimates of the differences in the wage, the likelihood of employer-sponsored health insurance, and the likelihood of a bonus using the nearest-neighbor propensity score matching. First, note that all three outcomes are higher for legal permanent residents than for undocumented agricultural workers in the original unmatched sample. The differences are large, and they are all statistically significant at the 1 percent level. In particular, both wages and the likelihood of employer-sponsored health insurance are 9 percent higher for legal permanent residents than for undocumented workers. These naïve estimates of the differences, however, may be biased (upwards) due to potential selection as the characteristics that affect individuals' choices to legally enter the U.S. most likely also affect their wages and benefits. To this end, we use the nearest-neighbor matching to properly select a control group of undocumented agricultural workers who are most like the treatment group of legal permanent resident workers.

The estimated differences using the matched sample are somewhat different. As expected, most of the estimates decline, likely due to the selection problem in the unmatched sample. The estimated difference in wages declines almost in half from 9 to 5 percent, though it is still statistically significant at the 5 percent level. The difference in the likelihood of receiving a bonus also declines from 18 percent to 11 percent, and it remains statistically significant at the 5 percent level. The estimate of the difference in the likelihood of receiving employer-sponsored health insurance does not change from the original sample to the matched sample. Both estimates, which are statistically significant at the 1 percent level, indicate that legal permanent residents enjoy about 9 percent higher likelihood of receiving employer-sponsored health insurance.

The low wage increase of 5 percent, which results from legalization and associated higher job mobility of legal permanent residents, is consistent with previous estimates by Kossoudji and Cobb-Clark (2002), who find that upon legalization wages increase only about 6 percent. However, because the National Agricultural Worker Survey contains further information on worker's compensation, we can additionally see that legalization and the associated increase in job mobility are accompanied not only by a modest increase in wages, but also by a sizable increase in the likelihood of receiving employer-sponsored health insurance and the likelihood of receiving a bonus. Hence, the overall increase in compensation is much greater than previously estimated. Interestingly, the rise in compensation is due to increases in all three components of total compensation – the wage, the likelihood of receiving employer-sponsored health insurance and the likelihood of receiving a bonus – underscoring the importance of the well-known substitution between wages and benefits.

### **IV.3 Robustness Checks**

To demonstrate that our findings are robust, we next perform nearest-neighbor matching using the propensity score model based on the probit instead of the logit specification in Table 2. The estimates presented in Panel B of Table 4 are very similar to those from the nearest-neighbor matching using the logistic propensity score model in Panel A of Table 4. The estimated difference in wages and the likelihood of receiving a bonus in Panel B declines slightly compared to the results in Panel A, and the estimates are now significant at the 10 percent-level. The estimated difference in the likelihood of receiving employer-

sponsored health insurance declines slightly, but still remains statistically significant at the 1 percent level.

Another robustness check we perform involves using the kernel matching instead of the nearest-neighbor matching technique outlined earlier. The results from the kernel matching are presented in Panel C of Table 4. The estimates are similar, but somewhat smaller than the nearest-neighbor matching results in Panels A and B, with the coefficients on the differences in the wage and the likelihood of receiving a bonus significant at the 10 percent level, and that of receiving employer-sponsored health insurance significant at the 1 percent level.

We can further improve the quality of the matches by restricting matched individuals to fall on the common support of the propensity scores for the treated and the controls, i.e. using observations whose propensity scores belong to the intersection of the supports of the propensity scores of the treatment and control groups (see Becker and Ichino 2002). Some legal permanent residents may have no comparable undocumented workers, so the estimate of legalization and the resulting job mobility in the absence of common support will reflect the effects of both treatment and other confounding variables for which we cannot properly control. To eliminate this bias, we exclude legal permanent residents with propensity scores larger than the maximum or smaller than the minimum of the propensity scores of the undocumented workers. This turns out to be a trivial restriction in the NAWS sample as there are only 3 (or 5 with the kernel matching estimator) individuals who are eliminated from the treatment group (legal permanent residents) due to this lack of common support. Incorporating this restriction does not change any of the estimates reported in Table 4.

Together, the results in Panels A, B, and C of Table 4 imply that legalization and the greater job mobility associated with it increase workers' total compensation. Consistent with previous findings by Kossoudji and Cobb-Clark (2002), the estimates indicate that the wage rises only slightly between 3 percent (kernel matching estimator) and 5 percent (nearest-neighbor matching estimator). However, we find that in addition to the modest increase in wages, legalization and the accompanied boost in job mobility further raise total compensation by increasing both the likelihood of receiving employer-sponsored health insurance between 6 percent (kernel matching estimator) and 9 percent (nearest-neighbor matching estimator), and also the likelihood of receiving a bonus between 6 percent (kernel matching estimator) and 11 percent (nearest-neighbor matching estimator).

## **V. Conclusion**

Estimating the wage premium associated with legalization may understate its true benefits, if other forms of compensation also increase following legalization. Using data from the National Agricultural Workers Survey and propensity score matching techniques, we evaluate the impact of legal status on total compensation, including wage, bonus, and health insurance. Consistent with the previous literature (Kossoudji and Cobb-Clark 2002), we find a modest wage premium of about 5 percent for legal permanent resident farm workers.

Further, we also show that, in addition to higher wages, legalization leads to about 9 percent higher likelihood of receiving employer-sponsored health insurance and about 11 percent higher likelihood of receiving a bonus. Previous studies understate the true

benefits to legalization because they do not consider other forms of compensation. We find that the increased job mobility resulting from legalization does increase all forms of compensation for agricultural workers.

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TABLES

Table 1. Descriptive Statistics

<b>Variable</b>	<b>Mean</b>	<b>St. Dev.</b>	<b>Min.</b>	<b>Max.</b>
Hourly Wage (constant 2006 dollars)	7.79	1.70	2.85	34.15
<i>ln</i> (Hourly Wage)	2.03	0.19	1.05	3.53
Employer-sponsored Health Insurance	0.06	0.25	0	1
Bonus	0.17	0.38	0	1
Legal Permanent Resident	0.15	0.36	0	1
Age (years)	27.32	9.90	14	74
U.S. Farm Work Experience (years)	6.61	6.95	1	46
U.S. Farm Work Experience Squared	91.97	196.69	1	2,116
Schooling (years)	6.46	3.01	0	16
English Proficiency (speaking)	1.53	0.73	1	4
Migrant	0.44	0.50	0	1
Employed by Contractor	0.21	0.41	0	1
Paid by the Piece	0.18	0.38	0	1
Children	0.04	0.20	0	1
Weekly Hours	47.05	9.05	35	97
Year: 2000	0.21	0.41	0	1
2001	0.16	0.36	0	1
2002	0.16	0.37	0	1
2003	0.15	0.36	0	1
2004	0.15	0.35	0	1
2005	0.10	0.29	0	1
2006	0.07	0.26	0	1
Region: East	0.12	0.32	0	1
Southeast	0.15	0.36	0	1
Midwest	0.10	0.30	0	1
Southwest	0.05	0.22	0	1
Northwest	0.13	0.33	0	1
California	0.45	0.50	0	1
Crop: Field Crops	0.11	0.31	0	1
Fruits and Nuts	0.41	0.49	0	1
Horticulture	0.21	0.41	0	1
Vegetables	0.21	0.41	0	1
Miscellaneous/Multi-Crop	0.06	0.23	0	1
Observations			3,933	

Note: Authors' calculations with data from the National Agricultural Worker Survey, 2000-2006.

Table 2. Propensity Score Model: Dependent variable – Legal Permanent Resident (LegPerRes).

Variables	<u>LegPerRes</u>	
	(1) <b>Logit</b>	(2) <b>Probit</b>
Age	0.03 <sup>***</sup> (0.01) [0.004]	0.02 <sup>***</sup> (0.01) [0.002]
U.S. Farm Work Experience	0.29 <sup>***</sup> (0.03) [0.04]	0.16 <sup>***</sup> (0.02) [0.02]
U.S. Farm Work Experience Squared	- 0.002 <sup>**</sup> (0.001) [- 0.0002]	- 0.001 <sup>**</sup> (0.001) [- 0.0001]
Schooling	0.06 <sup>**</sup> (0.02) [0.008]	0.03 <sup>**</sup> (0.01) [0.004]
English Proficiency (Speaking)	0.92 <sup>***</sup> (0.09) [0.12]	0.49 <sup>***</sup> (0.05) [0.06]
Migrant	0.15 (0.15) [0.02]	0.09 (0.08) [0.01]
Employed by Contractor	0.08 (0.18) [0.010]	0.02 (0.10) [0.002]
Paid by the Piece	- 0.09 (0.20) [- 0.010]	- 0.02 (0.10) [- 0.002]
Children	0.59 <sup>**</sup> (0.23) [0.08]	0.34 <sup>***</sup> (0.12) [0.05]
Pseudo R <sup>2</sup>	0.49	0.49
Log Likelihood	- 851.05	-854.01
Observations	3,891	3,891

Note: All specifications include year, region, and crop dummies. Standard errors are reported in parentheses; marginal effects in brackets. \*\*\* indicates statistical significance at the 1 percent level, \*\* at the 5 percent level, and \* at the 10 percent level.

Table 3. Comparisons between Legal Permanent Residents (LegPerRes) and Undocumented Workers (Undoc) in the Original (Unmatched) and the (Nearest-neighbor) Matched sample.

Variable	Original Sample				Matched Sample				
	LegPerRes	Undoc	t-test*	% Bias	LegPerRes	Undoc	t-test*	% Bias	%  Bias  Reduction
Age	38.75	25.21	35.38	132.70	38.75	37.98	1.17	7.60	94.30
U.S. Farm Work Experience	179.23	109.19	53.42	179.50	17.23	17.11	0.24	1.80	99.00
U.S. Farm Work Experience Squared	375.67	40.64	48.44	136.70	375.67	377.58	- 0.09	- 0.80	99.40
Schooling	5.89	6.57	- 5.16	- 21.30	5.89	6.12	- 1.15	- 7.30	65.90
English Proficiency (Speaking)	2.06	1.43	20.38	79.20	2.06	2.11	- 1.02	- 6.80	91.40
Migrant	0.32	0.46	- 6.57	- 29.90	0.32	0.36	- 1.71	- 9.70	67.60
Employed by Contractor	0.18	0.22	- 2.47	- 11.30	0.18	0.16	1.01	5.40	51.90
Paid by the Piece	0.14	0.18	- 2.87	- 13.30	0.14	0.11	1.23	6.40	51.90
Children	0.14	0.02	13.19	42.70	0.14	0.12	1.04	7.50	82.40
Average Propensity Score Difference between LegPerRes and Undoc		-					0.002		
Mean Absolute Standardized Bias		31.23					8.60		
Observations	599	3,292			599	264			

Note: \*t-tests for differences between Legal Permanent Residents (LegPerRes) and Undocumented Workers (Undoc).

Table 4. The effect of Legal Permanent Residency (LegPerRes) on the wage, employer-sponsored health insurance, and bonus.

Panel A: Nearest Neighbor Matching (Logit Model for Propensity Score)

Outcome	Sample	LegPerRes	Undoc	Difference	Stand. Err.	t-stat
<i>ln</i> (Hourly Wage)	Unmatched	2.10	2.02	<b>0.09</b> <sup>***</sup>	0.01	10.08
	Matched	2.10	2.05	<b>0.05</b> <sup>**</sup>	0.03	1.97
Health Insurance	Unmatched	0.14	0.05	<b>0.09</b> <sup>***</sup>	0.01	7.86
	Matched	0.14	0.05	<b>0.09</b> <sup>***</sup>	0.03	3.03
Bonus	Unmatched	0.32	0.14	<b>0.18</b> <sup>***</sup>	0.02	10.78
	Matched	0.32	0.21	<b>0.11</b> <sup>**</sup>	0.06	2.02

Panel B: Nearest Neighbor Matching (Probit Model for Propensity Score)

Outcome	Sample	LegPerRes	Undoc	Difference	Stand. Err.	t-stat
<i>ln</i> (Hourly Wage)	Unmatched	2.10	2.02	<b>0.09</b> <sup>***</sup>	0.01	10.08
	Matched	2.10	2.06	<b>0.04</b> <sup>*</sup>	0.02	1.78
Health Insurance	Unmatched	0.14	0.05	<b>0.09</b> <sup>***</sup>	0.01	7.86
	Matched	0.14	0.05	<b>0.08</b> <sup>***</sup>	0.03	2.64
Bonus	Unmatched	0.32	0.14	<b>0.18</b> <sup>***</sup>	0.02	10.78
	Matched	0.32	0.23	<b>0.09</b> <sup>*</sup>	0.05	1.78

Panel C: Kernel Matching (Logit Model for Propensity Score)

Outcome	Sample	LegPerRes	Undoc	Difference	Stand. Err.	t-stat
<i>ln</i> (Hourly Wage)	Unmatched	2.10	2.02	<b>0.09</b> <sup>***</sup>	0.01	10.08
	Matched	2.10	2.07	<b>0.03</b> <sup>*</sup>	0.02	1.82
Health Insurance	Unmatched	0.14	0.05	<b>0.09</b> <sup>***</sup>	0.01	7.86
	Matched	0.14	0.07	<b>0.06</b> <sup>***</sup>	0.02	2.69
Bonus	Unmatched	0.32	0.14	<b>0.18</b> <sup>***</sup>	0.02	10.78
	Matched	0.32	0.26	<b>0.06</b> <sup>*</sup>	0.03	1.84

Note: Bootstrapped standard errors (for Matched Sample). \*\*\* indicates statistical significance at the 1 percent level, \*\* at the 5 percent level, and \* at the 10 percent level.