The Labor Supply of U.S. Agricultural Workers

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1 Introduction

The U.S. agricultural labor market has historically been categorized by low wages and an abundance of available workers, however, this is changing. In recent years, the agricultural labor market has been seeing a lower supply of workers, and, as an effect, producers have been increasingly competing with each other to attract the necessary labor. Employers have been increasing wages and offering their workers non-pecuniary benefits such as: facilitating enrollment in welfare programs; offering food donations at the farm; and providing child care and health care services. However, the success of these employer efforts are unclear.

To better understand the changing agricultural labor market and the potential effects of these recent employer efforts to attract workers, this paper constructs updated elasticity of labor supply estimates for U.S. crop workers. These elasticity estimates explain how U.S. crop workers adjust their hours worked in agriculture in response to after tax wage changes. While aggregate elasticity measures are useful for depicting an industry broadly, elasticities for subsets of a population are more useful for examining the effects of compositional changes. This paper estimates elasticities for both the entire sample of U.S. agricultural workers
and for specific subsets, by separating workers based on legal status and welfare program participation.

There are two interesting questions that this paper addresses with these elasticity estimates. First, how do legal status and welfare program participation affect the elasticity of labor supply for U.S. crop workers? And second, does the changing composition of the workforce explain the ongoing changes in the agricultural labor market? To address the first question, the paper compares baseline aggregate elasticity estimates with estimates that: (1) separate workers by legal status; and (2) separate workers by welfare program participation. To address the second question, the paper examines the trends in the composition of the workforce, and discusses the implications in light of the elasticity estimates.

Previous literature that provides estimates of the elasticity of agricultural labor supply is now somewhat dated (e.g. Emerson and Roka, 2002; Pena, 2010; and Taylor and Thilmany, 1993). Significant changes in U.S. immigration policy since these estimates have resulted in major structural changes in the agricultural labor market that are not captured in existing elasticity estimates (Martin and Calvin, 2010; and Taylor, Boucher, Smith, Fletcher, and Yunez-Naude, 2012). Furthermore, previous estimates often relied on more aggregate data from sources such as the Farm Labor Survey and the U.S. Census of Agriculture. While these data sources may provide more observations, they are lacking accurate information data on legal status and welfare. Labor responsiveness to incentives has been well documented in the broader economic literature on labor supply, but has not yet been applied to the agricultural workforce (Gruber, 2000; Meghir and Phillips, 2008; Meyer and Rosenbaum, 2001; Mulligan,
2 BACKGROUND: THE U.S. AGRICULTURAL LABOR MARKET

Over the last decade, the number of hired U.S. farmworkers has been decreasing, while the average real wage rate has been climbing. To demonstrate this, figure 1 shows the annual average numbers of hired farmworkers on the left axis, and annual average wages (in CPI-adjusted $/hr) on the right axis. Historical decreases in the number of hired workers in U.S. agriculture have generally been attributed to changing demand due to increased mechanization and technological advancements. However, beginning with the passage of the
Immigration Reform and Control Act (IRCA) of 1986, most of the literature changed focus to supply driven changes in labor market (Taylor and Thilmany, 1993; Taylor, Boucher, et al., 2012; and Martin and Calvin, 2010).

At the time, the passage of IRCA was of major concern to agricultural employers and researchers. IRCA imposed major employer sanctions that made it illegal to hire or recruit illegal immigrants, and simultaneously legalized some qualified illegal immigrants. Concern in the agricultural sector was that this would reduce the supply of agricultural workers for two main reasons: (1) employers could no longer hire undocumented immigrants, greatly restricting their hiring options; and (2) because the legalization of many of their workers would facilitate their movement into different employment sectors. Figure 2 depicts annual changes in the composition of the U.S. agricultural workforce since 1990. This figure
nicely demonstrates that, if anything, there have been increasing numbers of undocumented workers over this span. Given the continued prevalence of undocumented workers in the agricultural sector, the former concern appears invalidated, however, the effects on worker provision of agricultural labor are somewhat less obvious.

Figure 2: The Legal Status Composition of U.S. Cropworkers

Note: This figure omits ‘other authorized’ workers.

Source: National Agricultural Workers Survey

Given the legal status composition of U.S. crop workers, and considering recent work that finds a large differential between the labor supply curves for citizen and undocumented men, legal status is an obvious way to segment the workforce (Borjas, 2016). If these workers have different wage responsiveness, then policies such as IRCA that affect worker legal statuses will affect the supply of labor without inducing workers to change work sectors. Estimating elasticities separately for workers of different legal statuses will capture the variation between
the wage responsiveness for these worker types. These elasticities can then be utilized to analyze the effects of U.S. immigration policy on the agricultural labor market.

A recurring topic in labor economics literature is the effect of welfare program benefits on labor supply. Historically, eligibility for welfare programs has often, but not always, been contingent on lawful presence in the country. However, many programs allow unauthorized parents to procure benefits for their resident children. Some programs additionally offer alternative options with lower benefit amounts for specific immigrant populations, one of which is migrant farm workers. While the labor supply effects of program receipts have been well studied in the literature, so far, no work has quantified the effects across different legal statuses.

Table 1 illustrates the legal status eligibility for four major federal welfare programs: Medicaid; the Supplemental Nutrition Assistance Program (SNAP); the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC); and Unemployment Insurance (UI). Each of these programs has different eligibility restrictions and benefit options based on legal status. For example, only citizens are eligible for unemployment insurance, while applicants of all legal statuses are eligible for WIC. Medicaid and SNAP, contrarily, offer reduced benefits for undocumented workers, but allow applicants to receive full benefits for their children.

Generally, program benefits are inversely related to total household income, so that when income increases, benefits are reduced; the rate at which benefits are reduced is known as the benefit reduction rate. Because of the direct relation to income, program benefits generally
have some negative effect on the provision of labor, and the expected magnitude of the effect depends on the benefit reduction rate. Interestingly, the benefit differential based on legal status can change the slope of the benefit reduction equation, which is likely to change the wage responsiveness. For these reasons, the second separating characteristic used in this analysis is welfare program participation. To examine the effects of program participation on labor supply, this paper compares elasticity estimates of participants and non-participants, using propensity score matching to control for observable characteristics associated with selection into participation. Further, this is done separately for citizens, green card holders, and undocumented workers to identify the differential effect based on legal status. To explore the variation among these worker types, in the next section I introduce the data for this paper, and summarize the legal status differentials with respect to these variables.

<table>
<thead>
<tr>
<th>Applicant Legal Status</th>
<th>Medicaid</th>
<th>SNAP</th>
<th>WIC</th>
<th>UI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citizens and Green Card Holders</td>
<td>Eligible</td>
<td>Eligible</td>
<td>Eligible</td>
<td>Eligible</td>
</tr>
<tr>
<td>Undocumented, with children*</td>
<td>Children Eligible, Emergency Care</td>
<td>Children Eligible, Emergency Food</td>
<td>Eligible</td>
<td>Not Eligible</td>
</tr>
<tr>
<td>Undocumented, with no children</td>
<td>Emergency Care</td>
<td>Emergency Food</td>
<td>Eligible</td>
<td>Not Eligible</td>
</tr>
</tbody>
</table>

*This table only documents program eligibility based on legal status; applicants must meet other conditions to receive benefits.

For SNAP, for a family of citizens, the benefit reduction amount is 30%, meaning that for every dollar earned, SNAP benefits are reduced by $0.30. For a family with undocumented income earners, this benefit reduction rate is actually lower due to the income proration equation used to calculate benefits.
3 Data

The data for this paper comes from the National Agricultural Workers Survey (NAWS); a survey administered annually by the U.S. Department of Labor. The survey began in 1989, and data is currently available through the 2012 survey round. The survey covers 545 counties and 43 states, however, the respondent’s location is only available as the coded region of the survey. To date, NAWS contains data from a total of 56,976 interviews with agricultural laborers throughout the United States. The survey includes questions on household demographics, income, program-use, country/state of origin, legal-status, wages, hours worked, worker type (e.g. migrant or seasonal), language, and many more. NAWS is the only nationally representative survey of agricultural workers, and because it provides detailed information on incomes, program participation, and legal-status, it is the ideal dataset for this analysis.

The data cleaning process involved dropping the first four years of the survey, because questions on program participation and tax rates were not collected until the 1993 survey round. Additionally, workers who were supervisors, who fell under the ‘other authorized’ category, and workers who were salaried or paid with a combination piece-rate and hourly wages, were dropped from the sample. Some additional observations were dropped due to missing responses to questions on wages, hours worked, age, education, and legal status. The final, cleaned dataset includes 41,351 observations spanning 1993 to 2012.

A majority of the variables included in the analysis are directly given in the NAWS data, but some variables have multiple choice options and two variables were constructed
by combining multiple responses. The variable used for farm wage rate comes from the
NAWS variable ‘waget1’, which is the farmworkers wage for their most recent task— pre-
harvest, harvest, post-harvest, semi-skilled, and other— with their most recent employer.
This variable was chosen as the main predictor variable in the elasticity regression because,
among the variables relating to payment, it is the only given variable that is not a function
of hours worked. The other option for the wage component of the regression would be
to use the payment on the most recent paycheck, and divide by the number of hours the
worker worked during that period. However, by construction, this creates an endogenous
relationship between the outcome and predictor variables, and should be avoided if possible.

A similar choice was made for the selection of the non-farm wage variable. Another
important clarification is that workers are not directly asked for their tax rate, but they
are asked for the value of their last paycheck both before and after taxes. Using these two
responses, the tax rate was calculated as: $1 - \frac{\text{After Tax Check Value}}{\text{Before Tax Check Value}}$.

4 Legal Status and Worker Characteristics

An overview of the legal composition of the workforce is provided in figure 2; to supplement
this, table 2 gives the legal composition of the workforce by gender. For both male and female
crop laborers in the sample, a majority are undocumented. Table 2 also provides summary
statistics on demographic characteristics, farmworker income, and program participation.
For most variables in the table, there is some variation in the mean by legal status. For both
males and females, citizens tend to be older, have higher educations, are less likely to be
migrant workers, have been working in U.S. agriculture for longer, and have smaller household sizes than undocumented workers. The summary statistics on income attributes reveal that citizens tend to have the highest farm and non-farm wages, and the highest tax rates, while green card holders work the most hours on the farm. Finally, the summary statistics on program participation indicate that green card holders have the highest participation rates in Medicaid, SNAP, WIC, and UI.
As introduced in the previous section, I expected there to be substantial variation across the three legal statuses in the program participation rates, which is confirmed by these summary statistics. For all programs, participation rates are actually highest for green card holders. For females, citizens have the lowest participation rates in medicaid and WIC, while
undocumented workers have the lowest participation rates for SNAP and UI. For males, citizens only have the lowest participation rates in WIC, whereas undocumented workers have the lowest rates in Medicaid, SNAP, and UI.

Considering the eligibility based on legal status for these four programs, outlined in table 1, some of these results are expected. First, only women, infants, and children are eligible for WIC, so the higher participation among females is expected. Furthermore, WIC has no restrictions based on legal status, so the use rates are more a reflection of the distribution of household earnings, than a legal status effect. Second, both SNAP and Medicaid have different eligibility criteria for undocumented applicants with and without children; this helps to explain the large difference in participation between undocumented males and females. As expected, the participation rates in UI are starkly different based on legal status, because only citizens and green card holders are eligible for benefits, and there are no exceptions based on the legal status of children in the household.  

The variation in program participation rates between the three legal statuses is not definitively due to the legal statuses of the workers; one alternative explanation is that this is instead due to the difference in total earnings across the groups. To explore the causation of the program participation rate differential between legal statuses, figure 3 shows the program participation rates for the four welfare programs used in this analysis, separated

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2 The fact that undocumented workers have a higher than 0% participation rate in UI is surprising given the strict restrictions based on legal status. I can identify three possible explanations for these positive participation rates: (1) it is possible that respondents enroll in the program using fake social security numbers; (2) the precise wording of the questions is has anyone in your household received benefits from unemployment insurance?, thus it is possible that another household member with legal status is actually receiving these benefits; and (3) this could be due to response error.
by household income group and worker legal status.\(^3\) Usually, program participation is expected to decrease with household income, however, given the average household sizes, and the range of these income categories, workers are likely not earning enough in most of these categories to push themselves out of benefit eligibility. For each benefit program, within an income group, there is still substantial variation based on legal status. For Medicaid and UI, across all income groups, green card holders have higher participation rates than undocumented workers. For WIC and SNAP, this relationship holds in the middle and lower income groups, but in the upper income groups, undocumented workers tend to have higher participation rates.

\(^3\)The categories are separated at the 33 and 66 percentiles of the income distribution for all workers. These income categories are: (low) $0-$7,500; (medium) $7,500-$15,000, and (high) >$15,000. I compared the results with several different income category specifications with similar results.
participation rates. Generally, these graphs provide convincing evidence that the program participation rate differentials between legal statuses is caused by more than just divergent income distributions.

5 Empirical Model and Results

A simple empirical approach to estimating labor supply elasticities is to use the double log regression to estimate the effect of after-tax wages on hours worked. The simplest form of this model can thus be written as:

\[ \log(h_i) = \alpha_0 + \alpha_1 \log(\omega_i) + \epsilon_i \]  

Where \( h_i \) is the worker \( i \)'s reported weekly hours worked and \( \omega_i \) is the hourly after-tax wage rate. In this model specification, the labor supply elasticity is estimated by \( \alpha_1 \). As is usual when estimating labor supply curves, I do estimate elasticities separately for males and females in the sample. The results of this initial regression are given in the first column in table 3. These elasticity estimates are slightly higher for females (0.185) than for males (0.114), and suggest that both female and male workers have fairly inelastic labor supply curves, i.e. they do not adjust their hours worked substantially in response to wage changes.

Because I am more interested in developing elasticity measures for subsets of the agricultural labor force, these estimates are not incredibly useful. I can derive elasticity measures separately for workers of different legal statuses using a slightly different model:
Table 3: Preliminary Elasticity Estimates

<table>
<thead>
<tr>
<th>Worker Type</th>
<th>EQ (1)</th>
<th>EQ (2)</th>
<th>EQ (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non Participants</td>
<td>Participants</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizens</td>
<td>0.114</td>
<td>0.108</td>
<td>0.117</td>
</tr>
<tr>
<td>Green Card Holders</td>
<td>0.121</td>
<td>0.117</td>
<td>0.120</td>
</tr>
<tr>
<td>Undocumented</td>
<td>0.097</td>
<td>0.092</td>
<td>0.101</td>
</tr>
<tr>
<td>Female</td>
<td>0.185</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizens</td>
<td>0.170</td>
<td>0.159</td>
<td>0.188</td>
</tr>
<tr>
<td>Green Card Holders</td>
<td>0.223</td>
<td>0.231</td>
<td>0.225</td>
</tr>
<tr>
<td>Undocumented</td>
<td>0.215</td>
<td>0.222</td>
<td>0.214</td>
</tr>
</tbody>
</table>

*Note: All estimates are significant at at least the 0.01 level.*

\[
\log(h_i) = \alpha_0 + \alpha_1 \log(\omega_i) \cdot C_i + \alpha_2 \log(\omega_i) \cdot G_i + \alpha_3 \log(\omega_i) \cdot U_i + \epsilon
\]  

(2)

Where \(C_i\), \(G_i\), and \(U_i\) are mutually exclusive indicator variables for the worker’s legal status that are equal to one if worker \(i\) is a citizen, green card holder, or unauthorized, respectively. The results from this regression are shown in the second column of table 3. For each legal status category, female workers, again, have higher elasticity estimates than males. Additionally, there is substantial variation in the elasticity estimates across legal statuses. For both males and females, green card holders have the highest elasticity estimates, 0.121 and 0.223, respectively. For males, undocumented workers have the lowest wage responsiveness (0.097), while for females, citizens have the lowest wage responsiveness (0.170).

Finally, while these elasticity estimates provide somewhat more insight into the labor supply behavior of agricultural workers, I can derive even more specific elasticity estimates
using the following regression equation:

\[
\log(h_i) = \alpha_0 + (\alpha_1 \log(\omega_i) \cdot C_i + \alpha_2 \log(\omega_i) \cdot G_i + \alpha_3 \log(\omega_i) \cdot U_i) \cdot P_i + \\
(\alpha_4 \log(\omega_i) \cdot C_i + \alpha_5 \log(\omega_i) \cdot G_i + \alpha_6 \log(\omega_i) \cdot U_i) \cdot NP_i + \epsilon_i
\]  

(3)

Where \( P_i \) and \( NP_i \) are indicator variables for whether worker \( i \) reports participating or not participating, respectively, in one of four welfare programs: Medicaid, SNAP, WIC, or UI. The results from this regression specification are shown in columns 3 and 4 of table 3, giving separate elasticity estimates for workers based on legal status and program participation. The results from this regression indicate that for male crop workers across all legal statuses, program participants are more wage responsive than non-participants. For females, the story is different— for green card holders and undocumented female workers, wage responsiveness is lower for program participants than for non-participants, while for citizens, wage responsiveness is higher.

While these preliminary elasticity estimates are interesting, particularly because they highlight the elasticity differential across legal statuses and program participation, they are not incredibly convincing. A well documented problem with estimating labor supply elasticities is the endogeneity of wages and hours worked— there are many other worker attributes that affect both of these variables (e.g. motivation and unearned income). Similarly, the elasticity differential between program participants and non-participants does not necessarily implicate program receipts as the causal mechanism, rather this could be due to worker
characteristics that affect both program participation and hours worked (e.g., education).

To combat the endogeneity issues with these two variables of interest, I begin with employing an instrumental variable (IV) approach. I use federal minimum wages interacted with the worker’s region in the first stage to obtain predicted values of farm wages. Finally, because the regressor of interest is the after tax wage rate, I estimate the after-tax minimum wage rates. To do this, I estimate the mean tax rate for each region-year-legal status group in the sample, so that the tax rate varies only across these factors. This regression can be expressed in two stages, in the first stage the regression is:

\[ \log(\omega_{it}) = \alpha + \gamma \log(\omega_{it}^m)R + \phi \log(\omega_{it}^{nf}) + u_t \] (4)

Where \( \omega_{it}^m \) is the after tax minimum wage rate at time \( t \), \( R \) is an indicator for the worker residing in one of the six regions, and \( \omega_{it}^{nf} \) is the non-farm wage rate. Then, using the predicted values of the farm wage rate, \( \log(\omega_{it}) \), the second stage regression is:

\[ \log(h_{it}) = \beta_0 + \eta_1 \log(\omega_{it}) + \eta_2 \log(\omega_{it}^{nf}) + e_{it} \] (5)

Where \( \eta_1 \) represents the final elasticity of labor supply estimate, and \( \eta_2 \) can be interpreted as the cross wage elasticity. The results from the second stage regression are given in table 4.

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\footnotesize{While state minimum wages would serve as a better instrument, NAWS unfortunately only includes a region for each worker, so specific state minimum wages cannot be incorporated. Instead, I use federal minimum wages interacted with an indicator for each region, so that there is some variation in the predicted values by location as well as by year.

While using the federal minimum wage rate removes endogeneity from many factors, another variable that is likely linked with both farm hours worked and the federal minimum wage is the off-farm wage rate of the worker. To combat this effect, I include the non-farm wage rate as a predictor in the main regression.}
Table 4: IV Elasticity Estimates

<table>
<thead>
<tr>
<th>Worker Type</th>
<th>Pooled Workers</th>
<th>Legal Status</th>
<th>Non Participants</th>
<th>Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>0.257</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizens</td>
<td>0.248</td>
<td>0.267</td>
<td>0.206</td>
<td></td>
</tr>
<tr>
<td>Green Card Holders</td>
<td>0.260</td>
<td>0.288</td>
<td>0.207</td>
<td></td>
</tr>
<tr>
<td>Undocumented</td>
<td>0.237</td>
<td>0.267</td>
<td>0.189</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.255</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citizens</td>
<td>0.275</td>
<td>0.286</td>
<td>0.287</td>
<td></td>
</tr>
<tr>
<td>Green Card Holders</td>
<td>0.319</td>
<td>0.350</td>
<td>0.316</td>
<td></td>
</tr>
<tr>
<td>Undocumented</td>
<td>0.312</td>
<td>0.344</td>
<td>0.304</td>
<td></td>
</tr>
</tbody>
</table>

*Note: All estimates are significant at at least the 0.01 level.*

The two stage process was repeated, in the same manner as the previous regressions, to generate elasticities separated by legal status and program participation.

The results from the IV regression are substantially different from those of the original double log model specification. First, these results indicate much lower elasticity differentials across gender and legal status, and generally depict much higher wage responsiveness than the original model. Still, for males, undocumented workers have the lowest labor supply elasticity, and green card holders have the highest, but the range between the estimates is now substantially smaller. Similarly, for females, citizens still have the lowest elasticity estimate and green card holders have the highest, with a slightly smaller range between the two. In the IV approach, the elasticity differential between program participants and non-participants becomes more consistent; across all worker types, participants have a lower wage responsiveness than non-participants (except for citizen females, who have a negligible difference between the estimates).
6 Labor Force Trends

As discussed in the introduction, one benefit to estimating elasticities separately based on observable worker characteristics is that trends in the labor force composition, with respect to those characteristics, can be explored as possible explanations for ongoing changes in the labor market. To begin examining the implications of these elasticity estimates, I utilize summary statistics generated from the entire sample of NAWS. During the first four years of the survey (1989-1992), the workforce was comprised of roughly 75% males, whereas in the most recent four years (1999-2012), this proportion has increased to 81%. Among both males and females, the proportion of unauthorized workers increased across this span— from 32% to 52% for males, and from 19% to 44% for females. Finally, figure 4 demonstrates the trends in program participation, separated by gender and legal status. The most noticeable trend in program participation rates throughout the sample period was an increase in participation amongst unauthorized workers of both genders.

Figure 4: Trends in Program Participation by Gender and Legal Status
Combining these statistics reveals an increase in the proportion of the population with the lowest elasticity estimates (male program participants), and a decrease in the proportion of the population with the highest elasticity estimates (female program non participants). The proportion of male program participants increased by 5 percentage points over this period, while the proportion of female non-participants decreased by 6 percentage points. The group with the largest relative increase was undocumented male workers who do not participate in welfare programs; the proportion of this worker type increased by 14 percentage points over the span of NAWS. These compositional changes have, overall, led to a workforce with a lower wage responsiveness, as estimated by this paper. According to these estimates, increasing wages is becoming a less viable tool for inducing U.S. agricultural workers to increase their hourly labor provision.
References


