DO H-2A GUEST WORKERS DISPLACE NATIVE FARMWORKERS?

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ABSTRACT

There is persistent evidence of acute labor shortage across farms in the U.S. Because of difficulty in finding willing native workers, more farms are resorting to the H-2A program to hire foreign temporary agricultural workers. In this paper, we study how the H-2A program responds to local unemployment and wages. The results indicate that a decrease in unemployment rate and an increase in AEWR increases H-2A demand. This suggests that farmers only use the H-2A program as a last resort and that H-2A guest workers do not displace native workers.

BIOGRAPHICAL SKETCH

Ejin Leah Kim is a second year M.S. student in the Dyson School of Applied Economics and Management at Cornell University, concentrating in food and agricultural economics. Originally from Chuncheon, South Korea, she has received her B.S. from the same program. She has previously worked at the Environmental Defense Fund, studying the relationship between corn, dairy diet composition and methane emission, and at Oxfam designing research framework to evaluate Oxfam's role in promoting women's land ownership in Tajikistan. She is interested in analyzing the impact of various agricultural policies on food security and environmental sustainability and hopes to address challenges in these areas using computational models and techniques.

Apart from her studies, She enjoys watching independent movies and experimenting different recipes in her kitchen.

This document is dedicated to all Cornell graduate students.

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CHAPTER 1

INTRODUCTION

1.1 Research Motivation and Question

Unauthorized immigrant farmworkers play a vital role in the agricultural industry. They comprise much of the agricultural workforce, performing manual labor essential to farm operations. The 2015-2016 National Agricultural Worker Survey (NAWS) estimates that 75% of farmworkers are foreign-born (69% from Mexico) and that 49% of farmworkers are unauthorized (Hernandez and Gabbard, 2018). Most farmworkers are employed in labor-intensive production: 37% in vegetables, 32% in fruit and nut crops and 19% in horticulture. 49% may be a conservative estimate for the share of unauthorized farmworkers since the survey relies on respondents to self-report their employment eligibility. Some grower surveys reveal numbers as high as 90% (Guan et al., 2015).

In the past decade, the inflow of unauthorized immigrants to the U.S. has been declining, resulting in acute labor shortages and putting a strain on many farm operations. The Pew Research Center estimates that the population of unauthorized immigrants decreased from its peak of 12.2 million in 2007 to 10.5 million in 2017 as immigration from Mexico slowed down (Passel and Cohn, 2019). Each year, there are countless reports of farmers having trouble finding adequate number of farmworkers, leaving their crops to rot in the field (Duvall, 2019). These personal stories are buttressed by empirical analysis such as Richards (2018) who finds persistent shortage of harvest workers in California and Hertz and Zahniser (2013) who finds evidence of local labor shortage across the country by analyzing wage and job growth by county, crop and farm activities.

There are a number of reasons for this decline. One is Mexico's own expanding agricultural sector which detracts farmworkers from migrating to the U.S.. Another is the growth of job opportunities outside of agriculture, which reduces the supply of workers entering agriculture (Zahniser et al., 2018; Taylor et al., 2012). Stricter border control and local immigration enforcement may also play a role since it increases the risks of deportation (Kostandini et al., 2014; Ifft and Jodlowski, 2016). In addition to these potential sources of decline, the decrease in internal migration rates of farmworkers within the U.S. reduces the availability of temporary workers during peak labor seasons. The farmworker population is aging and becoming more settled, traveling less between farms for work Fan et al. (2015).

With ongoing labor shortages, farmers have been resorting to the H-2A program to hire workers. The H-2A program allows farmers to hire non-immigrant foreign workers to perform seasonal or temporary agricultural work in the U.S. (OFLC, 2009b). The program has expanded tremendously the past decade, with an almost four times increase in the number of positions certified from 2006 to 2018 (Table 1.2). Despite growing participation, the application procedures are often reported to be burdensome and time-consuming, which presents a hurdle for farmers who must find workers in a short window of time. In order to participate in the program, farmers must prove that there were no “sufficient able, willing, and qualified U.S. workers available” to take the job, a rule that was created to ensure that no native farmworkers were displaced (OFLC, 2009b).

This rule motivates the research question of this paper, which is whether H-2A workers displace native farmworkers. If the number of H-2A workers is responsive to local supply of native workers, particularly if it increases when unemployment decreases and wage increases, this indicates the program is functioning as intended, in accordance with the rule that has been placed to ensure no displacement of native workers. Therefore, in order to detect the displacement of native farmworkers with H-2A workers, this paper will estimate the impact of local unemployment rate and wages on the number of H-2A workers. In the following section, the paper will review the recent literature on substitution between native and foreign-born workers.

1.2 Economics of Labor Substitutability

Research results on the impact of foreign workers on native wages and employment have been divergent. Some research has found that foreign workers systematically harm native wage and employment while others find imperfect substitution between the two and a modest impact on native wage and employment. One common method in the labor literature studying immigration is Constant Elasticity of Substitution (CES) technology function which treats native and immigrant groups as separate inputs of labor. In this form, the economy is a one-sector model with skill-neutral capital. Two broad research frameworks have emerged using this method–area analysis and national analysis. The two vary in their geographical scope. Area analysis estimates the impact of immigration by comparing outcomes across local labor markets, while national analysis finds this method unreliable and analyzes changes generated at the national level.

1.2.1 Area Analysis

Area analysis takes advantage of the geographical clustering of immigrants. It compares the local labor market outcomes between areas (hence the name "area analysis") with varying inflow of immigrants. There are two important limitations to this framework, which have been raised by Borjas (1994) and Borjas et al. (1997). The first is that local economies are not closed and that workers can relocate. In other words, the inflow of foreign workers may lead to outflow (or restrained inflow) of natives and partially offset the impact of immigration, leading to smaller estimates. The second is that immigrants do not settle randomly and may be drawn to regions with thriving local economies that may also draw native workers.

Subsequent researches in area analysis have sought to overcome these limitations. For the first limitation, Kritz and Gurak (2001) analyzes the outflow of native and older immigrants (immigrants who have settled before) in response to the inflow of new immigrants at the state level and finds that outflow was actually smaller for states that received large immigration. Card (2001), Card and DiNardo (2000) and Card (2009) compares the native outflow from a particular skill group in response to immigrant inflow across different cities. All three study finds that outflow is modest and insignificant. Good (2013) tests the reverse and finds that immigrant outflows do not lead to native inflows.

For the second limitation, a shift-share or enclave instrument which reflects historical patterns of immigrant settlement is most prevalent. Immigrants tend to settle in regions with strong immigrant presence and networks which is independent of local labor demands. For example, Altonji and Card (1991) uses the initial distribution of immigrants in 1970 to predict the flow of immigrants in the following decade. Card (2001) uses the initial distribution of immigrants among occupations instead of regions. Card and DiNardo (2000) uses the initial fraction of Mexican immigrants in a city to proxy for the rate of low-skilled immigrants.

In addition to overcoming these limitations, area analysis incorporates heterogeneity of immigrant workers. Card (2001) states that immigrant workers are extremely diverse in their background so the degree of competition between native and immigrant workers can only be accurately estimated between comparable subgroups. Card (2001) therefore partitions native and foreign workers along occupations lines and assumes that workers in the same occupation are perfectly substitutable. In order to classify workers into occupations, Card (2001) creates a set of multinomial logit models to assign probabilities of working in different occupations. Following Card and Lemieux (2001)'s findings that relative wage depends on the relative supply of workers, Card (2001) estimates how immigration impacts the relative supply and wage of workers in each occupation group. For example, a large inflow of less-skilled immigrant workers will affect the wage and employment rates of less-skilled native workers. If, however, the distribution of skill sets of immigrants is close to that of natives, the structure of wage and employment would remain unchanged. Card (2001) finds modest impact of immigration, with 10 percent increase in population share associated with 0.5 percentage point reduction in employment rate for OLS estimates and two, three times greater reduction for the IV estimate.

Once we admit heterogeneity of immigrant workers, the estimated impact of immigration is sensitive to how workers are distinguished and grouped together. Card (2009) advocates for a two skill (college-equivalent vs. high school-equivalent) model instead of four (high school dropouts vs. high school graduates vs. some college vs. college graduates). Because the immigrant population has a high fraction of high school dropouts, whether we further segregate high-school equivalents into graduates and dropouts or not is a consequential choice. Further segregation will concentrate the impact of immigration on high school dropouts leading to more negative estimates. Card (2009) regresses the ratio of the supply of workers on the ratio of their wage for any two skill groups across different cities. In order to control for any city-specific shift in demand for labor, Card (2009) uses the previous 10 years ratio of the two skill groups. Card (2009) finds that high school dropouts and high school graduates are almost perfectly substitutable with infinite elasticity of substitution. For college-equivalent and high-school equivalent workers, Card (2009) finds elasticity of substitution between 1.5 and 2.5. This means that a two skill model that pools high school dropouts and graduates together is more appropriate when evaluating the impact of immigration. For native and immigrant workers, Card (2009) finds that they are imperfectly substitutable albeit higher elasticity of substitution of 20.

Area analysis is particularly suitable for a quasi-experimental setting where policy changes induce differential immigrant inflows across regions. Dustmann et al. (2016) exploits a commuting policy in Germany implemented in 1991 that allowed Czech workers to work in the municipalities near the border. The paper compares the change in native wage and employment between border regions that were affected by the policy and inland regions that serve as control. The results demonstrate that a 1 percentage point increase in Czech inflow led to 0.13% decrease in wages and 0.93% decrease in native local employment, especially for older natives.

Policy changes also help design better identification strategies. One example is the dispersal policy in Denmark (Foged and Peri, 2016) and Germany (Glitz, 2012) which randomly allocated immigrants to municipalities to ensure even distribution of immigrants across the country. Foged and Peri (2016) and Glitz (2012) both construct instruments based on this exogenous allocation of immigration to eliminate bias. Foged and Peri (2016) finds positive impact of immigration on native workers. More importantly, the paper finds that immigrants do not displace natives but rather push them towards occupations that are less manually intensive. This upward mobility in occupation creates positive or null wage and employment effects. Glitz (2012) finds opposing results with 10 new employed immigrants leading to 3.1 resident workers losing a job. However, Glitz (2012) finds no significant impact on wages which may be due to more protective wage systems in Germany.

1.2.2 National Analysis

A counterpart to area analysis is national analysis, pioneered by Borjas (2003). Borjas (1994) and Borjas et al. (1997) argue that area analysis is flawed because it ignores native mobility and endogeneity in immigrant settlement. With regards to native mobility, Filer (1992) and Frey (1995) present evidence that inflow of immigrants leads to out-migration of natives, its effect concentrated in low-skilled less-educated—often the poorest residents—workers. Cascio and Lewis (2012) finds that this native out-migration is in part due to reduction in the demand for public schools. Increase in enrollment for low-English Hispanic households reduces the rate of settlement and enrollment for non-Hispanic households. Instead of framing this result as welfare loss for natives, Cascio and Lewis (2012) interprets it as residential isolation of immigrants and their loss of opportunity to assimilate into the country.

In order to avoid weakening of the estimates due to native mobility and endogeneity in settlement, Borjas (2003) conducts its analysis at the national level. Following Card and Lemieux (2001) and Card (2001), it relates labor market outcomes of a particular skill group with its relative supply of workers. It classifies workers by skill, based on educational attainment and work experience and assumes that workers classified into the same skill group are perfect substitutes. Borjas (2003) first obtains elasticity of substitution between different education and experience groups. After obtaining estimates for elasticity of substitution, Borjas (2003) then simulates how immigration inflows change the relative national supply and wage for each skill group. It finds that for 11% increase in the supply of working men induced by immigration, average native wages decreased by 3.2% between 1980 and 2000s, its impact more pronounced for high school dropouts whose wage fall by 8.9%. Borjas (2003) therefore concludes that immigration had adverse impact for native wage and employment. Aydemir and Borjas (2006) implements the same methodology to the U.S., Canada and Mexico and finds consistently negative impact of immigration on wages with 10% increase in labor supply associated with 3 or 4% decrease in wages for all three countries.

The discussion on how to classify workers is pertinent to national analysis as well. Ottaviano and Peri (2012) extends Borjas (2003) by exploring four different models of nesting education and experience levels. The substitutability between groups increases as they are nested more deeply within the model. For example, if experience is nested under education, then workers with different experience levels are more substitutable with each other than workers with different education levels. Ottaviano and Peri (2012) finds that a model that nests two different classification of education levels—first classification, low and high education level and second classification, no degree, high school, some college and college degree—

is better explained by their data. In other words, two elasticity of substitution should be used for education (one education level nested under the other) instead of one. In addition, instead of assuming that native and immigrant workers are perfect substitutes, it also tests their substitutability by nesting birthplace into the model. The preferred model obtains small but positive wage effect of 1.7% on less educated natives.

Manacorda et al. (2012) implements the national approach to the UK data. It divides workers by age and two education levels, university and high school education. Following Ottaviano and Peri (2012), it nests birthplace within age and education. The elasticity of substitution of native and immigrant workers came out to 7.8. The paper further estimates elasticity of substitution for recent and older immigrants separately and finds lower elasticity of substitution of 5. Immigration depresses the earnings of previous immigrants relative to the native- born, suggesting imperfect-substitutability between native and immigrants.

Borjas and Grogger (2012) contends with the results found in Ottaviano and Peri (2012) and Manacorda et al. (2012). The paper states that for Ottaviano and Peri (2012), the errors in the specification of the model such as inclusion of self-employed in calculation of wages, inappropriate logarithmic transformations and regression weights have resulted in smaller degree of substitutability for immigrant and native workers. Their corrected model with the same data source produces greater elasticity of substitution. Borjas and Grogger (2012) also questions the infinite elasticity of substitution between high school dropouts and graduates, found in Card (2009) and Ottaviano and Peri (2012) and adopted in Manacorda et al. (2012), because the estimates are unstable and change dramatically based on the shape of the trends. Aydemir and Borjas (2011) further suggests that the small impact of immigration generally reported in area analysis may be due to sampling errors in the fraction of the workforce that are foreign-born. Such error in the independent variable introduces attenuation bias, leading to smaller estimates.

1.2.3 Recent Approaches

Area analysis and national analysis both investigate the effect of skill-specific labor supply shocks, primarily on wage and unemployment. However, more recently, researchers are identifying and seeking to understand other mechanisms, besides wage and employment, that affect the labor market.

Lewis (2003) suggests two mechanisms. One, changes in relative supply of skill groups can be absorbed by changes in industry mix. Industries that experience an increase in the supply of skill groups they tend to employ will expand production (between industry changes). Second, changes can also be absorbed by changes in the intensity in the use of those skill groups in each industry. Each industry may hire more workers from the skill group that has become relatively more abundant (within industry change).

Lewis (2003) evaluates the importance of these two mechanisms. It regresses the changes in industry mix and relative factor intensity, separately, on labor supply mix in the 1980s. In order to address endogeneity due to demand shocks, Lewis (2003) uses the initial distribution of immigrants in 1970. Lewis (2003) finds that local industry mix did little to accommodate the changes in the supply of each skill group. In contrast, relative factor intensity absorbed at least half of the changes. Given little changes in relative wages, the more abundant type of labor is hired in a complementary fashion.

Dustmann and Glitz (2015)and Gonzlez and Ortega (2011) apply the same framework to the German and Spanish settings and reach the same conclusions. Both find that the changes in supply mix were mostly mediated by changes in relative factor intensity rather than changes in output mix.

Peri and Sparber (2009) further demonstrates that increase in relative factor intensity occurs due to workers finding their comparative advantage and complementing each other's work. Workers allocate their labor between manual and interactive tasks to maximize their labor income. With the increase in immigrant workers, native workers shift to interactive tasks which they have comparative advantage in instead of being displaced. Immigrant workers, on the other hand, take manual tasks and complement native workers. In other words, the production technology accommodates the relative increase in the supply of immigrant workers by increasing their relative factor intensity and reallocating native workers to interactive tasks.

The findings in this area of research—-that changes relative factor intensity tends to cushion the effect of immigration—-is meaningful because it partly explains why immigration has such a small impact on wage and employment found in area analysis. It lends support to Lewis (2013), that assumptions of area and national approach--one-sector model, skill-neutral capital–is tenuous and that allowing for multiple sectors and capital-skill complementarity might better estimate the impacts of immigration.

Research so far does not distinguish between different channels of immigration. One such channel is temporary work visa programs which include H-1B, H-2B and H-2A. There have been a number of papers studying the impacts of the H-1B program. H-1B program is the main channel which high skilled workers (mostly STEM) acquire work authorization. Papers studying H-1B exploit changes in policy to estimate its impact. One policy change in the annual cap of the number of visas issued. Kerr and Lincoln (2010) compares the impact of national cap in H-1B visa and state level program dependence on science and engineering(SE) employment across different states. The dependence on the program is estimated by the number of Labor Condition Application (LCA) which the employer or sponsor is required to file to the U.S. DOL. Kerr and Lincoln (2010) finds that a 10 percent growth in the national H-1B population corresponds with a 3-4 percent increase in non-citizen immigrant SE employment for each standard deviation increase in state dependence. The problem with this method is that supply shock may not be truly exogenous. Dependence on H-1B may be associated with features that affect labor demand. For example, nationwide technology change may increase both dependence on H-1B workers and labor demand.

Another policy change which may be used as a source of exogenous supply shock is the lottery system that allocates visas randomly when the number of applications exceeds the mandated cap. (Peri et al., 2015) uses the 2008, 2009 lottery system as a source of exogenous supply shock in foreign labor. Since two-thirds of the cap bound visas were computer-related workers, it examines the effect of negative H-1B supply shocks on computer-related wage and employment for cities that have high dependence on H-1B workers. Negative supply is calculated by taking the difference between the LCAs and the number of lottery winners who were offered visas in each city. The paper finds that a random negative H-1B shock of 1 percentage point results in an approximate 0.5 percentage point decline in native college-educated employment growth. The paper also confirms previous findings that cities with higher dependency on H-1B visas are more affected by this change. (Doran et al., 2014) finds contrary results using the 2006 and 2007 lottery system. Although marginal increase in H-1B visas leads to very small increase in total employment, a substantial crowding out of natives exists.

For the H-2A program, we were able to find two papers that study the impact of H-2A on native unemployment. Charlton et al. (2018) exploits the geographical variation in the growth of the H-2A program and tests whether demand for H-2A guest workers increases as local unemployment falls or as wage for fruit, vegetable and horticultural crops increases. The study finds a decrease in H-2A demand for increase in lagged unemployment rate but no effect for lagged weekly wage of fruit, vegetable and horticultural crops. Both unemployment rate and weekly wages are taken at the state level.

Wei et al. (2016) applies the national approach to the NAWS survey, using a three-layer nested CES framework. The paper groups workers by age, education and then based on their birthplace. Four nesting structures are tested and finds a large and significant degree of imperfect substitutability between immigrant and native farmworkers which was consistently found for all nesting structures.

In this paper, we analyze the relationship between H-2A and native workers at the local rather than the national or state level. Area analysis is more relevant to this research because these questions are best studied at a local context, as recommended Fisher and Knutson (2013), because "each agricultural enterprise have different labor requirements and local markets have unique supply and demand conditions and relationships due to a wide range of conditions including biological, weather, required skills and labor mobility." Further, we only distinguish farmworkers by their birthplace—-foreign-born H-2A workers or native workers—and not by their level of skill. We are only considering workers in a single occupation group and since the job mostly consists of manual labor that does not require special training or education, it is reasonable to assume that farmworkers have similar skill levels regardless of their birthplace. If they have different skill levels, then we should only compare the supply of H-2A and native workers within the same skill level.

1.3 Data Source and Description

1.3.1 H-2A Program Application Data

Information about the number of H-2A guest workers has been obtained from the U.S. Department of Labor Office of Foreign Labor Certification's disclosure data which ranges from year 2006 to 2018. The data contains detailed information such as certification begin and end dates, employer name and address, job type, number of workers requested and certified, basic unit of pay and basic rate of pay and etc.

US territories such as Guam, Puerto Rico, Palau and Virgin Islands were dropped. This resulted in 19 observations being dropped. District of Columbia was dropped because there were only 3 observations. Canadian addresses were dropped as well because they belonged to harvesting or shipping companies owned in Canada that operate in US farms. This resulted in 373 addresses dropped.

The employer addresses in each application record were geocoded using google API in R. Before geocoding, faulty employer addresses were dropped. For example, 50 addresses that did not include any city, street address and zip codes were dropped because they did not contain enough information to be geocoded. The remaining employer addresses were converted to latitude and longitudes using google API. The latitude and longitudes were then converted to county fips code using Federal Communications Commission's Block API. Addresses that could not generate latitude and longitudes or could not be converted to county fips code were also considered as faulty addresses and dropped. This resulted in 40 addresses being dropped.

Google API may generate wrong coordinates if the street address is not in the correct format. Therefore, in order to check for any incorrections in geocoding, we compared applicant based information, zip based information and google API based information altogether. Addresses whose zip code (provided by applicant) based fips code and API based fips code did not match were first filtered out. Among those addresses, if the zip code information matched the state/city information provided by the applicant, the API based fips was substituted with zip code based fips. If zip code and state/city information did not match, the addresses were dropped which resulted in 1,639 addresses being dropped. For addresses with wrong zip codes such as containing less than 5 digits, the applicant provided city/state information was compared with API based city/state information and those that do not match (250 addresses) were dropped from the dataset. Therefore, a total of 1,889 addresses were dropped in the last stage of the data clean up.

Pay rates were changed to each application's state Adverse Effect Wage Rate (AEWR) because the pay rate information contained many errors. In addition, AEWR is the minimum rate that farms must pay to H-2A workers to avoid depressing the local wages, so it is reasonable to assume that most farms are paying closely to the AEWR rate.

The resulting dataset has 119,556 observations in total, which means 119,596 of applications filed from 2006 to 2018. There were 1,235,718 H-2A workers requested, and 1,716,268 of those were certified. The greater number of certified workers than requested can be explained by the greater number of missing observations in requested workers. There were 41,294 missing observations for number of requested workers, while there were only 3,197 missing for number of workers certified. Since observations missing the number of certified workers take up a small share of the total data—about 3% of the data—we assume that this would not lead to significant error in estimation. Summing all the number of H-2A workers by year and county, we obtain 16,934 observations with 2,104 distinct fips codes. Each observation corresponds to the number of H-2A workers of a county in a specific year. We also aggregate the observations to agricultural district and commuting zone level. we have 3,576 observations with 306 distinct districts and with commuting zones with 6,747 observations with 645 distinct zones.

1.3.2 County Economic and Agricultural Data

Farm employment and agricultural cash receipts data were obtained from the Bureau of Economic Analysis (BEA) and county level unemployment rate was obtained from the Bureau of Labor Statistics (BLS). Total commodity sales and sales for fruits, vegetables, horticulture were obtained from the United States Department of Agriculture (USDA). AEWR was obtained from OFLC.

1.4 Data Summary

The average number of certified H-2A workers by county for all years is 101.35 workers. The number of H-2A workers varies widely between 0 to 12,080. The total number of H-2A workers each year continues to increase, except between 2009 and 2011 when it decreased. In 2018, there was a total of 259,524 H-2A workers, almost 4 times that of 2006.

Table 1.1: Summary of Number of H-2A Workers by County

	count	mean	sd	min	max
Number of H-2A Workers	16934	101.35	449.60	0	12080

Table 1.2: Sum of H2A Workers by Year

	Number of H2A Workers	percentage growth
2006	70313	0.00
2007	87903	25.02
2008	101099	15.01
2009	98289	-2.78
2010	92850	-5.53
2011	89111	-4.03
2012	98990	11.09
2013	114508	15.68
2014	134827	17.74
2015	160095	18.74
2016	186973	16.79
2017	221786	18.62
2018	259524	17.02

The percentage of H-2A workers with respect to farm employment or total number of farmworkers is increasing. With respect to farm employment, it has increased from 9% to 2006 to 15% in 2017, which is almost 2 fold. This percentage increase demonstrates that not only has the absolute number of H-2A workers has increased but also the intensity of their use by farmers.

Table 1.3: Percentage of H-2A Workers

	Percentage of H2A Workers in	
	Farm Employment	Total Number of Farmworkers
2006	0.09	.
2007	0.10	0.10
2008	0.09	.
2009	0.10	.
2010	0.10	.
2011	0.11	.
2012	0.11	0.10
2013	0.12	.
2014	0.13	.
2015	0.13	.
2016	0.14	.
2017	0.15	0.16
Total	0.12	0.12

The 10 states with the highest number of H-2A workers are presented for each year. North Carolina is consistently ranked as the state with the highest number of H-2A workers until 2016. After then, Florida ranks first. California's rank decreases until 2011 but rises afterward. Washington first enters the list in 2010 and is the third highest state that employs H-2A workers since 2013.

Table 1.4: Top 10 States with Highest Number of H-2A 2006-2012

	2006		2007		2008		2009		2010		2011		2012	
rank	state	nbr	state	nbr	state	nbr	state	nbr	state	nbr	state	nbr	state	nbr
1	NC	14180	NC	16313	NC	16883	NC	16262	NC	18507	NC	17184	NC	18678
2	GA	5315	GA	6741	GA	6274	LA	6717	LA	6500	LA	6846	FL	8321
3	CA	4188	FL	5271	KY	5711	GA	6499	KY	5616	GA	6697	GA	8092
4	VA	4118	KY	5053	LA	5688	KY	5902	GA	4784	FL	5789	WA	7094
5	KY	3619	VA	4333	CA	5423	FL	5684	FL	4763	WA	5073	LA	6387
6	FL	3507	LA	4325	FL	5404	NY	4407	WA	4246	KY	4806	KY	4912
7	LA	3463	NY	4007	NY	4224	CA	4088	ID	4194	VA	4086	CA	3764
8	AR	3270	AR	3853	VA	4198	VA	3919	CA	4031	NY	4071	VA	3747
9	NY	3131	CA	3435	AZ	3988	ID	3551	NY	3960	AR	2939	NY	3588
10	ID	2392	ID	2977	ID	3823	AZ	3143	VA	3360	CA	2929	AR	3218

Table 1.5: Top 10 States with Highest Number of H-2A 2013-2018

	2013		2014		2015		2016		2017		2018	
rank	state	nbr	state	nbr	state	nbr	state	nbr	state	nbr	state	nbr
1	NC	20902	NC	23933	NC	27420	FL	32328	FL	38965	FL	50684
2	FL	13004	FL	16449	FL	23085	NC	29151	NC	31141	NC	30553
3	WA	10549	WA	14874	WA	19042	WA	22458	WA	28243	WA	28800
4	GA	8368	GA	9429	GA	11830	GA	14774	GA	19989	GA	26384
5	LA	6036	CA	7289	CA	9725	CA	12340	CA	16881	CA	19891
6	KY	5779	KY	6639	LA	6903	LA	7206	LA	7616	LA	8919
7	CA	5107	LA	6467	KY	6621	KY	6718	KY	7361	NY	7649
8	NY	4781	VA	5020	NY	5120	NY	5575	NY	6921	KY	7402
9	VA	4234	NY	4761	VA	5072	VA	4987	VA	4855	IA	6055
10	AR	3379	MS	3533	MS	4709	MS	4708	ID	4590	ID	5328

We also look at the distribution of H-2A workers among metro and non-metro counties. Counties are classified as metro or non-metro based on the Rural-Urban Continuum Code, which has a scale of 1 to 13. It categorizes metro counties based on their population size and non-metro counties based on their degree of urbanization and closeness to the metro areas. Scale 1 to 3 are classified as metro counties and scale 4 to 13 are classified as non-metro counties.

The number of farmworkers or farm employment alone is greater for metro counties. However, the percentage of H-2A workers with respect to total number of farmworkers (or farm employment) is higher for non-metro counties than metro counties. For some counties, there are more H-2A workers than farmworkers (or farm employment). This is due to organizations such as grower's association jointly hiring workers and distributing them across counties. This problem persists when counties are aggregated to the commuting zone level but disappears when they are aggregated to agricultural district level. Since geographical operation of grower's association is more likely to be aligned with agricultural districts than commuting zones, it makes sense that this problem continues at the commuting zone level but not at the agricultural district level.

Table 1.6: Tabulation by Rural-Urban Continuum Code

	Nbr_H2A	Farm_employment	Nbr_farmworkers
1	81.95	1337.62	1399.12
2	134.69	1869.97	2649.38
3	140.39	1247.10	1834.15
4	242.69	1180.36	1098.41
5	94.70	1086.30	1512.50
6	106.13	949.70	890.76
7	76.40	733.95	673.01
8	38.11	550.23	446.58
9	23.93	481.15	388.20
Total	101.35	1086.82	1246.82

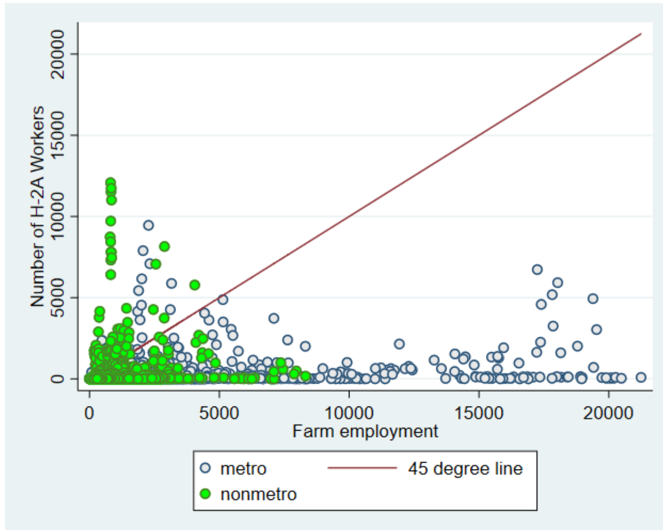

Figure 1.1: Ratio of Number of H-2A Workers to Farm Employment by Nonmetro and Metro Counties

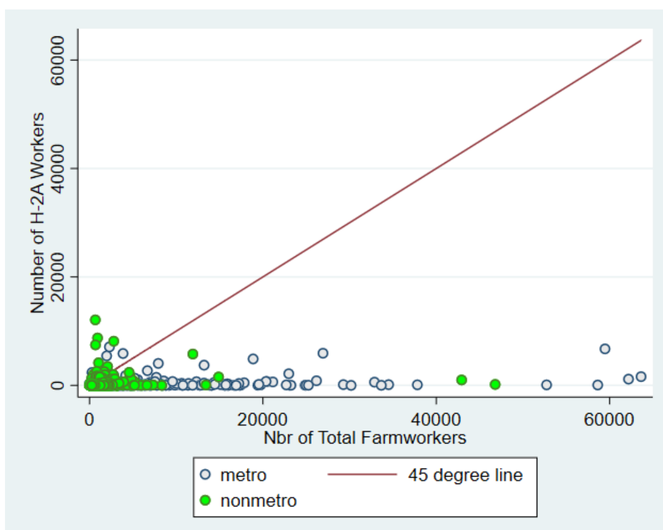

Figure 1.2: Ratio of Number of H-2A Workers to Farmworkers by Nonmetro and Metro Counties

We compare our summary statistics for the number of H-2A workers with those published by OFLC (2009a) and Luckstead and Devadoss (2019). Our summary statistics are different from those of OFLC. One reason is that OFLC uses work-site state instead of employer state. Work-site refers to the intended area of employment of the worker. Work-site information does not contain precise addresses. Work-site city is provided after 2008, zip codes are provided after 2015 and county information is provided after 2017, unlike employer location whose address, city, state and zip codes are provided throughout all the years. We will later use work-site city, state and county information to check the robustness of our models.

Another reason for the difference is that OFLC only includes master employers, while we also include sub employers. When OFLC receives application from association of employers who jointly hire their workers, it provides a unique case number for the employers. The first employer in the dataset for each is the master employer. Subsequent employers under the same case number are sub employers. Our summary statistics closely match the one presented in Luckstead and Devadoss (2019). The numbers are close but sometimes off by 100-200 workers, which causes minor differences in ranking.

CHAPTER 2

METHODS

2.1 Theoretical Model

Following Card (2001), Card (2009) and Wei et al. (2016) we model the demand for domestic and foreign (the sum of unauthorized and H-2A) workers as below.

$$Y_{ct} = F\,(K_{ct}, L_{ct}) \tag{2.1}$$

$$L_{ct} = \left(\beta_{ct}{}^{N} N_{ct}{}^{\rho} + \beta_{ct}{}^{M} M_{ct}{}^{\rho}\right)^{\frac{1}{\rho}} \tag{2.2}$$

Y_{ct} is agricultural good Y produced in a competitive market with non-labor input K_{ct} and labor input L_{ct} at year t and county c. L_{ct} is CES aggregate of heterogeneous agricultural labor inputs M_{ct} and N_{ct} with M_{ct} denoting the number of foreign farmworkers and N_{ct}, native farmworkers. β_t^M and β_{ct}^N represent relative productivity level of native and foreign farmworkers. The elasticity of substitution is $\sigma = \frac{1}{1-\rho}$. The first order condition that equates the marginal product of foreign and native farmworkers with their wage can be written as

$$\log N_{ct} = \theta_{ct} + \sigma \log \beta_{ct}{}^{N} - \sigma \log w_{ct}{}^{N} \tag{2.3}$$

$$\log M_{ct} = \theta_{ct} + \sigma \log \beta_{ct}{}^{M} - \sigma \log w_{ct}{}^{M} \tag{2.4}$$

where $\theta_{ct} = \sigma \log [\, q_{ct}\, F_L\,(\,K_{ct}\,, L_{ct})\, L_{ct}{}^{\frac{1}{\sigma}}]$ represents year and county specific component shared by native and foreign farmworkers. Combining equation 2.3 and 2.4, we obtain,

$$\log \frac{M_{ct}}{N_{ct}} = \sigma \log \frac{\beta_{ct}{}^M}{\beta_{ct}{}^N} \; - \; \sigma \log \frac{w_{ct}{}^M}{w_{ct}{}^N} \tag{2.5}$$

$$\log M_{ct} = \log N_{ct} \; + \; \sigma \log \frac{\beta_{ct}{}^M}{\beta_{ct}{}^N} \; - \; \sigma \log \frac{w_{ct}{}^M}{w_{ct}{}^N} \tag{2.6}$$

Assuming that the productivity level of foreign and native farmworkers are the same, which is quite plausible, equation 2.6 becomes

$$\log M_{ct} = \log N_{ct} \; - \; \sigma \log \frac{w_{ct}{}^M}{w_{ct}{}^N} \tag{2.7}$$

Equation 2.7 is the main equation of interest in this paper. The number of foreign farmworkers depends on the number of native farmworkers and the wage differential between the two workers.

The approach we take in studying the relationship between native and foreign workers reverses the equations normally studied in the labor economics literature. Instead of estimating the impact of foreign workers on native wages and employment, we look at how the demand for foreign workers responds to the supply of native workers. Since we do not have data that will allow us to estimate the wedge between native and foreign wages, we cannot directly compute the elasticity of substitution between native and foreign workers. However, if the number of foreign workers responds to the supply of native workers, more specifically, if demand decreases with increases in the supply of native workers, this would imply that native workers are not displaced.

If demand for foreign workers is unaffected by the supply of native workers, then this means that farmers are indifferent between native and foreign workers despite the rule that enforces farmers to recruit native workers first. This would either imply that some native workers are displaced by foreign workers or that the rule is not being enforced as planned.

Therefore, in this paper, we will look for evidence of displacement by exploring the relationship between the demand for H-2A workers and the supply of native workers instead of directly estimating equation 2.7.

2.2 Empirical Model

Our basic estimating equation is the following.

$$Y_{ct} = \alpha + \beta_1 U_{ct} + \beta_2 W_{ct} + \beta_3 S_{ct} + \tau_t + \lambda_c + \epsilon_{ct} \tag{2.8}$$

Y_{ct} is the number of H-2A workers at year t and county c. U_{ct} is the level of unemployment which represents natives who could be a potential source of farmworkers in the county. $W_c t$ is the wage that H-2A workers receive, and S_{ct} represents the sale of agricultural commodities which may affect farm labor needs. τ_t is year fixed effects and λ_c is county fixed effects.

We run a fixed effects model with separate regressions for years 2006-2017 and for census years (2007, 2012 and 2017). This is due to limited number of observations from the USDA data which only exists for the census years. The regressions are run in three levels, county, agricultural district and commuting zone level because we cannot ascertain the geographical scope of the market from which farmers recruit their workers. The market can be the local labor market which corresponds to the county level or a larger labor market which corresponds to the commuting zone level. The market may be closer to the agricultural market which corresponds to the agricultural district level. Farmers may also use an overlap of the labor and agricultural markets. Since we do not know which geographic level is most relevant to farmers, we run 6 (3 all years and 3 census years) regressions for each geographical level, a total of 18 regressions, and compare the results.

2.3 Selection of the Dependent Variable

We choose the number of H-2A workers and its percentage in total number of farmworkers and farm employment as our dependent variable. Percentage in total number of farmworkers and farm employment represent the intensity of H-2A use in each county. Farm employment from BEA is defined as the number of workers engaged in the direct production of agricultural commodities, either livestock or crops; whether as a sole proprietor, partner or hired laborer. It ranges from 2006 to 2017. The number of farmworkers at the county level were obtained from the USDA and only exist for census years, so we interpolate the number for years between. We also take a logarithmic transformation of the dependent variables because they are highly skewed to the right.

2.4 Selection of the Independent Variable

Table 2.1: Summary of Independent Variables, County Level by Year

	unemp_rate	AEWR	ag_cash_receipts	pct_FVH
2006	4.72	8.65	120.50	.
2007	4.65	9.00	135.41	0.16
2008	5.54	9.29	141.55	.
2009	8.54	9.72	131.82	.
2010	8.83	9.96	147.85	.
2011	8.36	10.07	166.77	.
2012	7.52	10.24	180.97	0.14
2013	6.97	10.53	184.80	.
2014	5.90	11.00	198.58	.
2015	5.25	11.20	172.49	.
2016	4.95	11.63	164.67	.
2017	4.39	11.93	168.44	0.15
2018	3.96	12.11	.	.
Total	6.02	10.51	159.93	0.15

We choose unemployment rate, AEWR, agricultural cash receipts and percent of FVH sales as our independent variables. For years 2006 to 2017, we use agricultural cash receipts and for census years we use percent of FVH sales. Unemployment rate is the percent of unemployed workers in the labor force at the county level. AEWR is the minimum rate that farms must pay to H-2A workers to avoid depressing the local wage. AEWR is determined at the state level, unlike other independent variables which are set at the county level. Agricultural cash receipts is cash receipts from marketing consisting of the gross revenue received by farmers from the sale of crops, livestock, and livestock products and of the value of defaulted loans made by Commodity Credit Corporation (CCC) and secured by crops from BEA and ranges from year 2006 to 2017. Its unit is 1 million dollars. Percent of FVH sales is the percent of agricultural sales of fruit, vegetable, horticulture sales which hire H-2A workers most intensively (Hernandez and Gabbard, 2018) in total commodity sales. The data is only available for census years.

CHAPTER 3

DISCUSSION OF RESULTS

3.1 Summary of Results

3.1.1 County Level

	(1)	(2)	(3)
VARIABLES	Log(H2A)	Log(%H2A of FW)	Log(%H2A of FE)
Unemp Rate	-0.027***	-0.049***	-0.026***
	(0.004)	(0.004)	(0.004)
AEWR	0.124***	0.114***	0.119***
	(0.011)	(0.012)	(0.011)
Ag Cash Receipts	0.005	-0.243	-0.074
	(0.134)	(0.176)	(0.134)
Observations	14,723	11,798	14,692
R-squared	0.048	0.063	0.043
Number of fips2	1,916	1,696	1,909

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.1: Main Regression Result at the County Level for All Years

A 1 percentage point increase in unemployment is associated with a 2.7 percent decrease in the number of H-2A workers, 4.9 percent decrease in the percent of H-2A workers in total number of farmworkers and a 2.6 percent decrease in the percent of H-2A workers in farm employment. These results suggest that the program is functioning as designed, that farmers are only using H-2A workers as a last resort. All of the coefficients are highly statistically significant at the 1% level.

A dollar increase in AEWR is associated with 12.4 percent increase in the number of H-2A workers, 11.4 percent increase in the percent of H-2A workers in total number of farmworkers and a 11.9 percent increase in the percent of H-2A workers in farm employment. A rising AEWR is indicative of a tightening labor market, which explains the increase in the number of H-2A workers. All of the coefficients are highly statistically significant at the 1% level as well.

Agricultural cash receipts do not have a statistically significant effect on the number of H-2A workers at the 10% level. One reason could be that agricultural cash receipts include the sales of all types of crops, livestock and livestock products which may or may not be eligible for H-2A.

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.058***	-0.077***	-0.053***
	(0.007)	(0.007)	(0.007)
AEWR	0.145***	0.170***	0.143***
	(0.013)	(0.013)	(0.013)
Percent of FVH Sales	0.047	-0.068	0.017
	(0.165)	(0.175)	(0.171)
Observations	3,799	3,784	3,755
R-squared	0.113	0.149	0.105
Number of fips2	1,716	1,709	1,696

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.2: Main Regression Result at the County Level for Census Years

The results align with the regression using all years. However, the effect of unemployment and AEWR on the number of H-2A workers employed is larger. Percent of FVH sales do not have a statistically significant effect on the number of for H-2A workers at the 10% level. The result is contrary to our expectations because FVH are primary industries that employ H-2A workers.

3.1.2 District Level

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.063***	-0.056***	-0.027***
	(0.009)	(0.009)	(0.009)
AEWR	0.212***	0.091***	0.136***
	(0.023)	(0.024)	(0.020)
Ag Cash Receipts	0.045	0.152*	0.024
	(0.033)	(0.083)	(0.041)
Observations	3,531	2,878	3,224
R-squared	0.171	0.089	0.077
Number of panelid	303	295	301

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Main Regression Result at the District Level for All Years

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.081***	-0.061***	-0.039**
	(0.013)	(0.015)	(0.015)
AEWR	0.227***	0.182***	0.165***
	(0.024)	(0.022)	(0.022)
Percent of FVH Sales	0.987	0.577	1.247
	(0.717)	(0.743)	(0.766)
Observations	815	815	812
R-squared	0.262	0.194	0.163
Number of panelid	295	295	294

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: Main Regression Result at the District Level for Census Years

The results at the district level are consistent with those at the county level. Unemployment rate has a statistically significant negative effect on the number of H-2A workers and AEWR, a positive effect, both at the 1% level. Agricultural cash receipts and percent of FVH sales have positive coefficients but are mostly statistically insignificant at the 10% level except for the second of the regression all years where it was statistically significant at the 5% level. The size of the coefficients for unemployment rate and AEWR is greater for the census years.

3.1.3 Commuting Zone Level

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.059***	-0.064***	-0.032***
	(0.007)	(0.007)	(0.007)
AEWR	0.195***	0.110***	0.138***
	(0.016)	(0.017)	(0.015)
Ag Cash Receipts	0.082*	0.176*	-0.029
	(0.047)	(0.097)	(0.079)
Observations	6,646	5,222	6,032
R-squared	0.138	0.088	0.066
Number of CZ	634	604	624

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Main Regression Result at the Commuting Zone Level for All Years

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.094***	-0.087***	-0.063***
	(0.012)	(0.012)	(0.011)
AEWR	0.209***	0.182***	0.154***
	(0.018)	(0.018)	(0.017)
Percent of FVH Sales	0.492	-0.154	0.549
	(0.526)	(0.378)	(0.400)
Observations	1,542	1,540	1,533
R-squared	0.223	0.192	0.143
Number of CZ	605	604	602

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Main Regression Result at the Commuting Zone Level for Census Years

The results at the commuting zone level are also consistent with those of county and agricultural district level. The size of the coefficient for unemployment rate is greater compared to the county level. Agricultural cash receipts are statistically significant for the first and second dependent variable at the 5% level but has a negative and statistically insignificant coefficient at the 10% level for the third dependent variable. Percent of FVH sales remains statistically insignificant at the 10% level.

3.2 Robustness Checks

The results of all of our regressions so far have been very consistent. In order to further test the robustness of our model, we run the regressions under different specifications, removing states with high non-citizen population and using worksite for grouping H-2A applications into counties instead of employer location.

3.2.1 Different specifications

We run regressions using farm compensation and total annual agricultural wage instead of AEWR at the county level. Farm compensation is the sum of farm wages and salaries and farm supplements to wages and salaries. It is re-scaled to 1000 dollars. Total annual agricultural wage is the sum of the four quarterly total wage levels for a given year in agriculture. It is re-scaled to 100 million dollars. These correspond to models (2) and (3) in Table 3.7 through 3.12.

We also run regressions using construction wage and employment at the county level since they may be more exogenous to H-2A demand. For construction employment, we use construction employment data from BEA which consists of construction wage and salary employment, construction proprietors employment and annual average construction employment from 2006 to 2017. We also use annual average construction employment from BLS which is the annual average of monthly employment levels for years 2006 to 2018. For construction wage we use construction compensation or total annual construction wage. Construction compensation data is from BEA and is the sum of Wages and Salaries and Supplements to Wages and Salaries in the construction industry from 2006 to 2017. It is re-scaled to 1000 dollars. Total annual construction wage is from BLS and is the sum of the four quarterly total wage levels for a given year in construction from 2006 to 2018. It is re-scaled to 100 million dollars. These correspond to models (4), (5), (6) and (7) in Table 3.7 through 3.12.

The coefficients for farm compensation and total annual agricultural wage in model (2) and (3) are positive and statistically significant at the 1% level across all dependent variables and set of years at the county level. For those models, the coefficient for unemployment rate remains negative and statistically significant still at the 1% level. The size of the coefficient is greater than the original model which is model (1). The signs and statistical significance of agricultural cash receipts depends on the choice of model specification and are therefore unstable. Percent of FVH sales is statistically insignificant across all models at the 10% level. Coefficients representing the impact of construction employment and wages are statistically insignificant at the 5% level except for model (6) and (7) using log of the percent of H-2A in farmworkers for census years (Table 3.11) where construction compensation and annual construction wage is statistically significant at 5% level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemp Rate	-0.027***	-0.035***	-0.036***			-0.036***	-0.037***
	(0.004)	(0.004)	(0.004)			(0.004)	(0.004)
AEWR	0.124***			0.135***	0.132***		
	(0.011)			(0.012)	(0.011)		
Ag Cash Receipts	0.005	0.051	0.159	0.034	-0.014	0.483***	0.448***
	(0.134)	(0.158)	(0.172)	(0.130)	(0.134)	(0.158)	(0.155)
Farm Comp.		0.009***					
		(0.002)					
Annual Ag Wage			0.220***				
			(0.070)				
Con. Emp.				0.000			
				(0.000)			
Average Emp. in Con.					0.000		
					(0.000)		
Con. Comp.						0.000	
						(0.000)	
Annual Con. Wage							0.007
							(0.011)
Observations	14,723	14,735	14,648	13,494	14,721	13,503	14,730
R-squared	0.048	0.021	0.017	0.043	0.042	0.014	0.014
Number of fips2	1,916	1,917	1,911	1,847	1,914	1,848	1,915

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.7: Regression with log (H-2A) as Dependent Variable for All Years at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemp Rate	-0.049***	-0.063***	-0.063***			-0.064***	-0.063***
	(0.004)	(0.005)	(0.005)			(0.005)	(0.005)
AEWR	0.114***			0.141***	0.140***		
	(0.012)			(0.013)	(0.013)		
Ag Cash Receipts	-0.243	-0.212	-0.338	-0.166	-0.245	0.104	0.041
	(0.176)	(0.192)	(0.216)	(0.164)	(0.177)	(0.138)	(0.146)
Farm Comp.		0.007***					
		(0.002)					
Annual Ag Wage			0.279***				
			(0.068)				
Con. Emp.				0.000*			
				(0.000)			
Average Emp. in Con.					0.000*		
					(0.000)		
Con. Comp.						0.000	
						(0.000)	
Annual Con. Wage							0.009
							(0.012)
Observations	11,798	11,798	11,731	10,836	11,795	10,836	11,795
R-squared	0.063	0.041	0.043	0.044	0.045	0.038	0.037
Number of fips2	1,696	1,696	1,689	1,622	1,694	1,622	1,694

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Regression with log (Percent of H-2A in Farmworkers) as Dependent Variable for All Years at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemp Rate	-0.026***	-0.034***	-0.034***			-0.034***	-0.035***
	(0.004)	(0.004)	(0.004)			(0.004)	(0.004)
AEWR	0.119***			0.131***	0.127***		
	(0.011)			(0.012)	(0.011)		
Ag Cash Receipts	-0.074	0.059	0.090	-0.043	-0.093	0.395***	0.354**
	(0.134)	(0.158)	(0.170)	(0.129)	(0.134)	(0.150)	(0.148)
Farm Comp.		0.007***					
		(0.002)					
Annual Ag Wage			0.201***				
			(0.068)				
Con. Emp.				0.000			
				(0.000)			
Average Emp. in Con.					0.000		
					(0.000)		
Con. Comp.						0.000	
						(0.000)	
Annual Con. Wage							0.007
							(0.011)
Observations	14,692	14,692	14,605	13,464	14,690	13,461	14,687
R-squared	0.043	0.016	0.014	0.039	0.038	0.012	0.012
Number of fips2	1,909	1,909	1,903	1,840	1,907	1,840	1,907

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.9: Regression with log (Percent of H-2A in Farm Employment) as Dependent Variable for All Years at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemp Rate	-0.058***	-0.074***	-0.073***			-0.069***	-0.071***
	(0.007)	(0.007)	(0.007)			(0.008)	(0.007)
AEWR	0.145***			0.160***	0.158***		
	(0.013)			(0.014)	(0.013)		
Percent of FVH Sales	0.047	-0.082	-0.054	0.116	0.095	-0.033	-0.043
	(0.165)	(0.177)	(0.169)	(0.185)	(0.174)	(0.181)	(0.169)
Farm Comp.		0.008***					
		(0.001)					
Annual Ag Wage			0.353***				
			(0.069)				
Con. Emp.				0.000			
				(0.000)			
Average Emp. in Con.					0.000		
					(0.000)		
Con. Comp.						0.000	
						(0.000)	
Annual Con. Wage							0.021*
							(0.012)
Observations	3,799	3,762	3,776	3,446	3,796	3,446	3,796
R-squared	0.113	0.050	0.054	0.091	0.090	0.038	0.040
Number of fips2	1,716	1,701	1,708	1,606	1,714	1,606	1,714

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.10: Regression with log (H-2A) as Dependent Variable for Census Years at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemp Rate	-0.077***	-0.095***	-0.094***			-0.090***	-0.093***
	(0.007)	(0.008)	(0.008)			(0.008)	(0.008)
AEWR	0.170***			0.191***	0.188***		
	(0.013)			(0.014)	(0.013)		
Percent of FVH Sales	-0.068	-0.217	-0.195	0.034	0.000	-0.171	-0.188
	(0.175)	(0.189)	(0.180)	(0.195)	(0.185)	(0.192)	(0.179)
Farm Comp.		0.008***					
		(0.001)					
Annual Ag Wage			0.390***				
			(0.072)				
Con. Emp.				0.000*			
				(0.000)			
Average Emp. in Con.					0.000		
					(0.000)		
Con. Comp.						0.000**	
						(0.000)	
Annual Con. Wage							0.025**
							(0.012)
Observations	3,784	3,747	3,761	3,432	3,781	3,432	3,781
R-squared	0.149	0.069	0.074	0.116	0.113	0.057	0.060
Number of fips2	1,709	1,694	1,701	1,600	1,707	1,600	1,707

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.11: Regression with log (Percent of H-2A in Farmworkers) as Dependent Variable for Census Years at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemp Rate	-0.053***	-0.068***	-0.067***			-0.063***	-0.066***
	(0.007)	(0.007)	(0.007)			(0.008)	(0.007)
AEWR	0.143***			0.159***	0.155***		
	(0.013)			(0.014)	(0.013)		
Percent of FVH Sales	0.017	-0.106	-0.089	0.089	0.076	-0.064	-0.080
	(0.171)	(0.174)	(0.173)	(0.182)	(0.179)	(0.178)	(0.174)
Farm Comp.		0.006***					
		(0.001)					
Annual Ag Wage			0.326***				
			(0.067)				
Con. Emp.				0.000			
				(0.000)			
Average Emp. in Con.					0.000		
					(0.000)		
Con. Comp.						0.000*	
						(0.000)	
Annual Con. Wage							0.021*
							(0.012)
Observations	3,755	3,755	3,732	3,439	3,752	3,439	3,752
R-squared	0.105	0.041	0.046	0.088	0.087	0.032	0.035
Number of fips2	1,696	1,696	1,688	1,601	1,694	1,601	1,694

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.12: Regression with log (Percent of H-2A in Farm Employment) as Dependent Variable for Census Years at the County Level

3.2.2 Dropping California and Texas

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.027***	-0.048***	-0.025***
	(0.004)	(0.005)	(0.004)
AEWR	0.125***	0.120***	0.122***
	(0.012)	(0.013)	(0.012)
Ag Cash Receipts	-0.164	-1.214***	-0.295
	(0.356)	(0.319)	(0.354)
Observations	12,836	10,291	12,813
R-squared	0.051	0.070	0.047
Number of fips2	1,678	1,481	1,672

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.13: Main Regression Result dropping California and Texas for All Years

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.066***	-0.083***	-0.060***
	(0.007)	(0.008)	(0.007)
AEWR	0.137***	0.161***	0.135***
	(0.013)	(0.014)	(0.013)
Percent of FVH Sales	-0.016	-0.127	-0.035
	(0.175)	(0.190)	(0.184)
Observations	3,319	3,305	3,276
R-squared	0.118	0.153	0.110
Number of fips2	1,501	1,495	1,482

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.14: Main Regression Result dropping California and Texas for Census Years

For regression including all the years, coefficients for unemployment and AEWR is very close to the original model. However, for the census years, the size of the coefficient for unemployment rate is greater, while it is smaller for AEWR. This implies that having a large non-citizen population—and possibly a large undocumented population—may influence the degree at which H-2A demand responds the local unemployment rates.

3.2.3 Work-site instead of Employer site

Work-site is the area of intended employment of the worker. We use work-site county to check the consistency of the results. 12 observations whose work-site were located in DC or outside the 50 states (US territories and Canada) were dropped. 53 observations whose employers were in Canada but whose work-site was in the U.S. were not dropped. Out of 106,693 observations, 4,710 addresses were not matched with a specific county. 4,672 of those had incorrect city names with no further information about zip codes or county names. 192 of the addresses had wrong state information and were located based on the postal code information.

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.060***	-0.076***	-0.058***
	(0.007)	(0.012)	(0.007)
AEWR	0.121***	0.244***	0.118***
	(0.013)	(0.023)	(0.013)
Ag Cash Receipts	-0.297	-0.787*	-0.354*
	(0.194)	(0.428)	(0.186)
Observations	12,694	6,480	12,676
R-squared	0.061	0.154	0.057
Number of fips2	2,092	1,742	2,086

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.15: Main Regression Result using Work-site instead of Employer site for All Years

VARIABLES	(1) Log(H2A)	(2) Log(%H2A of FW)	(3) Log(%H2A of FE)
Unemp Rate	-0.072***	-0.084***	-0.059***
	(0.018)	(0.018)	(0.018)
AEWR	0.200***	0.250***	0.211***
	(0.032)	(0.033)	(0.033)
Percent of FVH Sales	0.079	0.081	0.104
	(0.296)	(0.325)	(0.304)
Observations	2,760	2,755	2,738
R-squared	0.193	0.253	0.179
Number of fips2	1,757	1,753	1,743

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.16: Main Regression Result using Work-site instead of Employer site for Census Years

The results are in line with the ones using employer addresses. The signs and statistical significance match but the coefficients for unemployment rate and AEWR is greater for the regression using census years.

3.3 Comparing Results with Prior Studies

With regards to the broader economic literature on substitution between foreign and native workers, our results are in line with the conclusions of area analysis whose results demonstrate that foreign and native workers, once accounting for heterogeneity of workers, are imperfectly substitutable. Although we cannot derive any conclusions about the substitutability of native and H-2A workers based on our results, the results do indicate that H-2A workers are hired as a last resort. In other words, if there are willing native workers to take the job, they will not be displaced with H-2A workers.

Compared to two other agricultural economics papers, Charlton et al. (2018) and Wei et al. (2016) that are relevant to this research, our results also follow their conclusions. Charlton et al. (2018) finds consistent support across specifications that increase in lagged unemployment reduces H-2A demand and Wei et al. (2016) finds a small degree of substitution between native and foreign farmworkers within the same age and skill group.

CHAPTER 4

CONCLUSION

This study makes two contributions to the literature. First, we lend support to previous findings that native and foreign workers are not perfectly substitutable. We find an inverse relationship between local unemployment and H-2A use that is remarkably robust across a wide variety of specifications. The coefficients for unemployment and AEWR are consistent in their signs and statistical significance across all dependent variables, geographical units and range of years. The results are robust even when work-site is used to locate the workers into counties, when certain states are excluded from our analysis and when different proxies for unemployment and wages are used. From these results, we conclude that the decrease in unemployment and increase in AEWR, an indication of a tightening local labor market, increases the demand for H-2A workers. This also means that the program is working as intended. Farmers are using the H-2A program as a last resort when they cannot find willing native workers for the job.

Our second contribution is that we examine the number of H-2A workers at a more granular level by geocoding the applications into the county level. To our knowledge, the only paper that has organized the applications by geographical locations is Charlton et al. (2018), who did so at the state level. The process of geocoding the data also enhanced our understanding of H-2A program, the types of employers and counties (metro vs non-metro) that hire H-2A, the growth rate of the program by county and the difference in using employer-site and work-site for geocoding.

The paper still faces several limitations. First, there may be measurement error due to missing or incorrect observations. There are observations with missing number of certified workers, missing employer addresses or incorrect employer addresses which may underestimate the number of H-2A workers for some counties. We assume that the number of missing or incorrect observations is small enough for the effect of the error to be negligible. However, we can continue to minimize the errors in geocoding by checking for mistakes in employer addresses.

Second, the results indicate that intensity of fruit, vegetable and horticulture sales or general agricultural sales is not related to H-2A demand, which is contrary to what was expected. One reason for the instability and low level of statistical significance of agricultural cash receipts or FVH sales is that sales data do not accurately reflect the increase in production. Another reason could be that the percent of FVH sales is observed only for census years. There are only three years of data for FVH sales so it may not truly capture the relationship between H-2A demand and percent of FVH sales. Another reason could be that FVH sales include FVH that are mechanized and do not require manual labor. We should only include high-value fresh FVH production that is not mechanized but this is hard to tease out from aggregate FVH production.

Lastly, there still remain issues with identification because local unemployment may be related to unobserved determinants of H-2A demand. For example, the number of undocumented workers may both influence local unemployment levels and H-2A demand. In our robustness checks, we used construction employment and wage since they may be more exogenous to H-2A demand. However, the effect was unstable and statistically insignificant. One reason for this could be that the variables for construction employment and wages are constructed in a way that does not reflect local labor market conditions. For example, construction employment is the sum (or average) of employment for both hired workers and proprietors, and construction wages is the sum of all of the wage and salary in a given year. Since it sums all employment levels and wages, it may not be indicative of local labor market conditions. Another reason could be that workers do not tend to switch to agriculture. Even if employment level decreases in construction, workers may choose to stay unemployed or move to the retail or service instead of agriculture.

For future research, we suggest that first, to improve the accuracy of employer addresses to minimize the errors in geocoding. Second, we suggest using variables that better reflect changes in fresh, high value fruit, vegetable and horticulture production that is less mechanized. Third, we suggest including variables representing the proportion of non-citizen population of each county. Fourth, we suggest including variables that account for the wedge between the wage of native and foreign workers to better reflect the theoretical model and, finally, to explore variables such as the differential cost of participating in the program between each county that are related to unemployment rates but possibly unrelated to other determinants of H-2A.

According to our results, the number of farmers participating in H-2A is increasing and farmers are utilizing the program in a way that does not displace native farmworkers, which was a major principle of the legislation authorizing the program. This suggests the program is largely works as it was designed, or in other words, that farms in high unemployment counties are using H2A at a lower rate than low unemployment counties. This lends support to arguments that there may be opportunities to streamline the H-2A program in a way that reduces the administrative burden and cost for farmers.

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