PROPOSED IMMIGRATION POLICY REFORM & FARM LABOR MARKET OUTCOMES

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Overview

Immigration reform has generated much political debate in recent years. The last substantial revision of immigration law occurred in 1986 with the passage of the Immigration Reform and Control Act (IRCA), which authorized several policy instruments to discourage illegal immigration and employment. In the twenty years since however, it is apparent that IRCA has failed in its stated objectives for not only has illegal immigration increased significantly, but unauthorized immigrants have continued to gain employment in the U.S. particularly in the low-skilled, low-wage sectors of the economy (Passel, 2005; Passel and Suro, 2005; Passel, 2006; Mines, Gabbard and Steirman, 1997; Carroll et al. 2005).

The political debate began in earnest with the passage of two earlier proposals in the 109th US Congress. Legislative proposal H.R. 4437 (the *Border Protection, Antiterrorism, and Illegal Immigration Control Act of 2005*) was passed by the US House of Representatives in December 2005. It is arguably one of the more restrictive proposals introduced for consideration in the 109th Congress in that it contained no provisions for legalization of unauthorized workers or for a guest worker program. H.R. 4437 emphasized a pro-enforcement stance on immigration reform; it advocated criminal penalties for unauthorized immigrants and significant fines for the U.S. employers who would hire them. The proposal also argued for I-9 document reform and for increased worksite/interior/border enforcement, but made no mention of modifications to existing laws on legal immigration.

In contrast, S. 2611 (the *Comprehensive Immigration Reform Act of 2006*) passed by the U.S. Senate in May 2006 proposed earned legalization for unauthorized immigrants and modifications to existing laws on legal immigration. Though it favored stricter enforcement and I-9 reform, overall, it was not as severe as H.R. 4437 in the overall approach to illegal immigration. Specific provisions for the agricultural sector were proposed under AgJOBS (*Agricultural Job Opportunity, Benefits and Security Act of 2005* (S. 359/H.R. 884; S.2611 Subtitle B), which would streamline the H-2A program to improve wages, working conditions and minimum benefits (housing and transportation) for farm workers and establish a pilot program for earned legalization of eligible unauthorized workers.

Neither S.2611 nor H.R. 4437 was passed since Congress failed to reach a compromise between the two sets of views on immigration. The failure to achieve compromise can be linked directly to the competing interests that lawmakers had to contend with: disagreements on policy provisions between anti-immigration/pro-enforcement groups and pro-immigration groups, disagreements on specific reform measures between and within political parties in Congress, and intense lobbying from employer and worker advocacy groups for certain concessions. In many respects, the most divisive issue has been proposed legalization for unauthorized immigrants. There are segments of the American public that strongly oppose legalization on the grounds that it would reward illegal behavior and encourage future illegal immigration, as there are others that view legalization as the only viable means of bringing unauthorized immigrants into mainstream U.S. society, that is, in lieu of mass deportations.

Amidst these divergent views, employers of low skilled foreign labor – particularly farm employers – have expressed preference for increased access to immigrant labor to offset labor shortages. This issue is particularly important to farm employers that have high demand for manual labor over short periods during harvest time. Immigrant workers presently comprise a significant proportion of the crop farm workforce (78%), an estimated 53% of which is unauthorized for US employment (Carroll et al. 2005). Farm employers are justifiably concerned since these statistics clearly highlight their vulnerability to changes in immigration policy that may curtail their access to foreign labor.

Given this context, the purpose of this paper is to evaluate the implications of U.S. immigration policy reform for U.S. farm labor market outcomes, focusing specifically on proposed legalization for unauthorized immigrant workers. The study uses a treatment effects (TE) framework in which legalization is modeled as a treatment or (policy) intervention. The TE framework is a novel approach to immigration policy evaluation that has not been used in previous studies that have evaluated the potential impact of legalization for farm outcomes. The paper is organized as follows. Following this introduction, the second section comprises the analytical framework employed in the study, and the third section presents the study findings. Policy implications and concluding remarks are given in the final sections of the paper.

Treatment Effects Approach

The treatment effects approach measures the impact of "treatment" on outcomes of interest. In this context, treatment may refer to medical treatments, public programs or social interventions (Basu et al. 2007), and the causal effect of the treatment on the outcome is defined as the treatment effect. The standard problem involves the inference of a causal connection between participation (treatment) (*D)* and the potential outcome *(Y)*, where the potential outcomes for the participant (treated) (Y_1) and non-participant (non-treated) (Y_0) states are compared for the i^{th} individual to evaluate how his average economic outcome would change if he were to participate in a program or not. Following the latent variable framework of Heckman, Tobias and Vytlacil (2001; 2003) and Blundell and Costa Dias (2002), the potential outcomes based on observable characteristics (*x)*, and the participation decision for a program may be defined as:

$$\begin{aligned}
&Y_1 = g_1(x) + u_1 = \beta_1' X_i + u_1 \quad \textit{(treated/participant group)} \\
&Y_0 = g_0(x) + u_0 = \beta_0' X_i + u_0 \quad \textit{(untreated/nonparticipant group)} \\
&D^* = \alpha' Z_i + \varepsilon \qquad\qquad\qquad \textit{(decision to participate in treatment)} \\
&\textit{where } \; D = 1 \;\; \textit{if } D^* \geq 0; \quad D = 0 \textit{ otherwise}
\end{aligned} \tag{1}$$

In this setup, $g_1(x)$, $g_0(x)$ represent the relationship between the observable characteristics and the potential outcomes and u_1, u_0, ε , Z and *x* are unobserved and observed random variables, respectively. The errors are assumed to be independent of *x* and Z. *Ceteris paribus*, the treatment or causal effect is defined as shown by equation (4.2), and is the difference between the potential outcomes:

$$\Delta_i = Y_{1i} - Y_{0i} \qquad i = 1,\dots, N \tag{2}$$

This effect is not directly estimable as it is impossible to simultaneously observe an individual in both states. The observed outcome is actually:

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i} \tag{3}$$

where the unobservable portion of the effect is referred to as the counterfactual outcome. (For those individuals receiving treatment Y_0 is the counterfactual outcome; for those who do not, Y_1 is the counterfactual outcome.) The treatment effect of each person is independent of the treatment of other individuals, implying that an individual's potential outcomes are affected by his participation decision only and not the decisions of other individuals (Wooldridge, 2002; Caliendo, 2006).

Gains from treatment are typically defined as population averages. Some relevant parameters include:

- Average Treatment Effect (ATE). This is the expected gain from participating in a program for a randomly chosen individual (Heckman, Tobias and Vytlacil, 2001), calculated as the differences in expected outcomes before and after treatment:
$$\alpha_{ATE} = E(\Delta) = E(Y_1) - E(Y_0) \tag{4}$$

- Average Treatment Effect on the Treated (ATET). This is the average gain from treatment for those who select into the treatment (Heckman, Tobias and Vytlacil, 2001):
$$\alpha_{ATET} = E(\Delta \mid D=1) = E(Y_1 \mid D=1) - E(Y_0 \mid D=1) \tag{5}$$

- Average Treatment Effect on the Untreated (ATEU). This is the effect for non-participants which may be useful for future policy decisions on extending treatment to groups that were excluded from treatment (Caliendo, 2006):
$$\alpha_{ATEU} = E(\Delta \mid D=0) = E(Y_1 \mid D=0) - E(Y_0 \mid D=0) \tag{6}$$

- Marginal Treatment Effect (MTE).[1] This is the expected effect of treatment conditional on observed *(X)* and unobserved *(U_d)* characteristics of participants (Heckman and Vytlacil, 2005).[2] One interpretation is that it is the mean gain for an individual with characteristics X and unobservables U_d such that he is indifferent between treatment or not given a set of Z values, z, where $\Phi(\alpha' z)=u_d$. It is defined as:
$$\begin{aligned} MTE(X,U_d) &\equiv E(\Delta \mid X=x, U_d=u_d) = E(Y_1 - Y_0 \mid X=x, U_{di}=u_d) \\ &= E(\gamma \mid X=x, U_{di}=u_d) = X(\beta_1 - \beta_0) + E[u_{1i} - u_{0i} \mid U_{di}=u_d] \end{aligned} \tag{7}$$

The challenge posed by selection bias is evident from the ATET which shows a hypothetical outcome in the absence of treatment for those individuals who received treatment (Caliendo, 2006). With non-experimental data, this outcome is not equivalent to the outcome of non-participants:

$$E(Y_0 \mid D=1) \neq E(Y_0 \mid D=0) \tag{8}$$

Selection bias may arise since participants and non-participants may be deliberately selected groups with different outcomes, even in the absence of treatment, due to observable and unobservable factors that may determine participation (Caliendo, 2006):

$$E(Y_1 \mid D=1) - E(Y_0 \mid D=0) = \underbrace{E(Y_1 - Y_0 \mid D=1)}_{ATET} + \underbrace{[E(Y_0 \mid D=1) - E(Y_0 \mid D=0)]}_{Selection\ bias} \tag{9}$$

[1] Bjorklund and Moffitt (1987) are credited with introducing this concept to the literature.

[2] The unobserved characteristics are introduced into the model by the decision rule described by equation (1).

Much of the previous literature on treatment effects assumed homogeneous responses to treatment, meaning that based on certain observable characteristics, effects are constant across individuals and that they would derive identical benefits from treatment. Recent studies have given more attention to heterogeneous responses where the effects vary across individuals due to their observable or unobservable characteristics. Much of the focus is now on the role of unobservable characteristics in determining outcomes particularly in cases where individuals are otherwise identical in their observed characteristics (Basu et al. 2007; Caliendo, 2006). Basu et al. (2007) describe two instances in which heterogeneity (arising from unobservable characteristics) may factor into treatment evaluation. The first instance is where individuals with identical observable characteristics respond differently to treatment but do not opt for treatment based on their idiosyncratic benefits or gains (non-essential heterogeneity). The second instance is where individuals have identical observable characteristics and respond differently to treatment and are aware of the benefits to be derived from treatment. In this latter case, their treatment choices are influenced by anticipation of idiosyncratic gains (Basu et al. 2007). Basu et al. (2007) and Heckman, Urzua and Vytlacil (2006a; 2006b) refer to the second instance as *essential heterogeneity.*

In the context of this paper, heterogeneity of foreign farm worker responses to legalization is maintained and subjected to a statistical test. In the presence of heterogeneity, it is assumed that they obtained legalization because of individually perceived wage benefits, and that in the future, workers without legal status would proceed similarly in the presence of a program such as AgJOBS. The analysis follows a parametric approach developed by Heckman, Urzua and Vytlacil (2006b) to estimate the choice and outcome models, and the treatment effects of legalization; alternative non-parametric estimates are also evaluated. Their MTE algorithm was used for the analysis.[3] The overall models and estimation procedure are described in the following sections, and draw heavily on the theoretical expositions of Heckman, Urzua and Vytlacil (2006a; 2006b).

Parametric model with heterogeneous treatment effects

The parametric model with essential heterogeneity adopts the familiar latent variable framework shown:

$$\begin{array}{ll} D^* = \alpha' Z - \varepsilon = \mu(Z) - \varepsilon & \textit{Choice model/decision rule} \\ D = 1 \ \ if\ D^* \geq 0 & (\textit{if the worker opts for legal status}) \\ D = 0 & (\textit{otherwise}) \end{array} \qquad (10)$$

$$\begin{array}{ll} \ln Y_1 = \beta_1' X_i + u_{1i} & \textit{Wage outcome for treated group} \\ \ln Y_0 = \beta_0' X_i + u_{0i} & \textit{Wage outcome for untreated group} \end{array} \qquad (11)$$

where the Z and X are vectors of observable characteristics and $\varepsilon, u_{1i}, u_{0i}$ are error terms that encapsulate the unobservable characteristics of individuals. The decision to accept treatment (legal status) is defined by a choice model that allows for two separate log wage outcomes $(\ln Y_1, \ln Y_0)$.[4] The choice model may be interpreted as a net utility for individuals with the characteristics Z and ε. Similarly, the (log wage) outcomes are functions of the i^{th} worker's characteristics denoted by X_i and u_{ji} $(j = 0,1)$, respectively. The error of the choice model (ε) is assumed to be independent of Z given X. The parametric model assumes joint normality of the errors $(\varepsilon, u_{1i}, u_{0i})$, which are assumed to be independent of the observable characteristics (Z and X). Based on this assumption, the expectations on the errors of the outcome equations reflect the differences in legal status choice ($D=1$ if legalized/treated, $D=0$ if not legalized/untreated):

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[3] Information on the MTE is available at http://jenni.uchicago.edu/underiv/ (Cited as Heckman, Urzua and Vytlacil, 2006c in reference list). Also, see Heckman, Urzua and Vytlacil (2006a; 2006b).

[4] Parameters $\mu(Z)$ and ε are assumed to be additively separable as is the predominant specification in the literature.

$$E\left(u_1 \mid X = x, D = 1, P(Z) = p\right) = \rho_1 \left(- \frac{\phi\left(\alpha' Z \big/ \sigma_\varepsilon \right)}{P(Z)} \right) \tag{12}$$

$$E\left(u_0 \mid X = x, D = 0, P(Z) = p\right) = \rho_0 \left(\frac{\phi\left(\alpha' Z \big/ \sigma_\varepsilon \right)}{1 - P(Z)} \right) \tag{13}$$

where $\rho_1 = \frac{\sigma_{\varepsilon,1}}{\sigma_\varepsilon}; \rho_0 = \frac{\sigma_{\varepsilon,0}}{\sigma_\varepsilon}$ are the correlations between the disturbances of the respective outcome equations and the choice equation, and $\phi(.)$ denotes the standard normal density function (Heckman, Urzua and Vytlacil, 2006b).

The probability of becoming legalized is defined as:

$$Pr(z) = Pr(D = 1 \mid Z = z) = Pr(\alpha' Z > \varepsilon) = \Phi_\varepsilon(\alpha' Z) \tag{14}$$

where $\Phi(.)$ is the cumulative distribution of ε. Heckman, Urzua and Vytlacil (2006a) refer to this function as a propensity score, taken as a monotonic function of the mean utility of treatment (legal status). This is reflected in the acceptance decision:

$$D = 1\left[\Phi_\varepsilon(\mu(Z)) > \Phi_\varepsilon(\varepsilon)\right] = 1\left[P(Z) > U_d\right] \tag{15}$$

where U_d denotes the unobserved characteristics of individuals. The algorithm estimates the propensity score using a probit model, from which the predicted values for the treated and untreated groups are used to define values over which the marginal treatment effect (MTE) of legalization may be identified (Heckman, Urzua and Vytlacil, 2006b).

Since it is impossible to observe an individual in the treated and untreated states simultaneously, the actual outcome to be estimated:

$$
\begin{aligned}
\ln Y_i &= D_i \ln Y_{1i} + (1 - D_i) Y_{0i} \\
&= D_i \left[X_i(\beta_1 - \beta_0) + u_{1i} - u_{0i} \right] + \beta_0 X_i + u_{0i} \\
&= \gamma_i D_i + \beta_0 X_i + u_{0i}
\end{aligned}
\tag{16}
$$

where $\gamma_i = X_i(\beta_1 - \beta_0) + u_{1i} - u_{0i}$ is the heterogeneous return to legal status for the i^{th} foreign farm worker (i.e. the effect varies across all farm workers). If the heterogeneous effect were from a differential between the β_j terms only, this would be 'observed heterogeneity'; if it were to arise as a consequence of differences between the u_{ji} terms, it would be 'unobserved heterogeneity.' In either case, this parameter would imply different wage effects of legalization across foreign workers in the farm workforce even if they have identical observable characteristics. Note that for individuals who gain legal status (*D=1*), γ_i captures the benefit of legal status.

Treatment effect parameters

The literature on marginal treatment effects (MTE) spearheaded by Heckman provides several interpretations of the MTE which are equivalent under certain assumptions that apply in this analysis (see Heckman and Vytlacil (2007b) and references therein). One interpretation of the MTE presents it as a measurement of the marginal return to individuals who are indifferent between foregoing (*D=0*) or accepting treatment (*D=1*) when their mean utility ($\mu_d(Z)$) is equivalent to U_d. If $\ln Y_j$ are defined as value outcomes, it may be interpreted as a 'willingness to pay' measure for individuals with certain observable characteristics (*X*) and unobserved heterogeneity (U_d) at a specified margin of indifference (Heckman and Li, 2004; Heckman, Urzua and Vytlacil, 2006a). The other treatment effect estimators – the average treatment effect (ATE), the average treatment effect on the treated (ATET) and the average treatment effect on the untreated (ATEU) – are generated as weighted averages of the MTE (Heckman, Urzua and Vytlacil; 2006a; 2006b):

$$ATE = E(\gamma_i \mid X = x, U_d = u_d) = \int_0^1 \Delta^{MTE}(x, u_d) du_d \tag{17}$$

$$ATET = E(\gamma_i \mid X = x, D = 1) = \int_0^1 \Delta^{MTE} \omega_{ATET}(x, u_d) du_d \tag{18}$$

$$ATEU = E(\gamma_i \mid X = x, D = 0) = \int_0^1 \Delta^{MTE} \omega_{ATEU}(x, u_d) du_d \tag{19}$$

where the applicable weights based on the propensity score (P) are:

$$\omega_{ATET} = \frac{1 - \Phi_P}{E(P_i)} \quad and \quad \omega_{ATEU} = \frac{\Phi_P}{1 - E(P_i)} \tag{20}$$

Data

The data consist of 19,152 foreign workers with complete data from the National Agricultural Workers Survey (NAWS) for 1989 to 2006. Subsamples reflecting the treated (those who have obtained legal status; N_1=8097) and untreated (those without legal status; N_0=11055) worker groups are specified. Table 1 defines the variables that were used in the analysis. The variables reflect the demographic characteristics of the crop farm workforce and certain characteristics of the farm labor market. Dummy variables reflecting the location, time period of interview, and time period when the foreign workers would have entered the US to live or work are also included.

Results and Discussion

Table 2 reports the summary statistics for the variables that were used in the analysis. The treated group comprised 8,097 foreign workers whereas the untreated group comprised 11,055 foreign workers. One of the more interesting findings to emerge from the data is the difference in time spent abroad by workers of the two groups: workers who are not legalized have much longer overseas stays than their cohorts who are legalized (5 weeks on average). In addition, workers who gained legal status reported more months and weeks of farm work in the previous year on average than their cohorts who did not gain legal status. Although workers had similar foreign farm work experience, there was a sizeable difference in US farm work experience. On average, legalized workers reported 16.7 years of US farm work compared to 6 years for workers who were not legalized. Not surprisingly, legalized workers had migrated to the US much earlier (~12 years more) and had worked with their current employers for much longer periods (~4 years) in comparison to their cohorts who did not gain legal status. On average, 62% of the foreign farm workforce had migrated to the US to live and work after 1986. Among legalized workers, only 26% had migrated to US after 1986, whereas approximately 88% of unauthorized workers had entered the US since that period.

Tables 3 reports the estimated choice model results from the MTE algorithm. The instruments included in this model are farm work weeks, years with employer, years since immigration, after 1986 and weeks spent abroad. The characteristics that significantly increase the likelihood of legalization (treatment) are years with employer, English, and years since immigration; those that decrease the likelihood of treatment are farm work weeks, after 2001 and weeks spent abroad. The after 2001 dummy variable was included to distinguish between the pre- and post- 9/11 periods, and the after 1986 dummy was included to distinguish between the periods when workers first entered the US to live or work. The latter reflects the broad legalization through the SAWs program for those who were in the US and working prior to the passage of IRCA in 1986, and the relative difficulty of acquiring legal status since 1986. The direction of influence signaled by the after 2001 coefficient suggests that foreign farm workers were less likely to gain legal status following the September 2001 terrorist attacks; this makes sense given that enforcement efforts and security were heightened in the US following that event. Arguably legal status would have been more difficult to attain with the additional checks and safeguards that were put in place. That is not to say that the tightening on legal status would have necessarily had a significant adverse effect on foreign farm workers; if anything, these workers are more likely to have migrated illegally across the US border with Mexico. The magnitude of the after 1986 dummy suggests that legal status has been difficult to acquire since the last major legalization in 1986 (the SAWs program). The farm work weeks effect indicates that more weeks of farm work reduce the likelihood of having legal status.

Table 4 presents the parametric model wage results for the treated and untreated worker groups. Wage results for the nonparametric methods (polynomial, nonparametric I, nonparametric II) are reported in Table 5.[5] All parameter estimates have the expected direction of influence on the wage results, and the parameters are statistically significant at the 1% level of significance; the exceptions are the foreign farm work experience and age variables in the treated and non-treated groups, respectively. For both groups, the magnitude and statistical significance of the piece rate and after 2001 estimates suggest dominant influences on farm wages relative to the other variables of the model.

Table 6 reports the estimated treatment effects of legalization which are all positive. The average treatment effect (ATE) reflects the expected gain for a random foreign farm worker who became legalized, the average treatment effect on the treated (ATET) indicates the return to those workers who became legalized, and the average treatment effect on the untreated (ATEU) indicates the potential return for those who were not legalized. The order of magnitude of the estimates generated by each method indicates positive sorting on the gains associated with legalization (ATET>ATE>ATEU), wherein those foreign workers who were most likely to

[5] The three nonparametric estimators are different alternatives to assuming normality of the disturbances (Heckman, Urzua, and Vytlacil, 2006b).

participate in the legalization program benefited the most from it – more so than the average person and more so than their cohorts who were not legalized.

A comparison of the different estimation methods shows a striking difference between the parametric and nonparametric methods in the magnitude of sorting gains from legalization. The sorting gains are the difference between the ATET and ATE estimates – the average gains for the worker who opts for treatment (legalization) versus the worker who randomly selects into treatment. The parametric method reports the smallest sorting gain of the four estimation methods: the average earnings gain for the legalized (treated) foreign worker was 0.0023, implying that the average earnings gain to legalization was 0.23% greater than the average earnings gain for the average foreign worker who randomly selected into legalization. The gains for the nonparametric methods (polynomial, nonparametric I, and nonparametric II) range from 3.16% to 6.57%.

A comparison of the estimates reported within shows significant differences in the magnitude of average returns to legalization for the treated (legalized) and untreated (non-legalized) groups. The parametric method estimates are the exception in this respect: earnings gains average 10% across the board irrespective of treatment status. The differentials are largest for the nonparametric I method, followed by the nonparametric II and polynomial methods, respectively. The average earnings gain for the untreated (ATEU) range between 15% and 18%, and those for the treated (ATET) range between 24% and 26%. The ATEU are particularly informative as they suggest the potential gains of a future legalization for workers, most of whom would have entered the US after the SAWs program.

The relevant support for each marginal treatment effect (MTE) is given by the propensity score frequencies for foreign workers who were treated (legalized) and untreated (not legalized) shown in Figure 1. The marginal treatment effects generated by each method are shown in Figure 2 through Figure 5. The MTE is evaluated at values at which the propensity score $(P(z))$ and unobservable factors (u_d) are equivalent (Heckman, Urzua and Vytlacil, 2006a; 2006b). Heckman and Vytlacil (2005) emphasize the role of the unobservable characteristics in the interpretation of the MTE: for smaller values of the unobservables (u_d) (points closer to zero on the x axis), the MTE is the expected benefit for individuals who are **more** likely to participate in treatment and who would participate even if the mean scale utility ($\mu_d(Z)$) were small. Conversely, for larger values of u_d the mean scale utility ($\mu_d(Z)$) would have to be much larger to induce individuals' participation in treatment and they are **less** likely to participate. The MTE may also be interpreted as the mean gain for persons with observable characteristics (X) who would be indifferent between acquiring legal status or not, and may be viewed as a willingness to pay (WTP) measure if the outcomes are value outcomes (Heckman and Vytlacil, 2007a; 2007b).

The latter interpretation of the MTE is useful given the findings depicted in Figures 2 through 5 which seem to conflict with the positive sorting on the gains indicated by the average treatment effect parameters. Figure 2, which is based on the parametric method, suggests that the worker who became legalized (on account of having a low u_d) benefited less than the worker who was not legalized (on account of having a high u_d). Although this is difficult to reconcile with the positive sorting on the gains indicated by the average treatment effect parameters, the WTP interpretation of the MTE may offer reasonable explanation. The upward slope of Figure 2 would therefore suggest an increasing willingness to pay by workers who have larger unobservables that usually would make them less eligible for participation in the program. The increasing u_d values may be indicative of idiosyncratic enhanced productivity, and a larger willingness to pay for legal status in order to permit more options to earn better returns.

The MTEs generated by the nonparametric methods shown in Figures 3 through 5 are quite different from the parametric MTE. Again, the WTP interpretation may offer some explanation for the three different segments exhibited by the MTEs along the u_d range. On the downward sloping segments, individuals who have lower unobservables are more likely to participate in a legalization program and exhibit a large willingness to pay for legal status acquisition. Toward the middle segment of the MTEs (~0.51) however, it is possible that workers are more difficult to categorize in terms of legal status on the basis of their observable and unobservable characteristics and therefore are the least willing to pay for legal status relative to other individuals. Individuals with high unobservables fall within the upper segment of the MTE. They exhibit high willingness to pay for legal status, arguably because they have a lower likelihood of gaining legal status due to unfavorable unobservable characteristics. On account of the lower likelihood of becoming legalized, these individuals are likely to have fewer options for employment in other sectors but may possibly be more productive than their cohorts with legal status.

Policy Implications

Much of the political warring over immigration reform stems from proposed legalization of unauthorized immigrants – whether it would reward illegal behavior and encourage future illegal immigration or whether it would serve the nation's interests better to adjust unauthorized workers to legal status to prevent shocks to the labor intensive industries that mostly hire them. In addressing these issues, AgJOBS seeks to stabilize the crop farm workforce that is extremely vulnerable to immigration reform that may affect labor supply, wages and labor costs.

The average treatment effect on the untreated (ATEU) parameter offers key insight as to how earnings may be potentially affected by a legalization program such as AgJOBS. The average earnings gains range from 0.1002 to 0.1784, suggesting potential earnings increases between 10% and 18% for unauthorized workers that become adjusted to legal status. The findings are broadly consistent with previous work that assessed the earnings implications of legalization. Isé and Perloff (1995) estimated average wage increases of about 15% for unauthorized workers that are granted amnesty; if they were to become permanent residents however, their wages would increase by about 12%. Iwai, Emerson and Walters (2006a) found that unauthorized workers who gained legal status would, in general, earn higher wages. Wages would increase by as much as 31%: for example, unauthorized workers who selected into temporary authorized status had wage increases between 6% and 31% after 2001.[6]

Such results suggest cost increases for farm employers of unauthorized workers. Given the large percentage of the farm workforce that is currently unauthorized for US employment, the increased cost may be substantial for employers with large proportions of unauthorized workers among their crews, and for whom labor costs comprise significant portion of total cost. Employers may respond by using other production factors more intensively; Napasintuwong (2004) suggested that the degree of intensity to which capital and labor are used in agriculture have been affected by the availability of immigrant labor, which is in turn affected by immigration policy.

Concluding Remarks

This study sought to analyze the potential impact of proposed legalization on the wage outcomes of foreign farm workers. The results provide some insight as to how future legalization could impact farm wages and, by extension, labor costs for employers. The key distinction between this study and previous work is analytical framework: this study approached the problem from a treatment effects perspective with legalization modeled as a policy intervention

[6] These are based on specific simulations that account for location, time, payment type, etc. See Iwai, Emerson and Walters (2006a) for details.

or treatment. The application of this analytical framework is a significant contribution to the literature on immigration policy evaluation and farm labor markets as it had not been previously applied in this context. The study also assumed that essential heterogeneity existed, meaning that workers would not only display different responses to treatment but would also select into treatment based on idiosyncratic gains. The test of essential heterogeneity suggested by Heckman, Urzua and Vytlacil (2006a) was used to show that this assumption was indeed supported by the data.

The results show an overall positive impact of legalization on farm worker outcomes. There is positive sorting on the gains from legalization, implying that foreign workers who specifically sought legalization benefited more than the average worker and even more so than their cohorts who had not been legalized. The magnitude of gain is sensitive to the method of estimation used, with modest increases noted for the parametric method relative to the nonparametric methods. The findings from the marginal treatment effects are not entirely clear, and seem to conflict in most respects with the average treatment effect results. Given the stark differences between the parametric and nonparametric methods, it would appear that the assumption of joint normality (on which the parametric method is based) is not supported by the data. However, this is not to imply that the nonparametric MTEs offer less ambiguous interpretations. As they are presently, they are somewhat difficult to reconcile with the findings suggested by the positive sorting gains suggested by the average treatment effect parameters. If the MTEs are viewed in the context of willingness to pay measures however, the interpretations seem reasonable. Clearly, these findings suggest a need for future research. A likely starting point would be additional refinement of estimates based on the nonparametric methods as the normality assumption appears problematic. Most importantly, the results show that unauthorized workers may potentially gain from future legalization, with wage increases by as much as 18%. In this respect, the cost implications for farm employers are clear in that labor costs would increase if amnesty were to be granted to workers who are currently unauthorized. Whether this may encourage employers to shift to more capital intensive methods of production over time would depend on the magnitude of the cost increase and the degree of stringency and effectiveness of future legislation in controlling illegal immigration and employment.

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Table 1 Explanatory variables of the choice and parametric wage regression models

Variable [a]	Definition
LnWage	Natural logarithm of the real farm wage in 2006 dollars. Conversions from the nominal wage were made using the consumer price index for all urban consumers
Legal status	=1 if farm worker is authorized for U.S. employment (citizen, permanent resident, or has other work authorization) = 0 if otherwise (i.e. unauthorized)
Piece rate	= 1 if worker is paid by piece rate = 0 if otherwise (by the hour, hour/piece combination, or salary)
Seasonal worker	=1 if worker is employed on a seasonal basis = 0 if otherwise (year-round)
Female	=1 if female =0 if male
Mexican	= 1 if worker is of Mexican nationality =0 if otherwise
Education	Highest grade level of education completed by the farm worker, ranging from 0 to 16
Adult education[b]	=1 if worker had attended any adult education classes or school in the U.S. =0 if otherwise
After 1986	Dummy variable reflecting years before and after 1986 when foreign workers entered the United States for the first time to live or work
After 2001	Dummy variable reflecting the interview years following September 2001
California (CA)	Dummy variable reflecting employment in California at the time of the interview
English (speaking ability)	= 1 if 'none at all' = 2 if 'a little' = 3 if 'somewhat' = 4 if 'well'
Married	= 1 if 'married/living together' =0 if otherwise

Table 1. Continued.

Variable	Definition
Years with current employer	Number of years of employment worker has completed with current employer. One year is measured as one or more days per year (NAWS)
Farm work weeks	Farm work weeks completed in the last year
Foreign farm work experience	=1 if worker had been employed in agriculture, either full-time or part-time, while living in native (foreign) country =0 if worker had been employed in non-agricultural sector or had never worked while living in native (foreign) country
Grower	= 1 if employed by a grower = 0 if employed by a farm labor contractor
Age	Respondent age in years
Age^2	Age squared
Experience	Years of U.S. farm work
$Experience^2$	Experience squared
Farm work in the last year	Months of US farm work in the previous year (prior to work grid estimate)
Weeks spent abroad	Number of weeks abroad last year

[a] Data were sourced from the National Agricultural Workers Survey (1989-2006). Definitions enclosed in quotation marks are as they appear in the NAWS Codebook. [b] This would include English/ESL, citizenship, literacy, job training and Adult Basic Education classes, GED/high school equivalency classes, college or university classes, and Even Start and Migrant Education classes.

Table 2 Summary statistics of foreign farm workforce, NAWS, 1989-2006

Variable	N=19152 workers		N_1=8097 workers		N_0=11055 workers	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Lnwage	2.0351	0.2513	2.0876	0.2603	1.9966	0.2372
Weeks Spent Abroad	6.6531	12.2887	3.7974	8.4420	8.7447	14.1097
Specialty Crop	0.7986	0.4011	0.8176	0.3862	0.7846	0.4111
Adult Education	0.2007	0.4005	0.2812	0.4496	0.1417	0.3487
After 1986	0.6148	0.4867	0.2577	0.4374	0.8763	0.3293
After 2001	0.5198	0.4996	0.4763	0.4995	0.5517	0.4973
Female	0.1615	0.3680	0.1860	0.3891	0.1436	0.3507
Married	0.6314	0.4824	0.7866	0.4097	0.5177	0.4997
English	1.7231	0.8278	2.0042	0.9055	1.5172	0.6974
Mexican	0.8873	0.3163	0.8697	0.3366	0.9001	0.2998
Education	5.9630	3.2826	5.7599	3.4046	6.1118	3.1821
Experience	10.4756	9.0697	16.6972	9.1572	5.9188	5.6548
Age	33.7474	11.8152	39.9809	11.3513	29.1819	9.9084
Farm Work Done Last Year	7.4226	4.3196	8.6284	3.3334	6.5394	4.7268
Years Since Immigration	11.9724	10.0984	19.1250	9.4763	6.7336	6.7813
Year With Employer	4.5438	4.8579	6.8092	6.1175	2.8846	2.6388
California	0.3957	0.4890	0.5081	0.5000	0.3134	0.4639
Grower	0.8003	0.3998	0.8185	0.3855	0.7871	0.4094
Piece Rate	0.1839	0.3875	0.1601	0.3667	0.2014	0.4011
Seasonal Worker	0.6873	0.4636	0.6698	0.4703	0.7002	0.4582
Farm Work Weeks	36.4671	14.5541	37.7998	12.8602	35.4910	15.6077
Foreign Farm Work Experience	0.6830	0.4653	0.6684	0.4708	0.6936	0.4610

Table 3 Probit model estimates for legal status treatment

Variable	Parameter Estimate[a]	Standard Error
Constant	-0.5119***	0.0733
Farm Work Weeks	-0.0093***	0.0010
Years with Employer	0.0680***	0.0056
English	0.2464***	0.0134
Years since Immigration	0.0563***	0.0026
After 2001	-0.3544***	0.0276
Weeks Spent Abroad	-0.0192***	0.0013
After 1986	-0.7906***	0.0402

[a] Triple asterisks (***) indicate statistical significance at 1% level.

Table 4 Estimated parameters from parametric wage regressions for treated and untreated groups

	Authorized Status (Treated)		Unauthorized Status (Untreated)	
Variable	Parameter Estimate[a]	Standard Error	Parameter Estimate[b]	Standard Error
Constant	1.68363***	0.04438	1.73827***	0.01594
Age	0.00821***	0.00205	0.00122	0.00083
Age sq.	-0.00012***	0.00002	-0.00003**	0.00001
Farm Work Last Year	0.00530***	0.00086	0.00386***	0.00055
Experience	0.00328***	0.00111	0.00704***	0.00108
Experience sq.	-0.00005**	0.00002	-0.00019***	0.00004
English	0.03114***	0.00467	0.01498***	0.00417
Female	-0.06034***	0.00785	-0.04470***	0.00555
Piece Rate	0.21334***	0.00992	0.18298***	0.00746
Grower	0.07502***	0.00651	0.05197***	0.00487
Seasonal Worker	-0.04230***	0.00551	-0.01224***	0.00359
Education	0.00455***	0.00095	0.00534***	0.00059
Foreign Farm Work Experience	0.00189	0.00569	0.01565***	0.00436
After 2001	0.11875***	0.00496	0.06282***	0.00319
California	0.04137***	0.00447	0.04523***	0.00408
Rho	0.04599***	0.00799	0.03842***	0.00799

[a, b] Triple and double asterisks (***, **) indicate statistical significance at 1% and 5% levels of significance, respectively.

Table 5 Estimated beta coefficients and standard errors for the outcome equations estimated by polynomial, nonparametric I and nonparametric II methods

Variable[a]	Polynomial Method[b]		Nonparametric Method I[c]		Nonparametric Method II[d]	
	Coefficient	S.Error	Coefficient	S.Error	Coefficient	S.Error
Constant	1.79182	0.02072	----	----	---	---
Age	-0.00115	0.00117	-0.00104	0.00118	-0.00115	0.00117
Age sq.	0.00001	0.00002	0.00001	0.00002	0.00001	0.00002
Farm work last year	0.00192	0.00072	0.00180	0.00074	0.00192	0.00072
Experience	0.01189	0.00186	0.01282	0.00189	0.01189	0.00186
Experience sq	-0.00059	0.00010	-0.00065	0.00010	-0.00059	0.00010
English	-0.00392	0.00530	-0.00418	0.00533	-0.00392	0.00530
Female	-0.03970	0.00842	-0.03997	0.00827	-0.03970	0.00842
Piece rate	0.17784	0.00901	0.17786	0.00900	0.17784	0.00901
Grower	0.04105	0.00633	0.04085	0.00632	0.04105	0.00633
Seasonal worker	0.00011	0.00498	0.00033	0.00499	0.00011	0.00498
Education	0.00600	0.00084	0.00597	0.00084	0.00600	0.00084
Foreign farm work Experience	0.00620	0.00535	0.00630	0.00536	0.00620	0.00535
After 2001	0.06019	0.00683	0.05984	0.00650	0.06019	0.00683
California	0.04973	0.00376	0.04965	0.00376	0.04973	0.00376
Age*pscore	0.01188	0.00285	0.01167	0.00286	0.01188	0.00285
Age sq*pscore	-0.00016	0.00003	-0.00016	0.00003	-0.00016	0.00003
Farm work last year*pscore	0.00521	0.00164	0.00532	0.00168	0.00521	0.00164
Experience*pscore	-0.00584	0.00251	-0.00652	0.00242	-0.00584	0.00251
Experience sq*pscore	0.00047	0.00010	0.00054	0.00010	0.00047	0.00010
English*pscore	0.03746	0.00746	0.03962	0.00745	0.03746	0.00746
Female*pscore	-0.03008	0.01768	-0.02901	0.01753	-0.03008	0.01768
Piece rate*pscore	0.04276	0.01960	0.04278	0.01953	0.04276	0.01960
Grower*pscore	0.04555	0.01480	0.04666	0.01475	0.04555	0.01480
Seasonal Worker*pscore	-0.04703	0.01385	-0.04818	0.01388	-0.04703	0.01385
Education*pscore	-0.00254	0.00172	-0.00241	0.00174	-0.00254	0.00172
Foreign farm work Experience*pscore	0.00837	0.01151	0.00740	0.01152	0.00837	0.01151
After 2001*pscore	0.06955	0.01541	0.07020	0.01507	0.06955	0.01541
California*pscore	-0.01112	0.00848	-0.01116	0.00844	-0.01112	0.00848
Pscore	-0.15046	0.10896	----	----	---	---
Pscore^2	0.73697	0.44991	----	----	---	---
Pscore^3	-2.20958	0.61096	----	----	---	---
Pscore^4	1.47909	0.28288	----	----	---	---

[a]'Pscore' denotes the propensity score, which is the probability of becoming legalized. [b]The outcome equation is estimated as a polynomial in the propensity score (Heckman, Urzua and Vytlacil, 2006). [c]This is the LIV estimator from Heckman and Vytlacil (2001, 2005). [d]This method combines the nonparametric I and the polynomial approach.

Table 6 Treatment effects of legalization

Parameter[a]	Parametric[b] Method	Polynomial Method	Nonparametric Method I	Nonparametric Method II
ATET	0.1043	0.2385	0.2635	0.2538
ATEU	0.1002	0.1784	0.1459	0.1616
ATE	0.1020	0.2069	0.1978	0.2031
Sorting gain (ATET-ATE)	0.0023	0.0316	0.0657	0.0507

[a] A test for essential heterogeneity in the treatment effects yielded an F-statistic (p value) of 18.19 (0.0000), indicating self-selection arising from heterogeneous and unobserved gains for individuals in the sample (See Heckman, Urzua and Vytlacil, 2006). [b]The extent of selection bias is gauged with a comparison of the OLS and parametric model results: selection bias = OLS-ATET= 0.0359-0.1043= -0.0684. It shows that the OLS estimate of the average effect of legalization on earnings is downward biased, indicating a 3.6% average earnings gain relative to the 10% average gain suggested by the ATET estimate in the parametric method. The overall bias (OLS-ATE) is -0.0661.

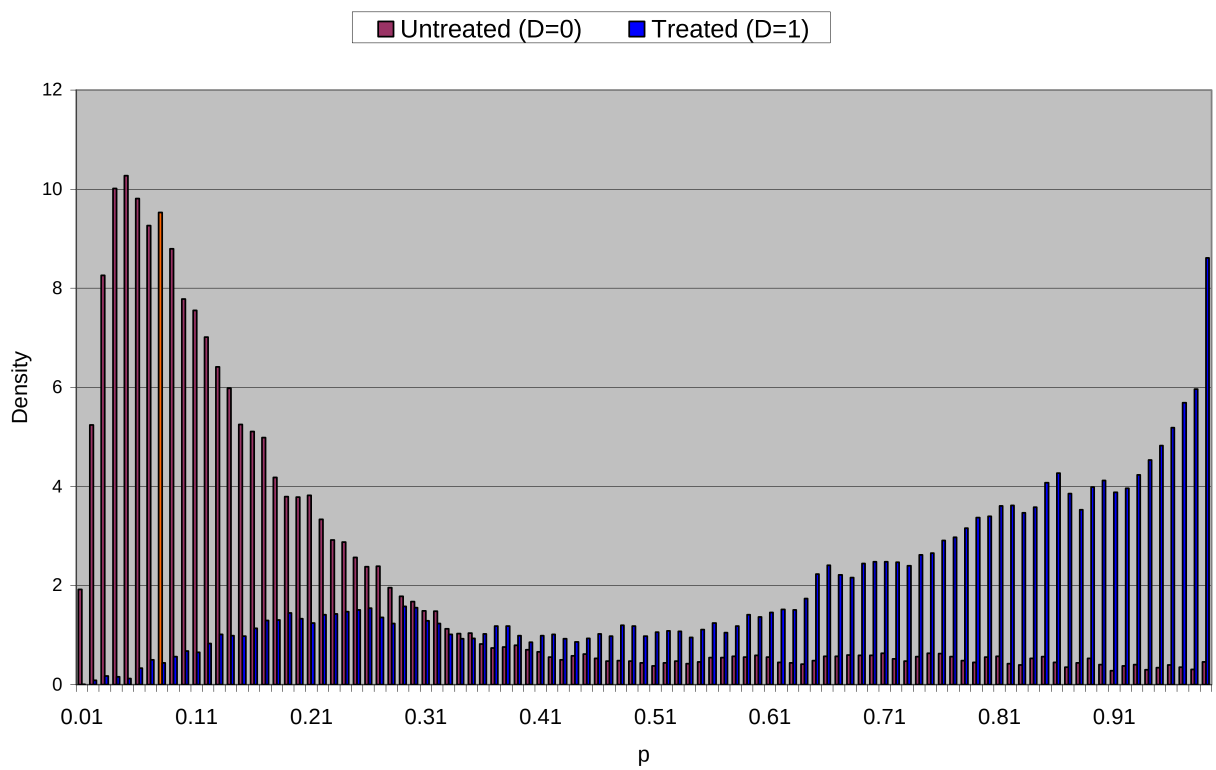

Figure 1 Frequency of propensity score by legal status

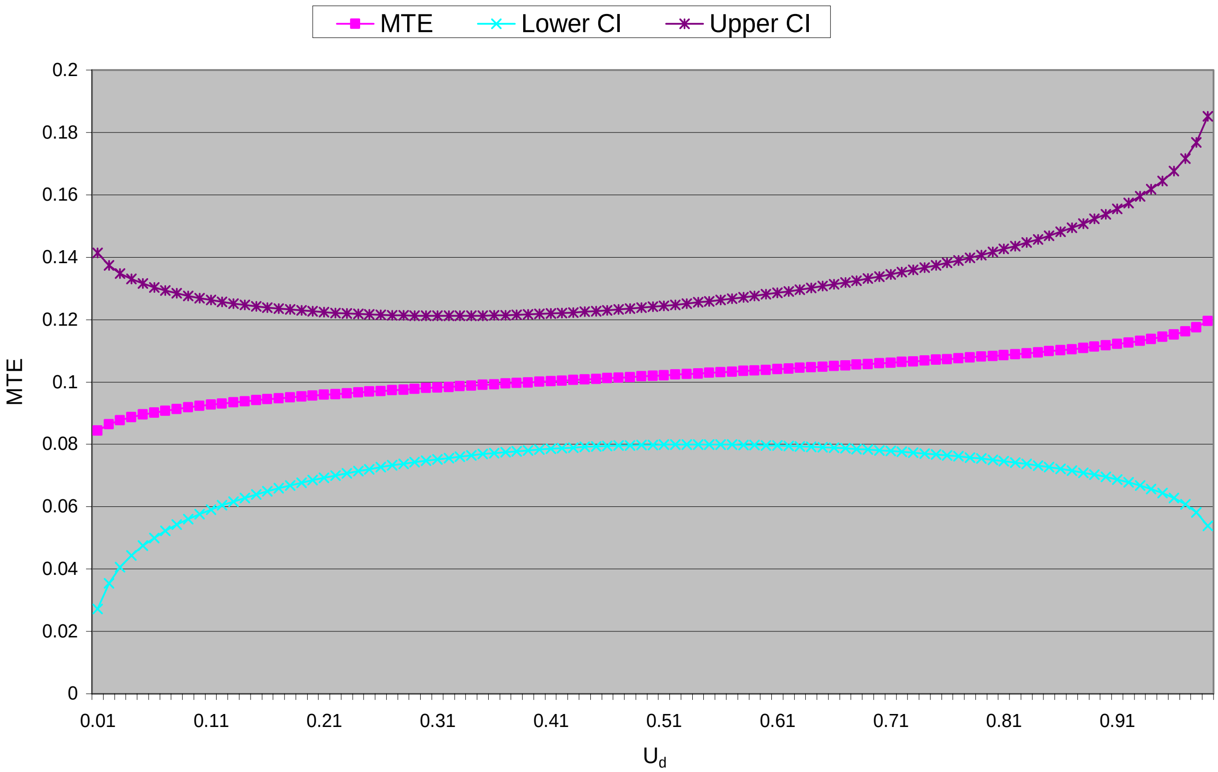

Figure 2 Marginal treatment effect (MTE) of legalization for foreign farm workers (with 95% confidence intervals), parametric method

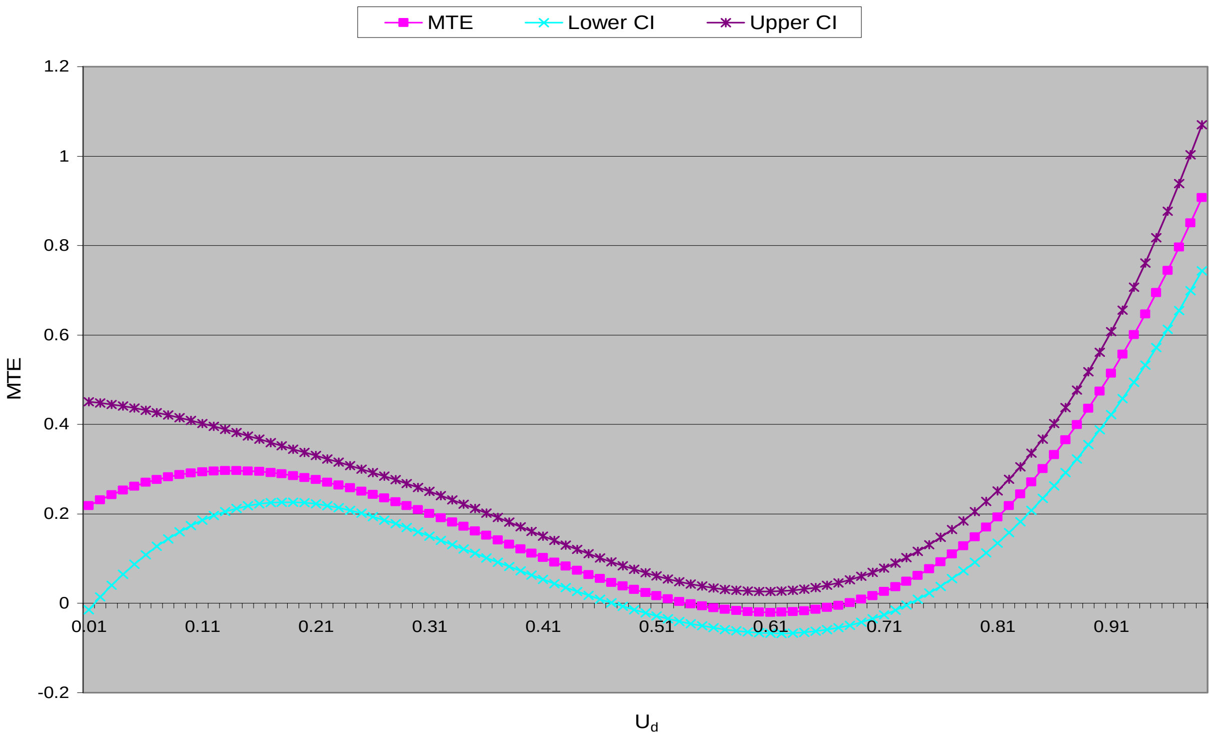

Figure 3 Marginal treatment effect (MTE) of legalization for foreign farm workers (with 95% confidence intervals), polynomial method

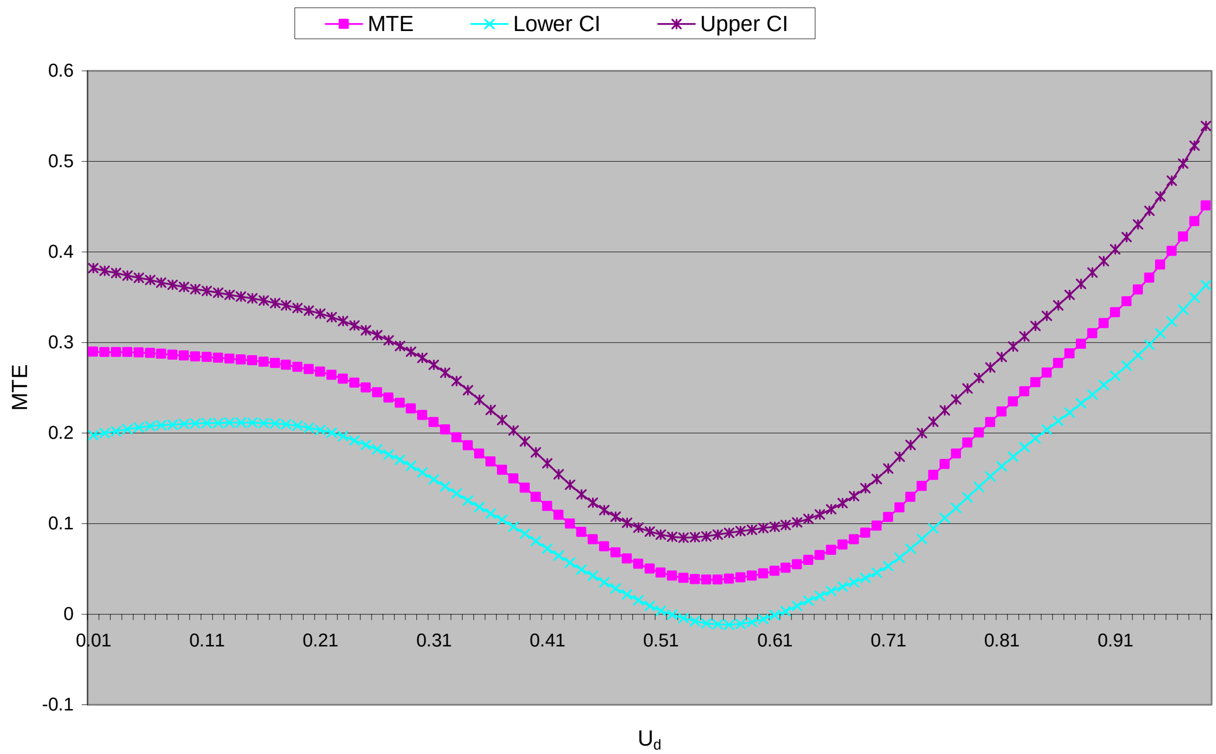

Figure 4 Marginal treatment effect (MTE) of legalization for foreign farm workers (with 95% confidence intervals), nonparametric method I

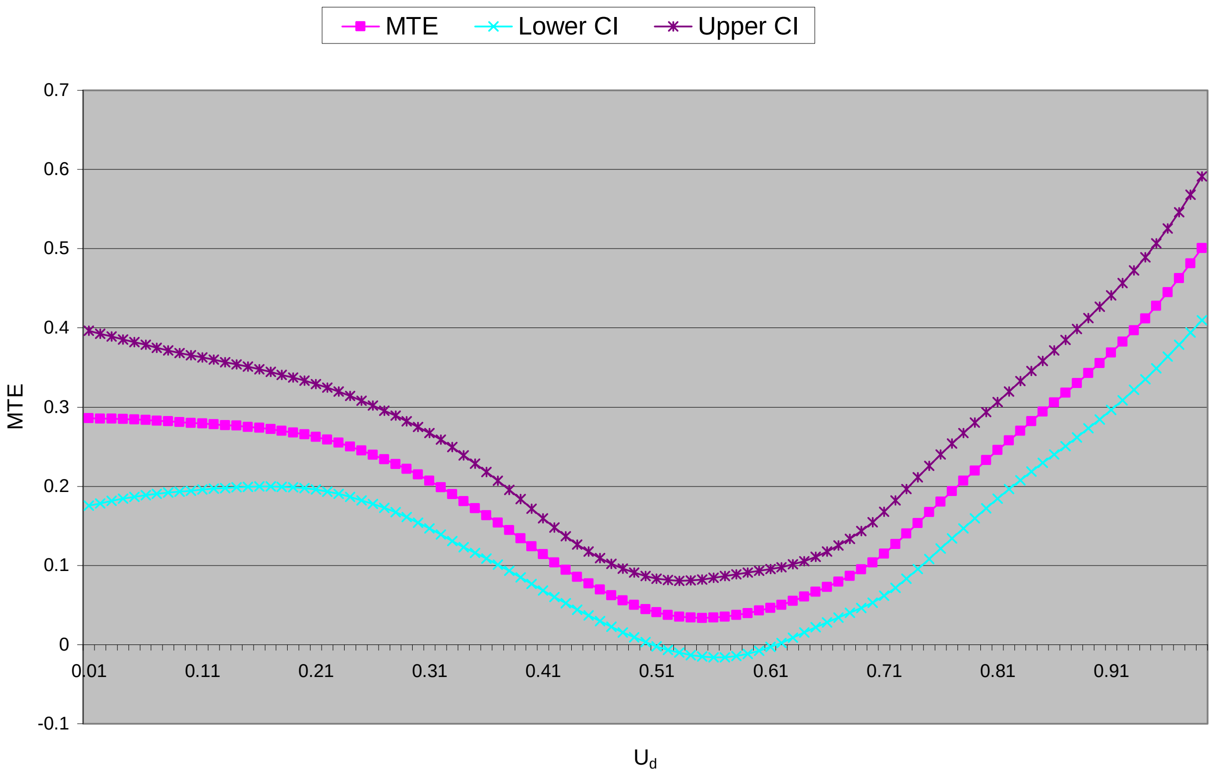

Figure 5 Marginal treatment effect (MTE) of legalization for foreign farm workers (with 95% confidence intervals), nonparametric method II

[i] Excerpted from: Walters, L.M. 2008. Three essays on immigration reform, worker self-selectivity and earnings in the U.S. farm labor market. Unpublished PhD Dissertation, University of Florida.