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The changing values of the U.S. farm workers' legal status and labor quality in the U.S. farm workforce:[1]

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The value of the U.S. farm workers' legal status: A hedonic price analysis

Abstract

This paper uses the most recently available data to provide current evidence about farm workers' wage determinants with a focus on legal status. The preliminary results show that while legal status contributes significantly to the wage differences, it is not the major factor. Higher educational attainment, farm work experience, better English-speaking skills, and work in field crop or horticultural production have significant and positive impacts on the wage rate. Legal status is associated with more than 3% higher wages on average. However, there are also structural changes on the legal status effect over a thirty-year time span under potential policy influences. After taking into account the compositional shift among demographic characteristics, employment types, types of work and other factors, the quality-adjusted hourly earnings still grew nearly three times (in nominal terms) over the past three decades.

Key words: Farm worker, U.S. agriculture, undocumented labor, legal status, hedonic analysis

JEL codes: J31, J43

I. Introduction

According to the USDA's agricultural productivity accounts, the composition of U.S. farm input use has gradually shifted from labor and land to machinery and intermediate inputs (e.g., materials, energy, agricultural chemicals, and purchased services) over the past seven

decades. Nevertheless, total labor input cost (including hired, self-employed, and unpaid family workers) still accounted for nearly twenty percent of total U.S. farm input cost in 2019 (USDA-ERS, 2022a). Moreover, for farms specializing in the production of specialty crops--including fruit, tree nuts, vegetables, beans (pulses) and horticultural nursery crops--total labor cost could account for nearly 40 percent of total cash expenses (USDA-ERS, 2022 b, Macdonald et. Al. 2013). Farmers in states with large special crops production are oftentimes report agricultural worker shortage, such as California (Blanco 2016). Given that specialty crops comprised about one-third of U.S. crop receipts and one-sixth of receipts for all agricultural products (Astill et al. 2020) an unstable labor supply could jeopardize U.S. farm productivity and farm income when automation technology and mechanization cannot step in to fill the labor shortage gap shortly.

The number of foreign-born workers has increased significantly over the past few decades in the U.S. labor market, especially for low-skilled farm works. To accommodate this situation, under the special agricultural worker (SAW) legalization program of Immigration Reform and Control Act (IRCA), more than 1.1 million Mexicans have become legal immigrants (Wu, 2007). Although the intention of the 1986 IRCA was to encourage employers to hire a more legal workforce, evidence has shown that IRCA did not reduce the flow of new immigrants into the farm labor market in the transition period (Taylor and Thilmany, 1993). During the 2014-2016 period nearly 50 percent of crop farm workers are unauthorized, and 67 percent of the workers are from Mexico (Wang et al. 2022). However, in recent years, the tightening immigration policy and enforcement (Guan et al. 2015) and the pandemic in 2020 (Charlton and Castillo 2021) have reduced the supply of farm workers and resulted in labor shortage especially during the harvesting season and increasing real wages.

Under such circumstances, H-2A guest worker demand has grown steadily over the years. In 2019, H-2A accounted for nearly 10% of the crop workforce (Costa and Martin 2020) and continued soaring through 2022 To reduce the impact of H-2A visa program on US domestic employment, employers are required to pay H-2A workers no less than the Adverse Effect Wage Rate (AEWR) based on the average hourly wage of farm workers from previous year in the USDA's Farm Labor Survey (Castillo, et al. 2021).

Given the critical role of labor input in producing outputs, there is a rich body of literature studying the impacts of immigration/labor policy and wage rates (Ifft and Jodlowski 2022, Charlton and Castillo 2021, Li and Reimer 2021, Albert 2021, Barnichon and Zylberberg 2019, Kandilov and Kandilov 2018, Richards 2018, Clemens et al. 2018, Pena 2010, Raphael and Ronconi 2009, Kossoudji and Cobb-Clark.Rivera-Batiz 2002, Francisco L. 1999, Isé and Perloff, 1995, Borjas 1990, among others.) Researchers are in agreement that there is a wage premium for workers with legal status. The differences can range from 3% to 6% in general under various policy impacts (Kandiloy and Kandiloy (2018), Pena (2010), Kossoudji and Cobb-Clark.Rivera-Batiz 2002, for examples.) However, it is not clear what the shadow value of the legal status is or to what extent employers are willing to pay for an authorized farm worker and if that value could vary along with labor policy changes. Additionally, wage rate can be affected by a worker's productivity affected by demographic characteristics embodied in that labor unit and not only legal status (Borjas 1990). It can also be affected by employment types and tasks of work and those have been oftentimes ignored in the legal premium study.

In the productivity analysis framework economists term this fraction of price changes due to labor quality, such as experience, education, gender, etc. as quality-adjusted price

(Bowlus and Robinson 2012, Jorgenson et al. 2018, Wang et al. 2022). After accounting for other determinants of wage rate, the quality-adjusted wage rate may be more useful in understanding the impacts of labor policy changes on labor market and wage rate with constant labor efficiency (Jorgenson et al. 1987). In a US farm labor and productivity study Wang et al. (2022) use decennial Census of Population and American Population Survey to measure a long time series of quality-adjusted labor prices over the last seven decades. However, those estimates do not account for workers' legal status given data limitation in Census. In this paper we utilize the National Agricultural Workers Survey (NAWS) dataset, which includes a wide range of worker's demographic characteristics variables and detailed information on tasks of work, employment type, and more importantly worker's legal status. Since the difference in earnings can be generated by the quality characteristics of the farm workers, we employ a hedonic framework to estimate the wage function and thus the shadow price of the legal status of farm workers.

Therefore, the purpose of this study is three-fold. First, we estimate a hedonic model of U.S. farm workers' wages to determine how workers' demographic characteristics, legal status, farm work types, employers, and other geographical and time factors may affect the wage rate. Second, we estimate the shadow price of the legal status and examine if that value can change under different timeframe to reflect policy impacts or structural changes. Third, we estimate quality adjusted wage rates at the national and regional levels to identify the trend growth of quality-adjusted labor prices and wage differentiation across regions. We contribute to the empirical literature on measuring the shadow value of legal status and constructing quality-adjusted wage rates between 1989 and 2021 that can be used in understanding policy impacts from the past and inform future policy decisions.

II. Methodology

In the hedonic framework, a good or service is viewed as a bundle of characteristics that contribute to output or utility derived from its use. Accordingly, the price of the good or service represents the valuation of the characteristics "that are bundled in it", and each characteristic is valued by its implicit price (Rosen, 1974). Following Rosen (1974), we employ hedonic framework in estimating the wage function for U.S. farm workers. The labor input is viewed as a bundle of characteristics which contribute to the productivity derived from its use. The imputed prices of labor quality characteristics are the marginal prices valid at the sample means compared with actual average prices. A hedonic function in terms of years of farm work experience, gender, education attainment measured as schooling years, language skill, and legal status are estimated with controlled variables on employment type—hired or contracted, crop type—such as fruit and nuts, horticulture, vegetables, task type—such as pre-harvesting, harvest, postharvest, and other geographical and time variables.

An econometric problem associated with the hedonic wage equation is that the probability of hired by contractor or directly by farmers may also be correlated with an error term in the wage equation. To correct for possible sample selection bias, we employ the hazard technique suggested by Heckman (1979).

Consider a hedonic wage function with a general form:

$$w_i = \boldsymbol{\beta}' \mathbf{x}_i + \boldsymbol{\gamma}' \mathbf{z}_i + \delta D_i + \varepsilon_i \quad (1)$$

where w_i represents a hedonic price of the labor input; $\boldsymbol{x}_i$ is a vector of quantities of the characteristics embodied in the labor service—including experience, age, gender, and education attainment, and language skill; $\boldsymbol{z}_j$ is a vector of features that may affect the level of wage rate, such as legal status, employment type, work type, workers' position; and D_i is a binary variable representing the labor's selection of working as a hired labor or contracted worker. We also add time and region dummies to control for the time- and geography-variant factors.

Employment type selection is one of the explanatory variables in equation (1). However, the decision to the employment type may also be endogenous and can be explained by other independent variables shown as equation (2).

$$D_i^* = \tau \mathbf{Z}_i + u_i; \qquad (2)$$

where $\boldsymbol{Z}i$ is a vector of independent variables. $Di=1$ if $Di^*>0$, 0 otherwise.

If some of the independent variables are the same as the variables in the wage function, the selection problem will arise as

$$E[\delta\varepsilon] \neq 0. \qquad (3)$$

The error terms in equations (1) and (2) can be assumed with a joint normal error distribution to account for the selection bias as follows:

$$\begin{bmatrix} \varepsilon \\ u \end{bmatrix} \text{iid}\sim \text{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \rho \\ \rho & 1 \end{bmatrix} \right) \qquad (4)$$

Expected wage rate by a worker with contracted worker status can be expressed as

$$E[w_i|D_i=1] = \boldsymbol{\beta}' \mathbf{x}_i + \boldsymbol{\gamma}' \mathbf{z}_i + \delta + E[\varepsilon_i | D_i=1] = \boldsymbol{\beta}' \mathbf{x}_i + \boldsymbol{\gamma}' \mathbf{z}_i + \delta + \rho\sigma\lambda_i \quad (5)$$

where λ_i is the inverse Mills ratio. The parameters of the treatment-effects selection model are estimated using full maximum likelihood.

III. Data and variables

The data on characteristics of farm workers is drawn from the Department of Labor, Employment and Training Administration's National Agricultural Workers Survey (NAWS), which is a national, random sample of seasonal agricultural service (SAS) workers. The data spans the period 1989 to 2021. The NAWS uses stratified multi-stage sampling to account for seasonal and regional fluctuations in the level of farm employment. The stratification includes three interviewing cycles per year and 12 geographic regions, resulting in 36 time-by-space strata. Sampling and post-sampling weights are used in the NAWS to adjust the relative value of each interview so that population estimates may be obtained from the sample. Workers are sampled from 12 regions and have been collapsed into six production regions—East, Southeast, Middle West, Northwest, Southwest, and California. Since workers can be paid by

hourly wage, piece rate, or salary we impute hourly wage for workers not paid by hours so we can have a complete wage dataset for all workers using their total hours worked information along with total pieces worked, time of work, etc. As shown in table 1, total observations increase from 57, 952 to 69,433. The mean wage of the complete wage dataset, which include the imputed wage rates, are slightly higher than the mean wage of those paid by hour in the original hourly wage data pool. However, the complete wage sample has larger variation as shown in table 1 and figure 1 due to the nature of the tasks can be distinct among works that are not paid by hours.

Table 1 Dataset comparison: with and without imputed hourly wage

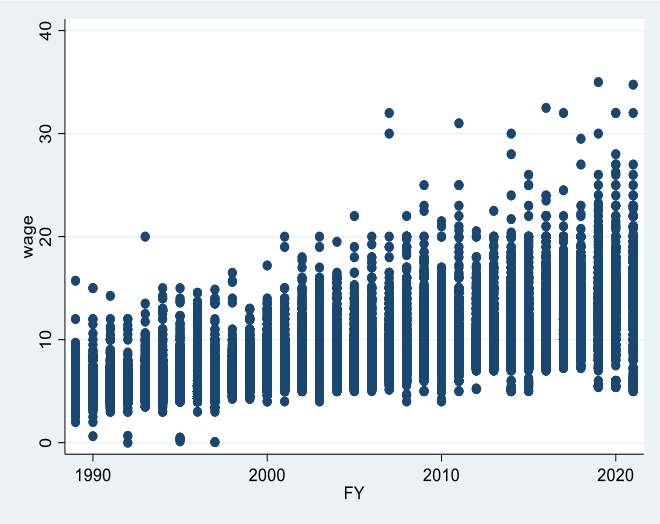
Variable	Obs	Mean	Std. dev.	Min	Max
Wage	57,952	7.77	2.95	0	35
Complete wage	69,433	7.94	3.42	0	40

Note: Complete wage includes imputed hourly wage for those paid by piece rate or other means.

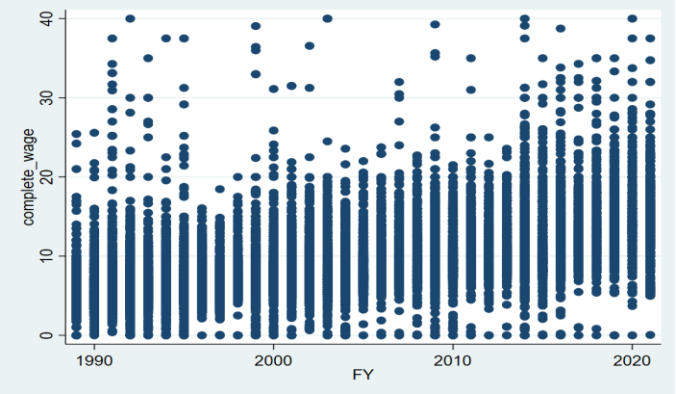
Source: Authors' calculations.

Figure 1. Dataset comparison: with vs. without imputed hourly wages

Panel A. Hourly wage sample distribution



Panel B. Comple wage sample istribution



Source: Authors' calculation.

IV. Results

Descriptive analysis

We present summary statistics of variables of our interest in table 2. Comparing two time periods--1989-1991 vs. 1999-2021--we observe that the composition of farm workers' demographic characteristics has shifted toward workers with more on-farm experiences and higher educational attainment. Crop farms producing fruits and horticulture crops have increased while vegetable farms have decreased. Overtime, the composition shift among demographic characteristics and other factors can influence the wage structure.

Table 2. Summary statistics

	1989-1991					2019-2021				
Variable	Obs	Mean	Std. Dev	Min	Max	Obs	Mean	Std. Dev	Min	Max
hourly wage (US$)	4,949	4.71	1.05	0.63	15.7	2,871	13.30	2.77	5	35
U.S. farm work experience (years)	6,357	10.19	9.74	0	69	3,248	16.12	12.73	1	63
education (schooling years)	6,357	7.77	3.96	0	16	3,248	8.65	4.15	0	16
gender (1: female, 0: male)	6,357	0.27	0.44	0	1	3,248	0.34	0.47	0	1
legal (1: authorized, 0: unauthorized)	6,357	0.60	0.49	0	1	3,248	0.57	0.49	0	1
field crops	6,357	0.13	0.34	0	1	3,248	0.13	0.34	0	1
fruits	6,357	0.26	0.44	0	1	3,248	0.39	0.49	0	1
horticulture	6,357	0.20	0.40	0	1	3,248	0.22	0.42	0	1
vegetables	6,357	0.34	0.47	0	1	3,248	0.23	0.42	0	1
miscellaneous crops	6,357	0.06	0.24	0	1	3,248	0.03	0.17	0	1
paid by piece rate (1: yes)	6,357	0.01	0.11	0	1	3,248	0.02	0.14	0	1
English skill (1: yes)	6,357	0.13	0.34	0	1	3,248	0.35	0.48	0	1
harvest task	6,357	0.37	0.48	0	1	3,248	0.22	0.42	0	1
post-harvest task	6,357	0.14	0.34	0	1	3,248	0.19	0.39	0	1
semi-skilled	6,357	0.19	0.39	0	1	3,248	0.32	0.47	0	1
supervisor position (1: yes)	6,357	0.01	0.09	0	1	3,248	0.00	0.00	0	0

Source: Authors' calculation

We present our hedonic function along with selection equation estimates in table 3 and table 4 based in five model specifications. In table 3 there are four specifications with dependent variable—wage rate—being in logarithmic form or linear form. We also test for structural changes on the shadow value of farm worker's legal status. When the dependent variable is in the logarithmic form the coefficient of each variable indicates a percentage change in the wage rate in response to a unit increase of corresponding variable. According to the likelihood estimates semi-log specifications are superior to the linear model specifications with larger likelihood. There are also more statistical significant variable in the hedonic functions. Overall, more years of farm work experience, higher educational attainment, legal status, better English-speaking skill, work as a supervisor can all result in higher wage rates than others. For those paid by piece rate could earn less than those paid by hourly wage rate from their employers. When considering structural changes on shadow value of legal status under various pollical environment regarding immigration or labor policy we find while there is a wage premium of about 9.1 percent higher for authorized workers the gap has shrunk in the second half of the sample period—post 2011. However, we did not see more breaks in later years. While the break date was determined arbitrarily, it can still shed light on the changing value of legal status under various immigration policy reforms. From the estimates of selection function the results are quite consistent across four specifications. In general, workers with more experience on farm work, female, unauthorized labor, less English speaking or reading skill are less likely to be recruited by contractors. If we also consider types of task or crop types in the sample selection model setup, we crop farms specializing on field crops, fruits, and vegetables are likely to purchase contract labor service through

contractor (table 4). According to the results we also find female workers earn 2 to 17 percent less than male workers when others being equal based on semi log functions.

After taking account of the quality changes (composition shift among demographic characteristics or task types, among others) wage rates still increased by more than 2.5 times from 1990 to 2021 less than the unadjusted price series (figure 2). Wage rate can vary across regions over the years. In general, Southwest region has the lowest quality adjusted farm wage rate among all six regions (figure 3).

Table 3. Econometric results I

	semilog1			linear1			semilog2			linear2		
variables	Coef.	Std.Err.	P>|z|	Coef.	Std.Err.	P>|z|	Coef.	Std.Err.	P>|z|	Coef.	Std.Err.	P>|z|
Dependent variabl	lnwage			wage			lnwage			wage		
expr	0.005	0.000	0.00	0.050	0.002	0.00	0.003	0.000	0.00	0.050	0.002	0.00
edu2	0.020	0.002	0.00	0.185	0.023	0.00	0.007	0.003	0.04	0.188	0.022	0.00
edu3	0.087	0.007	0.00	0.750	0.064	0.00	0.077	0.008	0.00	0.750	0.064	0.00
gender	-0.020	0.004	0.00	-0.169	0.033	0.00	-0.050	0.003	0.00	-0.166	0.033	0.00
legal	0.091	0.004	0.00	0.683	0.035	0.00	0.022	0.003	0.00	0.658	0.035	0.00
legal2011	-0.031	0.006	0.00	-0.082	0.057	0.15						
legal2017	-0.009	0.012	0.42	0.039	0.145	0.79						
legal2020	0.004	0.018	0.81	-0.040	0.270	0.88						
field	0.187	0.102	0.07	0.232	0.202	0.25	0.088	0.050	0.08	0.231	0.201	0.25
fruits	0.187	0.102	0.07	0.212	0.202	0.29	0.077	0.050	0.12	0.212	0.201	0.29
horti	0.215	0.102	0.04	0.413	0.200	0.04	0.112	0.050	0.03	0.414	0.199	0.04
vege	0.173	0.102	0.09	0.104	0.202	0.61	0.064	0.050	0.21	0.104	0.201	0.60
misc	0.230	0.102	0.02	0.559	0.203	0.01	0.131	0.050	0.01	0.559	0.202	0.01
piece_hourly	-0.152	0.012	0.00	-1.170	0.105	0.00	-0.128	0.012	0.00	-1.167	0.106	0.00
eng	0.063	0.005	0.00	0.664	0.053	0.00	0.017	0.005	0.00	0.662	0.053	0.00
harv	-0.006	0.003	0.07	-0.049	0.030	0.10	-0.005	0.003	0.15	-0.051	0.030	0.09
postharv	-0.002	0.004	0.56	-0.017	0.033	0.61	-0.005	0.004	0.24	-0.017	0.033	0.60
semi	0.010	0.003	0.00	0.104	0.035	0.00	0.009	0.004	0.01	0.104	0.035	0.00
super	0.287	0.031	0.00	1.859	0.235	0.00	0.298	0.030	0.00	1.865	0.235	0.00
contract	0.231	0.009	0.00	2.305	0.041	0.00	-0.201	0.015	0.00	2.304	0.041	0.00
_cons	1.049	0.101	0.00	2.350	0.210	0.00	1.350	0.051	0.00	2.367	0.209	0.00
selection function												
contract												
expr	-0.030	0.001	0.000	-0.031	0.001	0.000	-0.030	0.001	0.000	-0.031	0.001	0.000
gender	-0.266	0.026	0.000	-0.231	0.026	0.000	-0.266	0.026	0.000	-0.231	0.027	0.000
legal	-0.484	0.023	0.000	-0.384	0.022	0.000	-0.484	0.023	0.000	-0.384	0.022	0.000
eng	-0.647	0.040	0.000	-0.682	0.040	0.000	-0.648	0.041	0.000	-0.683	0.040	0.000
/athrho	-1.128	0.073	0.000	-1.341	0.071	0.000	-1.129	0.073	0.000	-1.341	0.071	0.000
/lnsigma	-1.630	0.011	0.000	0.614	0.012	0.000	-1.629	0.011	0.000	0.614	0.012	0.000
ρ	-0.810	0.025		-0.834	0.017		-0.811	0.025		-0.872	0.017	
σ	0.196	0.002		1.891	0.022		0.196	0.002		1.848	0.022	
lambda	-0.159	0.006		-1.533	0.040		-0.159	0.006		-1.611	0.040	
Wald test of indep. Equns. (rho=0)												
	chi2(1)=236.93		Prob>chi	chi2(1)=360.76		Prob>chi	chi2(1)=238.6		Prob>chi2	chi(2)=358.98		Prob>chi2

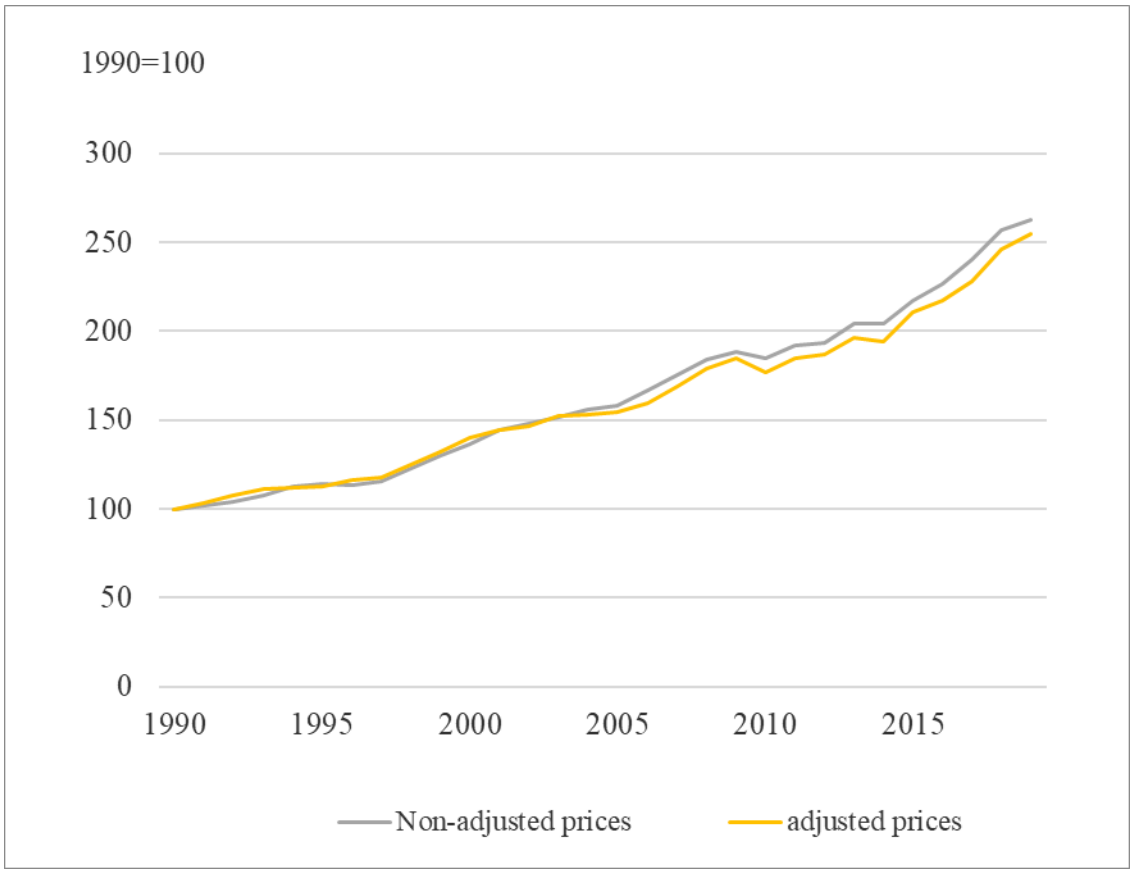
Source: Authors' calculation

Table 4. Econometric results II

variables	semilog3		
	Coef.	Std.Err.	P>|z|
Dependent variable			
expr	0.004	0.000	0.000
edu2	0.022	0.002	0.000
edu3	0.091	0.007	0.000
gender	-0.042	0.003	0.000
legal	0.059	0.004	0.000
legal2011	-0.027	0.006	0.000
legal2017	-0.006	0.011	0.616
legal2020	0.000	0.018	0.993
field	0.178	0.094	0.058
fruits	0.143	0.094	0.129
horti	0.227	0.094	0.016
vege	0.124	0.094	0.187
misc	0.234	0.095	0.013
piece_hourly	-0.150	0.012	0.000
eng	0.037	0.005	0.000
harv	-0.003	0.004	0.423
postharv	0.018	0.004	0.000
semi	0.013	0.004	0.002
super	0.285	0.030	0.000
contract	0.210	0.010	0.000
_cons	1.139	0.094	0.000
selection function			
contract			
expr	-0.013	0.001	0.000
legal	-0.228	0.027	0.000
eng	-0.340	0.042	0.000
field	0.346	0.074	0.000
fruits	0.819	0.073	0.000
horti	-0.372	0.084	0.000
vege	0.884	0.073	0.000
harv	-0.036	0.031	0.242
postharv	-0.299	0.043	0.000
semi	-0.023	0.031	0.459
_cons	-1.209	0.070	0.000
/athrho	-1.028	0.077	0.000
/lnsigma	-1.674	0.010	0.000
rho	-0.773	0.031	
sigma	0.188	0.002	
lambda	-0.145	0.007	
Wald test of indep. Equns. (rho=0)			
	chi2(1)=367.22		Prob>chi2=0

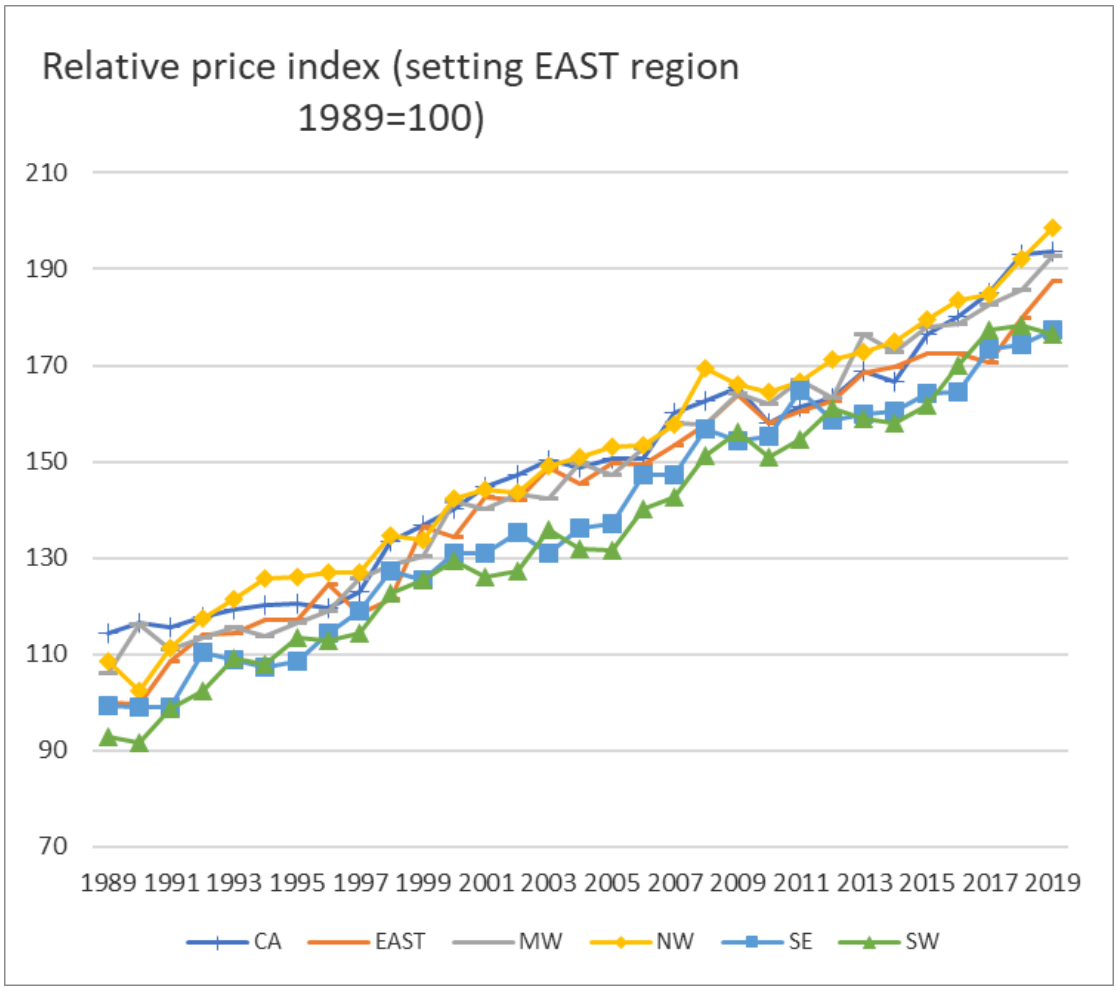
Source: Authors' calculation

Figure 2. Quality-adjusted labor prices vs. unadjusted prices



Source: Authors' calculation

Figure 3 Quality adjusted wages for U.S. farm worker by region



Sources: by authors.

Notes: CA: California; East: includes states ME, NH, VT, NY, MA, CT, PA, NJ, DE, MD, WV, VA, KY, TN, and NC; MW: Midwest, includes states ND, SD, NE, KS, MN, IA, and MO; NW: Northwest, includes states WA, OR, ID, MT, NV,WY, CO, and UT; SE: Southeast, includes states AR, LA, MS, AL, GA, FL, and SC; SW: Southwest, includes states AZ, NM, TX, and OK.

V. Concluding Remarks

This paper uses new National Agricultural Workers Survey (NAWS) data to provide more current evidence on the farm workers' wage determinants with a focus on the workers' legal status. The preliminary results show that while legal status did contribute significantly to the wage differences it is not the major factor. Also, after taking account of the composition shift in demographic characteristics, the quality adjusted labor prices still doubled in the past two decades. This study provides more information on the shadow value of workers' legal status based on a hedonic framework. This information could be applied to further analysis in identifying the impact of immigrant reform or regulations on farm production cost as well as the labor market.

References

Albert, C. 2021. The labor market impact of immigration: Job creation versus job competition. American Economic Journal: Macroeconomics, 13(1), 35-78.

Astill, Gregory, Agnes Perez, and Suzanne Thornsbury. 2020. Developing Automation and Mechanization for Specialty Crops: A Review of U.S. Department of Agriculture Programs.

Bowlus, A. J. and C. Robinson, 2012. "Human Capital Prices, Productivity, and Growth." American Economic Review, 102(7): 3483–3515.

Borjas, G.J. 1990. Friends or Strangers: The Impact of Immigrants on the United States Economy. New York: Basic Books.

Calvin, Linda, Philip Martin, and Skyler Simnitt. 2022. Adjusting to Higher labor costs in selected U.S. fresh fruit and vegetable industries. EIB. 235. July 2022.

Castillo, Marcelo, Philip Martin, and Zachariah Rutledge. August 2022. The H-2A Temporary Agricultural Worker Program in 2020, EIB-238, U.S. Department of Agriculture, Economic Research Service.

Charlton, Diane and Marcelo Castillo. 2021. Potential Impacts of a Pandemic on the US Farm Labor Market. *Applied Economic Perspectives and Policy* (2021) volume 43, number 1, pp. 39–57.

Clemens, M. A., Lewis, E. G., & Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. American Economic Review, 108(6), 1468-1487.

Guan, Zhengfei, Feng Wu, Fritz Roka, and Alicia Whidden. 2015. Agricultural Labor and Immigration Reform. Choices 30(4)

Heckman, J.J., "Sample selection bias as a specification error". Econometrica 47, 1979; pp.153-161.

Ifft, J., & Jodlowski, M. (2022). Is ICE freezing US agriculture? Farm-level adjustment to increased local immigration enforcement. Labour Economics, 78, 102203.

Isé, Sabrina, and Jeffrey M. Perloff, "Legal Status and Earnings of Agricultural Workers", American Jpirnal of Agricultural Economics, vol. 77, No. 2 (May, 1995), pp.375-386.

Jorgenson, D., M. Ho, and J. Samuels. 2018. "Education, Participation, and the Revival of U.S. Economic Growth" in Education, Skills, and Technical Change: Implications for Future U.S. GDP Growth, C. Hulten and V. Ramey, eds. National Bureau of Economic Research, University of Chicago Press.

Kandilov, A., & Kandilov, I. T. (2018). The Impact of the Minimum Wage on Employment, Earnings, Wages, and Hours in the US Agricultural Sector.

Kossoudji, S.A., and D.A. Cobb-Clark. 2002. Coming out of the Shadows: Learning about Legal Status and Wages from the Legalized Population. Journal of Labor Economics 20 (3): 598–628.

Li, A., & Reimer, J. J. (2021). The US market for agricultural labor: evidence from the National Agricultural Workers Survey. Applied Economic Perspectives and Policy, 43(3), 1125-1139.

MacDonald, James M. Penni Korb, and Robert A. Hoppe. 2013. Farm Size and the Organization of U.S. Crop Farming. USDA-Economic Research Service. ERR 152.

Martin, Phillips and Linda Calvin, "What Does it Means for Agriculture and Rural America?", Applied economic Perspectives and Policy, volume 32 Number 2 (Summer 2010)., pp. 232-253.

Pena, A.A. 2010. Legalization and Immigrants in U.S. Agriculture. B.E. Journal of Economic Analysis & Policy 10 (1): 1–22.

Raphael, Steven, and Lucas Ronconi. 2009. "The Labor Market Impact of State-Level Immigration Legislation Targeted at Unauthorized Immigrants." http://laborcenter.berkeley.edu/pdf/2009/ronconi_raphael09.pdf

Richards, Timothy J. Immigration reform and farm labor markers. Amer.J. agr. Econ. 100(4): 1050-1071. June 13, 2018.

Rivera-Batiz, Francisco L., "Undocumented workers in the labor market: an analysis of the earnings of legal and illegal Mexican immigrants in the United States", Journal of Population Economics (1999), 12:91-116.

Rosen, S.M. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." Journal of Political Economy 82(1974):pp. 34-55.

Rutledge, Z., & Taylor, J. E. (2019). California farmers change production practices as the farm labor supply declines. ARE Update, 22(6), 5-8.

Sampaio, B., Sampaio, G. R., & Sampaio, Y. (2013). On estimating the effects of immigrant legalization: Do us agricultural workers really benefit? *American Journal of Agricultural Economics*, 95(4), 932-948.

Taylor, Edward, Dian Charlton, and Antonio Yunez-Naude. 2012. The end of Farm Labor Abundance. *Applied Economic Perspectives and Policy*

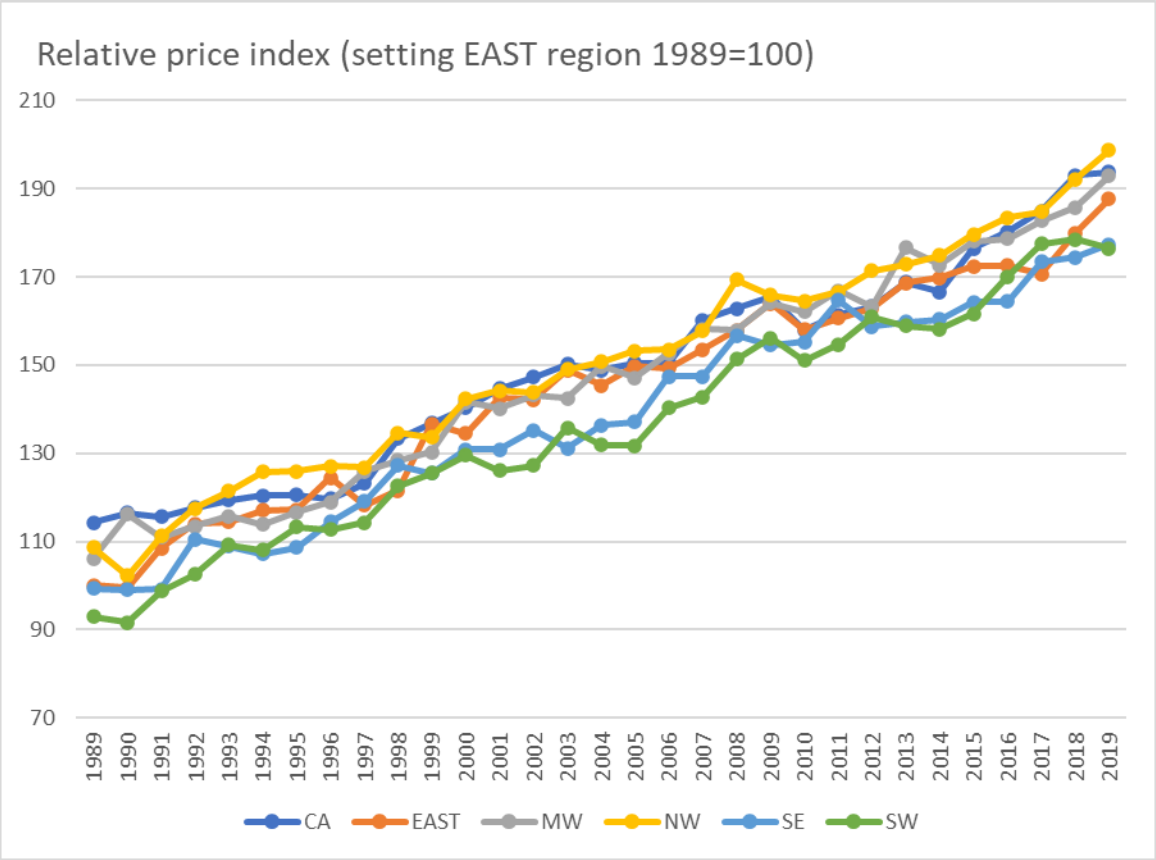
Taylor, J. Edward, and Dawn Thilmany, "Worder Turnover, Farm Labor Contractors, and IRCA's Impact on the California Farm Labor Market", *American Journal of Agricultural Economics*, vol. 75, No. 2 (May 1993), pp: 350-360.

USDA-ERS, 2022a. Agricultural Productivity in the U.S., updated Jan. 2022. Accessed at https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-u-s/

USDA-ERS. 2022b. Specialty Crop Farms Have the Highest Labor Cost as a Portion of Total Cash Expenses. USDA-ERS. Accessed at https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=104773

Wang, S. L., Hoppe, R. A., Hertz, T., & Xu, S. (2022). Farm Labor, Human Capital, and Agricultural Productivity in the United States (Economic Research Report No. 302; p. 43, February). Economic Research Service, U.S. Department of Agriculture. https://www.ers.usda.gov/webdocs/publications/103267/err-302.pdf?v=8829

Wu, Ximing, "Overview: Immigration, U.S. Agriculture, and Policy Reform", Choices, 1st Quarter 2007, 22(1)



Sources: by authors.
Notes: CA: California; East: includes states ME, NH, VT, NY, MA, CT, PA, NJ, DE, MD, WV, VA, KY, TN, and NC; MW: Midwest, includes states ND, SD, NE, KS, MN, IA, and MO; NW: Northwest, includes states WA, OR, ID, MT, NV,WY, CO, and UT; SE: Southeast, includes states AR, LA, MS, AL, GA, FL, and SC; SW: Southwest, includes states AZ, NM, TX, and OK.