THREE ESSAYS ON U.S. FARM WORKERS' WAGE DETERMINANTS, HEALTH CARE SERVICE UTILIZATION TRENDS, AND WORK TIME ALLOCATION DECISIONS UNDER A STRICTER IMMIGRATION POLICY ENVIRONMENT

by

TIANYUAN LUO

(Under the Direction of Cesar L. Escalante and Genti Kostandini)

ABSTRACT

The first chapter of the dissertation analyzes issues related to the U.S. hired farm workers' utilization of health care services and their specific choices among health care provider and health bill payment method options. Using data from the National Agricultural Workers Surveys for the years 2000 to 2012 and controlling for other demographic factors, this study's results indicate that undocumented hired farmworkers are 10.6% and 8.4% less likely to use U.S. and foreign health care, respectively, compared to documented immigrant hired farmworkers. Moreover, the general preference of hired farmworkers in the U.S. tends to lean towards patronizing private clinics and settling their health care bills using out-of-pocket funds.

The second chapter of the dissertation investigates the employment time allocation choices of U.S. workers between farm and non-farm work alternatives using individual level data from the National Agricultural Workers Survey (NAWS). Green card farm workers are found to devote smaller share of working time to the farm sector than citizen and undocumented workers, which raises the concern that the legalization of immigrant status could possibly exacerbate farm labor shortage conditions. Language barrier and length of residence in the country are found to

play important roles in the time allocation of farm workers between farm and non-farm employment. Moreover, external economic shocks could more easily induce citizen and green card farm workers to abandon farm employment while undocumented workers tend to remain in their farm jobs during such difficult times.

The third chapter of this dissertation analyzes the impact of undocumented immigrants emigration caused by E-verify on the wages of the natives and immigrants in the adopting states. Using data from the Current Population Survey for the 2000-2014 period, we examine the heterogeneous wage effects on non-migrant natives and immigrants by industrial and educational group. Immigrants and natives who work in manual industries are found to experience decreases in their wages, while other industries are more likely to witness wage increase. The wage effects of E-verify on natives are found to be smaller and insignificant.

INDEX WORDS: Healthcare utilization, Hired farmworkers, Undocumented immigrants, Foreign healthcare, Time allocation, Green card holders, Determinants, Emigration, E-verify mandates, Wage impact, Native workers

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by

TIANYUAN LUO

B.A., Minzu University of China, China, 2009

M.S., Minzu University of China, China, 2012

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

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by

TIANYUAN LUO

Major Professor:	Cesar L. Escalante
	Genti Kostandini
Committee:	Octavio Ramirez
	Brady Brewer

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
May 2017

DEDICATION

This dissertation is dedicated to my parents, Qun Luo and Qiongying Ye, for their selfless love and encouragement.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

This dissertation includes three manuscripts, investigating two types of labor: U.S. farmworkers and immigrants by employing various econometric methods. The primary objectives involve assessing the health care use and employment time allocation of farm workers as well as the wages change of immigrants in the U.S. under stringent immigration enforcement. The motivations for this research are the current strengthened immigration enforcement in U.S. that may affect many immigrants as well as the population of farmworker that has a high share of immigrant workers. The primary procedures employed are probit, multinomial logit and Difference-in-Differences model.

Efforts aimed at sustaining a healthy labor force would not only promote individual health but also ensure a productive labor force that supplies the needs of a growing economy. This is particularly true for the agricultural sector whose production activities are relatively more dependent on the quality and quantity of its labor force than other industries (Zahnister et al. 2012). Several studies have pointed out that the strenuous, rigorous nature of farm work and its greater physical demands, prevailing working conditions in farms, and the workers' lack of health knowledge and information could have significant adverse effects on the health of hired farmworkers in the U.S.(Hoerster et al. 2011; Villarejo 2003;Arcury and Quandt 2007; Frank et al. 2013). The first chapter adds to these key factors by introducing the significantly low patronage rates of health care services among hired farmworkers compared to the average American population. Rose and Quade (2006) find that only 50% of farmworkers in California

availed of health care services in 2005, which is 25% lower than the utilization rate estimated for the non-Hispanic white population in the U.S. (Ezzati-Rice and Rohde 2009). The disparity in health care patronage could possibly lead to serious public health issues as well as inflict severe damages to the $374 billion U.S. farm sector if no attention and definitive actions are made to improve the health care use patterns of U.S. hired farmworkers.

It is therefore of importance to examine the health care utilization decisions of hired farm workers in general as well as stratified categories of these workers according to their legal statuses. (Hired farmworkers with different legal status could be expected to adopt different patterns of health care use due to disparities in their cultural attributes, social dynamics, and economic conditions). The first chapter focuses on analyzing several facets of the health care utilization decision of U.S. hired farmworkers that include, not just their utilization rates, but also their choices of among health care provider and medical bill payment alternatives. The first chapter also aims to discern the key determinants that could either restrain or encourage the use of health care services among hired farmworkers to provide valuable insights and implications that may be considered in attempts to eliminate inequities in health care service patronage of hired farmworkers and workers from other industries.

The second study contends that farm workers of varied legal statuses could consider different motivations for seeking and retaining farm employment. For instance, the predominance of undocumented workers in the farm industry, even under stricter immigration controls, could possibly be induced by economic necessity and the lack or absence of other employment alternatives. However, when the same workers are granted the proper work authorization (perhaps through an amnesty grant) to expand their employment options, it would be interesting to validate whether their employment decisions would also change.

The second chapter is designed to provide empirical support to the legal status argument of farm labor decisions of potential farm workers. In this study, the general categories of documented and undocumented farm workers will be used to discern the determinants of these workers' employment choices and the resulting labor supply pattern of the U.S. farm workers. Specific sub-categories for documented workers will be considered to address two separate issues. This study's analysis of the employment time allocation decisions of green card holders, who are immigrants that successfully obtained permanent residence status, could shed light on the issue of whether farm employment decisions are primarily influenced by the job uncertainties and deportation risks faced by undocumented workers. In other words, this analysis seeks to determine if the elimination of such risks and uncertainty under permanent residence status would translate to abandoning farm employment in favor of more promising, lucrative opportunities in other sectors. This study's results for the sub-category of farm workers with citizenship status would be useful in discerning attitudes towards farm employment, especially during more difficult economic periods when job opportunities are scarcer.

Employment verification mandate (E-verify) gained much popularity among state government across the U.S. as a way to curb the undocumented immigration trend. As suggested by numerous previous studies, E-verify is quite efficient in reducing undocumented immigrants, even though there may exist issues such as identity fraud and firm noncompliance (Amuedo-Dorantes and Bansak 2012; Meissner and Rosenblum 2009; Nowrasteh 2012). For example, Lofstrom, Bohn, and Raphael (2011) find that the number of non-citizen Hispanic immigrants in Arizona dropped by about 92,000 persons due to the E-verify mandate during 2008-2009 period. Bohn and Lofstrom (2013) find a decline of 11% in the rate of formal employment for unauthorized workers in Arizona. Orrenius and Zavodny (2016) examine the impact of E-verify

in a more general case (for seven E-verify adoption states) and suggest that the number of recent immigrants in states that adopted universal employment verification mandates falls by approximately 40%. Additionally, there are more studies that reach similar conclusions (Bohn, Lofstrom, and Raphael 2014; Amuedo-Dorantes and Bansak 2012; Amuedo-Dorantes and Lozano 2015).

In addition to the goal of deterring the hiring of undocumented workers, E-verify mandate is also expected to improve the labor market opportunities for natives and legal immigrants who compete with undocumented immigrants for jobs in the U.S.(Orrenius and Zavodny 2015). This article evaluates whether E-verify has completed the goal of supporting native and legal workers through changes in their wages, and if so, who, in which industry and by how much?

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CHAPTER 2

HEALTH CARE UTILIZATION DECISION OF HIRED FARMWORKERS IN THE U.S.[1]

[1] Luo, Tianyuan and Cesar Escalante. Submitted to the European Journal of Health Economics, April 3, 2017.

Abstract

This article analyzes issues related to the U.S. hired farm workers' utilization of health care services and their specific choices among health care provider and health bill payment method options. Using data from the National Agricultural Workers Surveys for the years 2000 to 2012, this article employs a probit model for examining the U.S. and foreign health care utilization and a multinomial logit model for health care provider and medical bill payment methods choices. Controlling for other demographic factors, this study's results indicate that undocumented hired farmworkers are 10.6% and 8.4% less likely to use U.S. and foreign health care, respectively, compared to documented immigrant hired farmworkers. Moreover, the general preference of hired farmworkers in the U.S. tends to lean towards patronizing private clinics and settling their health care bills using out-of-pocket funds. Overall, hired farmworkers have a lower health care utilization rate than average non-Hispanic white population, and among them, undocumented hired farmworkers have the lowest utilization rate at 48%. In addition, the problems of minimal use of safety net services and low public health benefit coverage have been verified to be persistent among all hired farmworkers.

2.1 INTRODUCTION

Efforts aimed at sustaining a healthy labor force would not only promote individual health but also ensure a productive labor force that supplies the needs of a growing economy. This is particularly true for the agricultural sector whose production activities are relatively more dependent on the quality and quantity of its labor force than other industries (Zahnister et al. 2012). Several studies have pointed out that the strenuous, rigorous nature of farm work and its greater physical demands, prevailing working conditions in farms, and the workers' lack of health knowledge and information could have significant adverse effects on the health of hired farmworkers in the U.S.(Hoerster et al. 2011; Villarejo 2003;Arcury and Quandt 2007; Frank et al. 2013). This study adds to these key factors by introducing the significantly low patronage rates of health care services among hired farmworkers compared to the average American population. Rose and Quade (2006) find that only 50% of farmworkers in California availed of health care services in 2005, which is 25% lower than the utilization rate estimated for the non-Hispanic white population in the U.S. (Ezzati-Rice and Rohde 2009). The disparity in health care patronage could possibly lead to serious public health issues as well as inflict severe damages to the $374 billion U.S. farm sector if no attention and definitive actions are made to improve the health care use patterns of U.S. hired farmworkers.

It is therefore of importance to examine the health care utilization decisions of hired farm workers[2] in general as well as stratified categories of these workers according to their legal statuses. (Hired farmworkers with different legal status could be expected to adopt different patterns of health care use due to disparities in their cultural attributes, social dynamics, and

[2] The modifier "hired" is used to distinguish skilled and unskilled farmworkers who are actually hired by farm businesses from family members and business owners who also work on the farm.

economic conditions). This study focuses on analyzing several facets of the health care utilization decision of U.S. hired farmworkers that include, not just their utilization rates, but also their choices of among health care provider and medical bill payment alternatives. This study also aims to discern the key determinants that could either restrain or encourage the use of health care services among hired farmworkers to provide valuable insights and implications that may be considered in attempts to eliminate inequities in health care service patronage of hired farmworkers and workers from other industries.

The demographic profile of hired farmworkers in U.S. indicates the sector's dependence on immigrant (foreign) workers, of which over 50% do not have legal authorization to work in the country (Martin 2016). These workers' unauthorized legal status would further restrict their access to and utilization of available health care services as some immigration enforcement and public health policies in the U.S. nowadays impose strict limitations on the undocumented immigrants' use of medical resources and services (such as the stipulations provided in the Personal Responsibility and Work Opportunity Reconciliation Act of 1996). This study provides an empirical estimation of this gap in health care use between documented and undocumented hired farmworkers. Results indicate that undocumented hired farmworkers are 10.6% less likely to avail of health care services compared to their peer workers with legal employment authorization.

In addition, the large proportion of immigrants in the farm labor force also suggests a larger demand for health care services in foreign countries, especially in terms of their connection to their home countries. Foreign health care can be an important supplementary alternative to U.S. health care services that can help attend to the health care needs of immigrant hired farmworkers. A recent study has established that foreign health care has indeed become a

popular option among immigrants due to their experiences of discrimination in accessing U.S. health services, lack of knowledge of the U.S. health care system, and even the enforcement of certain restrictive provisions of the Immigration Naturalization Service public charge laws[3] (Bergmark, Barr, and Garcia 2010). The consideration of foreign health care use among hired farmworkers, in addition to their patronage of U.S. health care services, would provide a more comprehensive understanding of the health care needs and utilization patterns of hired farmworkers.

During the recent decades, the U.S. government carried out a series of public health policies designed to improve the health status of disadvantaged groups and encourage their utilization of available medical services. These efforts include constructing a broader and more accessible safety net through building more community/migrant health centers and reforming public health benefit systems (e.g. Affordable Care Act 2010). As one of most economically disadvantaged groups in the U.S. (Hertz 2013), hired farmworkers are expected to significantly change their patterns of use of public safety net facilities in the wake of reforms initiated by U.S. government. This study verifies whether such change indeed has occurred among hired farmworkers by analyzing their choices among health care provider and medical bill payment options available to them. The empirical results obtained raise concerns on these workers' overall low rate of utilization of safety net services and public health benefits. On one hand, private clinics have been the most popular choice as approximately 45% of hired farmworkers would rather patronize such service instead of relatively cheaper service alternatives (such as migrant/community health centers). On the other hand, on average hired farmworkers have a

[3] Many immigrants think that the use of public health benefit would decrease their probability of obtaining green cards or citizenship.

probability of over 50% to settle their medical bill with personal funds. The combined effects of these two decisions could potentially lead to greater financial strain that threatens the liquidity conditions and economic viability of the households of hired farmworkers.

The remainder of this article is organized as follows. The subsequent section presents a background on the challenges experienced by U.S. farm workers in their efforts to address their health care needs. The following sections present a description of the dataset and the empirical framework for analyzing health care utilization decisions. These are followed by a section that summarizes and analyzes the estimated results while the final section presents conclusions.

2.2 BACKGROUND

The provision of health care services is an urgent issue for hired farmworkers given the onerous and risky nature of farm work that entail, among others, excessive physical demands, prolonged exposure to chemical inputs, more accident-prone operations, and mentally stressful tasks. Arcury and Quandt (2007) have articulated such claim through their contention that agriculture is one of the most dangerous industries in the U.S. Hoerster et al. (2011) provide further supporting evidence by pointing out that farmworkers in the U.S. are more relatively burdened with serious illnesses that eventually translate to high mortality rates associated with incidences of cancer and injuries. Vallarejo (2003) and Zahm and Blair (2001) provide further evidence on the apparent linkage between chemical exposure in the farm workplace and a high prevalence of certain types of cancer among farmworkers. Meanwhile, the more rigorous nature of physically demanding tasks in farms could also result in more job-related injuries such as sprains, strains, fractures, and other musculoskeletal injuries (Weigel and Armijos 2012). In addition to the physical tolls of farm work, hired farmworkers are also likely susceptible to developing serious mental or

psychological stress problems (Arcury and Quandt 2007). Magana and Hovey (2003) validate that an overall elevated level of depression and anxiety exists among Mexican migrant farmworkers in the Midwest. These adverse mental or psychological conditions could arise from the workers' worries about, among other factors, rigid work demands, poor housing conditions, and inadequately low family incomes. This finding is in line with the assertion made by Arcury and Quandt (2007) and Vallarejo (2003) that U.S. farmworkers are usually characterized by a low socioeconomic status reflected by their low incomes, poverty living conditions, and harsh working environments. Hired farmworkers in the U.S. face diverse challenges in dealing with their own health concerns and confronting the risks posed by their work environments (Anthony, Williams, and Avery 2008; Slesinger and Ofsted 1993) and thus demonstrates a pronounced need for health care and treatment services. However, as will be shown next, their health care service use appears to fall short of their actual medical needs.

The U.S. farm sector has been a major employer of its immigrants, including those who are undocumented that comprise over 50% of this category of workers (Martin 2016). It therefore follows that the industry's patterns of health care use intended for its hired farmworkers should largely cater to the needs of the majority of the suppliers of farm labor input. Several studies, however, indicate that immigrants (both adults and children) have lower health care utilization rates than natives in the U.S. Mohanty et al. (2005) analyzed the health care expenditures of 2,843 immigrants and 18,398 US-born citizens. Their findings indicate that immigrants' per capita total health care expenditures are 55% lower than those incurred by U.S. citizens. Ku (2009) provides additional empirical support to this contention that the health care costs incurred by immigrants are about 14% to 20% less than those of U.S. natives. Equivalently,

his results suggest that the immigrants who make up 5% of the U.S. population are beneficiaries of only 1% of funds allocated for public health services.

In regard to farmworkers' health care utilization, Arcury and Quandt (2006) suggest that there are some significant barriers to the farmworkers' utilization of medical services. These include linguistic differences, financial strain, lack of legal documentation, and a shortage of health care providers. Vallarejo (2003) points out that hired farmworkers would usually only resort to availing of health care services when it is absolutely urgent and necessary. His results also identify the lack of health insurance as another barrier to adequate and easy health care access. Hoerster et al (2011), on the other hand, address the need for improvements in health care outreach services. Other studies (Frank et al. 2013; Hoerster 2010) also cite that the unattended and unmet health needs of farmworkers are primarily due to underdeveloped public safety nets, such as the inadequate capacities of community/migrant health clinics and the delayed actions or responses of available health services to the workers' more pressing needs.

It has also been noted that immigrant farmworkers, who are mostly from Mexico (Martin 2016), would also consider seeking medical attention in foreign countries. Wallace, Mendez-luck, and Castanda (2009) find that 15% of tenured Mexican immigrants in California used health care in Mexico during the past year of interview. Bergmark, Barr, and Garcia (2010) also find that 46% of current and former immigrants in California reported that relatives or close friends have returned to Mexico for medical treatment. According to these studies, the workers' decisions to seek health care overseas are a result of the workers' lack of insurance, the implementation of recent stricter immigration control policies, dissatisfaction with previous unsuccessful treatment in U.S., and the workers' preference for Mexican care. However, even though foreign health care may be able to effectively address the health care needs of immigrant

farmworkers, the financial costs of international travel and the high possibility of delayed treatment may nonetheless have adverse effects on the farmworkers' overall welfare. Moreover, the intensified enforcement of immigration control policies especially along the US-Mexico border could dissuade undocumented farmworkers from leaving the U.S. to seek medical services in their home countries or elsewhere overseas. True enough, only 6% of undocumented hired farmworkers in this study's sample have actually relied on foreign health care in the past two years prior to their interviews. This rate is only half of the foreign health care rate registered by hired farmworkers who are legal permanent residents.

2.3 DATA DESCRIPTION

The data used in this article are obtained from the National Agricultural Workers Survey (NAWS), which is an individual micro-level cross-sectional dataset collected from the general hired farmworker population in the United States. No personal identifier is provided by this survey to ensure the anonymity of each individual interviewee. The dataset includes information on demographic characteristics, health care choices and health status of worker respondents. The sample size of this study's dataset comprises more than 28,000 hired farmworkers and is categorized into three groups according to their legal status: citizens, green card holders, and undocumented workers. This article's time period spans from the start of the NAWS collection of health care utilization data in 2000 until the most recently available annual data for 2012. In addition, the data for farmworker's choice of health care providers are only available from 2007 to 2012.

Panel (A) in Table 1.1 presents the various categories of the dependent variables considered in this article. The first set of dependent variable is the farm worker's binary choice

in utilizing health care services in the U.S. and foreign countries for hired farmworkers. The variables "U.S. healthcare" and "Foreign healthcare" capture the farmworker's decision to access any domestic and foreign health care service, respectively, within 2 years prior to the interview. The summary statistics indicate that 51.4% of hired farmworkers have used U.S. health care services while 13.8% of hired farmworkers have used foreign health care services. The workers' partial reliance on foreign health care services, even when health care services are locally available, could suggest either the workers' concerns about utilization due to prevailing legal restrictions of immigration and health policies or their deliberate decisions to avoid patronage of such domestic services.

The other two dependent variables shown in Panel (A) involve multiple options related to health care provider and payment method alternatives available to the hired farmworkers. Health care provider options include community health centers, private clinics, hospitals, migrant health clinics, and other service providers. Among these health provider alternatives, private clinics appear to attract the largest group of workers (45.4%) while the other more affordable health service providers usually patronized by most residents registered relatively lower utilization rates. The medical bill payment arrangement results further complicates the workers' economic predicament. Among the payment options considered in this analysis, the most predominant arrangement is the payment of medical bills using out-of-pocket funds. The low application rates for other payment options such as Medicare/Medicaid (10.3%) and employer-provided health insurance (16.5%) may reflect the workers' difficulty in obtaining these types of financial assistance due to existing restrictions. The combined repercussions of these more predominant health care provider and payment arrangement choices among farmworkers can only further aggravate the economic status of these workers' households.

Panel (B) in Table 1.1 presents the covariates included in the model. The average hired farmworker in this study's sample is 36 years of age and has stayed in the U.S. for about 18 years. The sample is distributed among the legal categories as follows: 26% as U.S. citizens, 24% as green card holders, and 51% as undocumented workers. The latter figure is very close to the estimate of 55% reported by Martin (2016). Consistent with the self-selected immigration argument whereby healthier workers would have a greater tendency to migrate (McDonald and Kennedy 2004), statistics for this study's dataset (with a larger proportion of undocumented workers) indicate a low incidence of chronic diseases (such as asthma, diabetes, and high blood pressure).[4] The better health status of farm workers could partly explain their lower rate of health care service utilization.

In addition, this dataset's average farm worker has spent approximately 7 years in school. Moreover, other studies have identified the language as a potential barrier that could affect health care access of immigrant workers (Perkins and Youdelman 2008; Anton and Munoz de Bustillo 2010; LeClere et al. 1994). This has been taken into account in this analysis by including categorical English speaking and reading variables that capture several levels of proficiency. The summary in Table 1.1 indicates that the average U.S. farm worker has a minimal speaking and reading proficiency in English.

[4] All the chronic disease dummy variables are classified under "need variables." Their marginal effects are not reported in the regression results table and are available upon request.

2.4 ECONOMETRIC AND INDENTIFICATION STRATEGIES

This article uses the probit model to investigate the farm workers' probability of accessing health care services through a binary response dependent variable. The model used to investigate health care utilization choices is defined as follow:

$$\text{Healthcare}_{itr} = \alpha_0 + \beta X'_{itr} + \gamma_t + \rho_r + \varepsilon_{itr}$$

Healthcare_i equals one if a farm worker i in year t and region r has utilized health care (in U.S. or in foreign countries) within last two years, and equals zero if otherwise. X'_{itr} includes other demographic variables controlled in the probit model. γ_t and ρ_r are time and region fixed effects, and ε_{itr} is the error term.

Workers with better health conditions may be less likely to require health care services while frequent visits to medical centers would promote favorable health conditions. This contention is explored by many studies, but the existing body of health economics literature provides little evidence to uphold the contention of a potential simultaneous relationship between health care utilization and health status (Fisher et al. 2003; Skinner et al. 2001; Lichtenberg 2002; Currie and Gruber 1996; Anderson and Chalkidou 2008). Moreover, in order to eliminate the potential endogenous problem caused by the health status variable, reported incidences of chronic diseases are considered to capture the worker's long-term health situation. The indicators of chronic diseases are often used in previous studies and contribute to the model's predictive power (Anton and Munoz de Bustillo 2010; Devillanova 2013). The dummy variables for chronic diseases included in this study include asthma, diabetes, high blood pressure, tuberculosis, heart diseases, urinary diseases and other diseases. Moreover, the results are found to be consistent when excluding these health status indicators from regressions.

Taylor (1992) states that undocumented farmworkers may misreport their legal status and the number of undocumented farmworkers may, therefore, be understated. To account for this possible understatement, the approach proposed by Orrenius and Zavodny (2015) is used in this analysis whereby immigrants who have at most a middle high school diploma, are from Mexico, have been staying in the U.S. for less than 10 years, and claimed to be green card holders are reclassified in this analysis as undocumented immigrants. This adjustment scheme reclassified 457 self-reported green card holders to the undocumented worker category. The estimates of undocumented worker unadjusted and adjusted sample are shown in Table 1.3.

In addition to domestic and foreign health care utilization, this article also investigates on differences in farm workers' choices of health care providers and methods of payment using the multinomial logit model. When using health care services, there are various options available to a farm worker such as private clinics, community health centers or hospitals. These providers differ in their methods of treatment, the cost of their services as well as government funding support. Meanwhile, farm workers may also have diverse preferences for methods of payment depending on their demographic and economic conditions.

There are identifiers for five types of health care providers and six types of methods of payment for the health care services in the dataset. The results for each dependent variable are presented in Table 1.4 and Table 1.5. By applying multinomial logit model, the probability that the ith individual chooses the kth alternative is:

$$P_{ik} = \Pr[y_i = k] = \frac{\exp(\beta_k x_i)}{\sum_{n=1}^{k} \exp(\beta_n x_i)}$$

$$\sum_{n=1}^{k} P_{ik} = 1 \; and \; 0 < P_{ik} < 1$$

Specifically, k=5 in the health care provider regression and k=6 in the methods of payment regression. x_i denotes demographic control variables. By applying multinomial logit regression, we can identify significant determinants influencing the farm workers' choices among health care provider and payment methods options and also verify any differences in decisions made on these issues by farm workers with different legal statuses.

2.5 EMPIRICAL RESULTS

This section presents the results of models that identify the significant determinants of the probability of health care utilization by farm workers, their choices of health care provider, and the methods of payment used to settle health care service bills.

2.5.1 Health care service utilization

Table 1.2 shows the marginal effect of each variable that may have an impact on the U.S. hired farmworkers' probability of using U.S. and foreign health care services. Columns (1) and (3) report the estimates for the sample without any adjustment made on the number of undocumented workers. Columns (2) and (4) report the results of the adjusted sample resulting from the undocumented worker reclassification scheme discussed earlier. As can be gleaned from the results, each pair of variable estimates produced for both samples are not statistically different from each other.

The results indicate that language barrier is a significant factor. As the English speaking and reading proficiency levels increase, the probability of U.S. health care utilization would significantly increase by 3.0% and 6.1%, respectively. Moreover, farm workers who are single are less likely to avail of health care services while female workers are more likely to obtain U.S. health care services.

As for the foreign health care utilization decisions of farm workers, the marginal effects for some independent variables have the reverse signs compared to results obtained in the U.S. health care model. For instance, the higher the workers' English speaking proficiency, the less likely they would go abroad for medical treatment thereby validating the language barrier in using U.S. health care services. Older and more educated farm workers are also more inclined to patronize foreign health care services while immigrant farm workers with longer residence tenure in the U.S. would less likely seek foreign health care.

From the results in Table 1.2, it can be gleaned that the probabilities of availing of local health care services for citizens and green card holders are not statistically different from each other while undocumented workers reflect a significantly lower probability (10.6%) of using U.S. health care services given their similar health conditions. Such disparity could be explained by a host of factors. Undocumented farmworkers could possibly have limited essential information about the U.S. health care systems (Hoerster et al. 2011), lack of confidence in seeking U.S. medical treatment, or be overcome by fear of deportation once they have become more visible in the social scene through their dealings with health care providers (Hoerster et al. 2011).

Meanwhile, there are some legal restrictions in place that regulate these workers' access to many public benefit programs. The Affordable Care Act (ACA), a health care reform policy recently passed, explicitly excludes the undocumented population from the list of beneficiaries of public health care programs. The results in columns (3) and (4) indicate that both citizen and undocumented hired farmworkers are less likely to use foreign health care compared to green card holders. These results are consistent with the reality that green card holders can easily travel abroad and receive cheaper medical treatment, while citizens may lack the network that could

help them use foreign health care. On the other hand, undocumented workers would find it riskier to return to their native countries because of anticipated difficulties of reentering into the U.S.

The plots in Figure 1 compare the probability of health care utilization for hired farmworkers across legal status. The right plot shows that citizen farmworkers have the highest probability of receiving health care in the U.S. at 61%, which is still lower than the rate estimated for non-Hispanic white people in the U.S. Green card farm workers registered the second highest probability (59%) while undocumented workers had the lowest probability at 48%. However, the confidence intervals calculated for all three types of farm workers validate the results in Table 1.2 establishing that the probability of using U.S. health care for undocumented hired farmworkers is statistically lower than that for documented workers.

The plots also indicate that the probability of utilizing foreign health care services has peaked at 14% among green card holders while undocumented hired farmworkers again have registered the lowest utilization rate of only 6%. The large gap in the patronage of both U.S. and foreign health care services between documented and undocumented immigrants shows that the lack of proper immigration documentation has indeed become a significant factor that hinders health care utilization for the majority of hired farmworkers. As proper and immediate health care may be difficult to access and avail of, the health of undocumented hired farmworkers, who constitute the majority of the labor force in U.S. agriculture (Martin 2016), might deteriorate quickly while the available health coping mechanisms they consider could further drain the financial resources and economic stability of their households.

2.5.2 Health care provider decisions

Drawing upon the earlier results that undocumented farmworkers have a significantly lower likelihood of utilizing both U.S. and foreign health care resources than documented hired farmworkers, we then proceed to explore on specific types of health care services that are selected by farm workers. With their average lower socioeconomic stature, constrained mobility, skills endowment, and cultural practices and beliefs, immigrant workers may find themselves in a more disadvantageous position in accessing social resources (Massey et al. 1994). This could impose significant barriers for them to use better medical services.

Table 1.3 reports the marginal effects of the independent variables for each health care provider. Results indicate similar preferences for health care providers among green card holders and citizen farm workers given the insignificance of the coefficient estimates for the citizen hired farmworkers dummy variable. Undocumented workers significantly differ from green card holders in terms of their patronage of migrant health clinics with a higher probability of 1.9%. Moreover, undocumented hired farmworkers are 8.8% less likely to use private clinics compared to green card holders. This is not surprising as our sample statistics show that undocumented hired farmworkers have significantly lower incomes than documented workers.

In addition, estimates of the total income impact indicate that higher incomes would increase the probability of using private clinic services and decrease the probability for migrant health centers. The limited financial capability of undocumented workers would thus decrease the likelihood of their visits to private clinics that usually charge relatively higher fees for similar treatment or service obtained elsewhere.

Furthermore, a closer scrutiny of the impact of the legal status of farm workers on their probability of choice of health care providers is presented in Figure 2. The private clinic is the

most preferred health care option among farm workers. Even undocumented workers, who are usually more budget-constrained, have registered a 42 percent probability of visiting private clinics. Community health centers are also popular among farm workers. Citizen farm workers have the highest probability of patronizing such option at around 25%. Undocumented workers registered the second highest rate while green card workers would be least likely to make such choice. The probability rankings for the three groups of users have been observed to be lower in the patronage of hospitals and migrant health clinics.

2.5.3 Health care payment methods

This section focuses on the methods that farm workers use to pay for the health care services they obtained. The multinomial model is again used to examine the determinants of payment methods chosen by farm workers as well as the probability of each payment method selected by different types of farm workers.

Table 1.4 shows that citizen and green card hired farmworkers do not have significantly differentiated choices in their methods of payment except for the ”other payment” option, while undocumented farm workers are significantly less likely to settle their medical bills using either individual or public health insurance plans (Medicare/Medicaid). Unauthorized workers are more likely to use free clinics and pay out of their own pockets. It is evident that undocumented workers are more economically disadvantaged compared to legal permanent residents in terms of settling their medical financial burden and public benefit access. Compared to green card holders, undocumented farm workers are 9.1% more likely to pay using out-of-pocket funds to settle bills for medical treatments, which could possibly further exacerbate their economic conditions. Figure 4 portrays the choices across hired farmworkers with different legal status for paying medical expenses.

Figure 3 shows that farmworkers, in general, have a high probability of paying for health care service using their own funds, with undocumented farmworkers registering the highest probability at 55 percent. For those without legal immigration status, the high probability of paying health care using personal funds could be mainly caused by lack of health insurance. Workplace hazards and risks raise the health insurance premium significantly such that farmworkers could have been discouraged from purchasing any individual health plan (Sundaram-Stukel and Deller 2009). Besides, farmworkers also have an EPHI utilization rate at only 32.6%, which is considered low when compared to management and professional jobs that enjoy a rate of 89.4% (U.S. Census Bureau 2010). In addition, the undocumented workers' immigration status could inhibit them from using any public benefit programs such as Medicare. Recalling the trends shown in Figure 2, undocumented workers have a high likelihood of using private clinic as these venues could be less strict or concerned about verifying identities and/or immigration status, although these providers may charge much higher fees than public health care providers. The combined effect of choosing private clinics with the out-of-pocket payment decision would only validate the reality of increased medical expenses and worsen financial woes of both documented and undocumented hired farmworkers needing medical attention. The second most prevalent payment scheme is the EPHI method, although this option's probability is less than half of the estimate obtained for out-of-pocket payments. Moreover, an even smaller portion of farm workers would use Medicaid/Medicare and individual health plans to pay for health care services. The lack of available public health benefit programs for farmers in the U.S. largely increases their financial burden as well as health risks. To promote the physical health and financial welfare of farm workers in the U.S., more efficient and effective farmer-targeted health programs are needed in order to relieve farm workers of such financial

and economic burdens associated with their health demands. As a matter of fact, the U.S. government could draw some guidance from other countries that designed special insurance and pension programs for the benefit of their own agricultural workers.

2.6 CONCLUSION

This article investigates several facets of the health care utilization issue among farm workers of varied legal statuses. The empirical issues addressed include the determinants of the farm workers' overall utilization of health care services, their specific choices among several health care provider options, and their choices of the method(s) of payment for settling bills for their health care treatments.

This article's results indicate that undocumented hired farmworkers have a statistically lower probability of using health care compared to documented workers. This is easily attributed to, among other things, their undocumented status, limited English speaking and reading proficiency, and low average income. Moreover, the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 policy and other similar restrictive policies adopted by federal and local governments would further limit the health care service utilization of immigrant hired farmworkers.

This study has also established that foreign health care service alternatives are also not fully exhausted by undocumented hired farmworkers, whose utilization probability rate is significantly lower than those estimated for other groups of documented hired farmworkers. This discrepancy can be attributed to the undocumented immigrants' concerns about enhanced border patrol policing activities and heightened implementation of worksite immigration control enforcement policies led by the U.S. Immigration and Custom Enforcement (ICE), usually in

collaboration with local police authorities in recent decades. Furthermore, private clinics and community health centers were identified as the two most popular health service providers for all hired farmworkers. These choices, however, can be linked to the options for settling health care bills available in varying degrees to the different farm worker categories. True enough, for workers with constrained access to health insurance and public welfare benefit programs, personal (out-of-pocket) funds are used to pay for health care services obtained. Under this condition, the financial strain of allocating some portion of the limited household disposable income of immigrant hired farmworkers, especially the undocumented category, would compel the workers to either forcibly limit or postpone their health care service demands. In both cases, deterioration in the health status of farm workers could adversely affect the productivity and viability of the farm industry.

This article thus draws attention to the need for a re-examination of existing restrictions on health care use of immigrants hired farmworkers as well as the effectiveness of promoting the public safety net services in the U.S. The farm sector continues to rely on immigrant workers to supply labor inputs for the more taxing farm tasks shunned away by domestic residents with a wider range of employment options. As this trend of immigrant labor dependence persists, it is, therefore, imperative to assist the farm sector in ensuring the demands of health care from hired farmworkers are met for the sake of maintaining a healthy, able, and reliable workforce that can supply the economy with its growing needs.

Table 2.1: Descriptive statistics of dependent and independent variables

Variable	Definition	Mean	Std. Dev.
	Panel (A): Dependent variables		
U.S. healthcare	Has used U.S. health care service in last 2 years=1, otherwise=0	0.514	0.500
Foreign healthcare	Has used foreign health care in last 2 years=1, otherwise=0	0.138	0.344
Healthcare provider			
Community health center	Has used U.S. health care service in last 2 years and chose community health center=1, otherwise=0	0.252	0.434
Private clinic	Has used U.S. health care service in last 2 years and chose private clinic=1, otherwise=0	0.454	0.498
Hospital	Has used U.S. health care service in last 2 years and chose hospital=1, otherwise=0	0.172	0.378
Migrant health clinic	Has used U.S. health care service in last 2 years and chose migrant health clinic=1, otherwise=0	0.089	0.285
Other	Has used U.S. health care service in last 2 years and chose other healthcare service=1, otherwise=0	0.032	0.176
Methods of payment			
Out-of-pocket	Has used U.S. health care service in last 2 years and paid out of pocket=1, otherwise=0	0.478	0.500
Medicaid/Medicare	Has used U.S. health care service in last 2 years and paid by Medicaid/Medicare=1, otherwise=0	0.103	0.304
Free clinic	Has used U.S. health care service in last 2 years and paid by free clinic=1, otherwise=0	0.072	0.258
EPHI[a]	Has used U.S. health care service in last 2 years and paid by EPHI=1, otherwise=0	0.165	0.371
Individual plan	Has used U.S. health care service in last 2 years and paid by individual health insurance=1, otherwise=0	0.082	0.275
Other	Has used U.S. health care service in last 2 years and paid by other methods=1, otherwise=0	0.101	0.301
	Panel (B): Independent variables		
Age	Age(years)	35.883	12.624
Years in the US	Years stayed in the U.S. (years)	18.660	15.760
Citizen	If U.S. citizen=1, otherwise=0	0.256	0.437
Green card holder	If U.S. greencard holder=1, otherwise=0	0.238	0.426
Undocumented	If undocumented immigrant=1, otherwise=0	0.505	0.500
Single	If single=1, otherwise=0	0.334	0.472
Education	Years of education (years)	7.336	3.798

Speaking[b]	Level of English speaking proficiency (categories)	2.164	1.172
Reading[b]	Level of English reading proficiency (categories)	2.014	1.197
Farm workdays	Number of days working on farms	217.920	83.774
Total income	Total income ($)	7.666	3.483
Female	If female=1, otherwise=0	0.186	0.389
Asthma	Has asthma=1, otherwise=0	0.028	0.164
Diabetes	Has diabetes=1, otherwise=0	0.037	0.188
High blood	Has high blood pressue=1, otherwise=0	0.079	0.269
Tuberculosis	Has tuberculosis=1, otherwise=0	0.006	0.075
Heart	Has heart disease=1, otherwise=0	0.010	0.100
Urinary	Has urinary disease=1, otherwise=0	0.014	0.119
Other	Has other chronical diseases=1, otherwise=0	0.039	0.193
Mexican\American	If a Mexican\American=1, otherwise=0	0.063	0.242
Mexican	If a Mexican=1, otherwise=0	0.711	0.453
Chicano	If a Chicano=1, otherwise=0	0.006	0.078
Other Hispanics	If other Hispanics=1, otherwise=0	0.044	0.205
Puerto Rican	If a Puerto Rican=1, otherwise=0	0.009	0.093
Not Hispanic	If not a Hispanic=1, otherwise=0	0.168	0.374

Notes: [a]EPHI denotes employer-provided health insurance. [b]Speaking and Reading are categorical variables that measure how well a farm worker speaks and reads English; proficiency categories are defined as follows: 1. Not at all, 2. A little, 3. Somewhat, and 4. Well.

Table 2.2: Probit Model's Marginal Effects of Determinants of U.S. and Foreign Health Care Utilization of Hired Farmworkers in U.S.

	US Healthcare[b] Probit[a] (1)	**US Healthcare** Probit (2)	**Foreign Healthcare[c]** Probit (3)	**Foreign Healthcare** Probit (4)
Age	-0.001	-0.001	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
Years in US	0.000	0.000	-0.001**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Citizen	0.019	0.022	-0.057***	-0.056***
	(0.029)	(0.029)	(0.019)	(0.019)
Undocumented	-0.106***	-0.093***	-0.084***	-0.084***
	(0.019)	(0.020)	(0.011)	(0.012)
Single	-0.050***	-0.051***	0.007	0.006
	(0.016)	(0.016)	(0.007)	(0.007)
Education	0.001	0.001	0.003***	0.003***
	(0.003)	(0.003)	(0.001)	(0.001)
English Speaking	0.030**	0.031**	-0.022***	-0.022***
	(0.015)	(0.015)	(0.007)	(0.007)
English Reading	0.061***	0.062***	-0.005	-0.005
	(0.015)	(0.015)	(0.008)	(0.008)
Total income	0.026***	0.027***	-0.012***	-0.011***
	(0.003)	(0.003)	(0.001)	(0.001)
Female	0.366***	0.370***	-0.068***	-0.065***
	(0.020)	(0.020)	(0.009)	(0.009)
Observations	27406	27406	24364	24364
Undocumented workers adjusted[d]	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes
Other covariates[e]	Yes	Yes	Yes	Yes
McFadden R^2	0.247	0.247	0.201	0.199

Notes: [a] Huber-White robust standard errors are reported in parentheses. [b] US Healthcare is a dummy variable that equals one if a farm worker utilized any U.S. health care service within 2 years prior to the interview and equals zero if otherwise. [c] Foreign Healthcare is a dummy variable that equals one if a farm worker utilized any foreign health care service within 2 years prior to the interview and equals zero if otherwise. [d] Undocumented workers adjusted denotes that the sample used has been adjusted with the re-classification of observations as "undocumented" farmworkers that could have misreported their legal status according to the criteria discussed earlier in the text. [e] Other covariates include the number of days working in farms, chronic disease conditions (including asthma, diabetes, high blood pressure, tuberculosis, heart disease, urinary disease, and other), Hispanic origin (Mexican, Chicano, Other Hispanic, Puerto Rican, Not Hispanic). Models are weighted by the sample weight provided by NAWS. *p ‹ 0.10; **p ‹ 0.05; ***p ‹ 0.01.

Table 2.3: Multinomial Logit Model's Marginal Effects of Determinants of Health Care Provider Choices of Hired Farmworkers in U.S.

	Community health center	**Private clinic**	**Hospital**	**Migrant health clinic**	**Other**[b]
	Mlogit[a]	Mlogit	Mlogit	Mlogit	Mlogit
	(1)	(2)	(3)	(4)	(5)
Age	0.000	0.003	-0.003**	0.000	0.000
	(0.001)	(0.002)	(0.001)	0.000	(0.001)
Years in US	-0.002	0.002	0.000	0.001**	-0.002
	(0.002)	(0.002)	(0.001)	0.000	(0.001)
Citizen	0.039	-0.069	0.006	-0.007	0.031
	(0.040)	(0.050)	(0.030)	(0.007)	(0.041)
Undocumented	0.033	-0.088**	0.003	0.019**	0.033
	(0.028)	(0.035)	(0.023)	(0.008)	(0.026)
Single	-0.039	0.020	-0.008	0.004	0.023
	(0.026)	(0.030)	(0.022)	(0.005)	(0.022)
Education	-0.005	0.005	-0.001	0.000	0.003
	(0.004)	(0.005)	(0.003)	(0.001)	(0.004)
Speaking	0.004	-0.013	0.037*	-0.002	-0.025
	(0.021)	(0.033)	(0.020)	(0.005)	(0.031)
Reading	-0.021	0.029	-0.044**	-0.003	0.039
	(0.021)	(0.032)	(0.022)	(0.006)	(0.031)
Total income	-0.006	0.013**	-0.002	-0.003**	-0.002
	(0.005)	(0.006)	(0.003)	(0.001)	(0.004)
Female	0.014	0.078**	-0.030	0.000	-0.062***
	(0.026)	(0.032)	(0.023)	(0.007)	(0.023)
Observations	5346	5346	5346	5346	5346
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes	Yes
Other covariates[c]	Yes	Yes	Yes	Yes	Yes
McFadden R^2	0.072	0.072	0.072	0.072	0.072

Notes: [a] Huber-White robust standard errors are reported in parentheses. [b] Other healthcare providers include traditional healers, emergency room services, chiropractor, dentist, and other healthcare providers. [c] Other covariates include the number of days working in farms, chronic disease conditions (including asthma, diabetes, high blood pressure, tuberculosis, heart disease, urinary disease, and other), Hispanic origin (Mexican, Chicano, Other Hispanic, Puerto Rican, Not Hispanic). Models are weighted by the sample weight provided by NAWS. *p ‹ 0.10; **p ‹ 0.05; ***p ‹ 0.01.

Table 2.4: Multinomial Logit Model's Marginal Effects of Determinants of Healthcare Payment Choices of Hired Farmworkers in U.S.

	Out-of-pocket	**Medicaid/ Medicare**	**Free clinic**	**EPHI**[b]	**Individual plan**	**Other**[c]
	Mlogit[a]	Mlogit	Mlogit	Mlogit	Mlogit	Mlogit
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.002*	-0.001	0.001	0.000	0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years in US	-0.003**	0.003***	-0.001	0.000	-0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Citizen	-0.056	0.006	-0.019	0.007	0.014	0.048**
	(0.034)	(0.023)	(0.019)	(0.022)	(0.026)	(0.022)
Undocumented	0.091***	-0.043***	0.024**	-0.017	-0.059***	0.005
	(0.024)	(0.013)	(0.012)	(0.016)	(0.017)	(0.012)
Single	0.075***	-0.043***	0.022**	0.005	-0.014	-0.045***
	(0.019)	(0.013)	(0.010)	(0.013)	(0.011)	(0.013)
Education	0.000	-0.003*	-0.002	0.001	0.004*	0.000
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Speaking	-0.013	0.005	0.007	0.005	0.014	-0.017
	(0.021)	(0.012)	(0.008)	(0.013)	(0.018)	(0.013)
Reading	-0.002	-0.005	-0.013	0.004	0.005	0.011
	(0.021)	(0.012)	(0.009)	(0.013)	(0.019)	(0.013)
Total income	-0.009**	-0.013***	-0.008***	0.032***	0.001	-0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.060***	0.066***	-0.013	0.041***	0.001	-0.035***
	(0.019)	(0.010)	(0.010)	(0.014)	(0.011)	(0.012)
Observations	14057	14057	14057	14057	14057	14057
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates[d]	Yes	Yes	Yes	Yes	Yes	Yes
McFadden R^2	0.143	0.143	0.143	0.143	0.143	0.143

Notes: [a] Huber-White robust standard errors are reported in parentheses. [b] EPHI denotes employer-provided health insurance. [c] Other healthcare payment methods include other plans, mixed plans, billed/did not pay, and workers' compensation. [d] Other covariates include the number of days working in farms, chronic disease conditions (including asthma, diabetes, high blood pressure, tuberculosis, heart disease, urinary disease, and other), Hispanic origin (Mexican, Chicano, Other Hispanic, Puerto Rican, Not Hispanic). Models are weighted by the sample weight provided by NAWS. *p ‹ 0.10; **p ‹ 0.05; ***p ‹ 0.01.

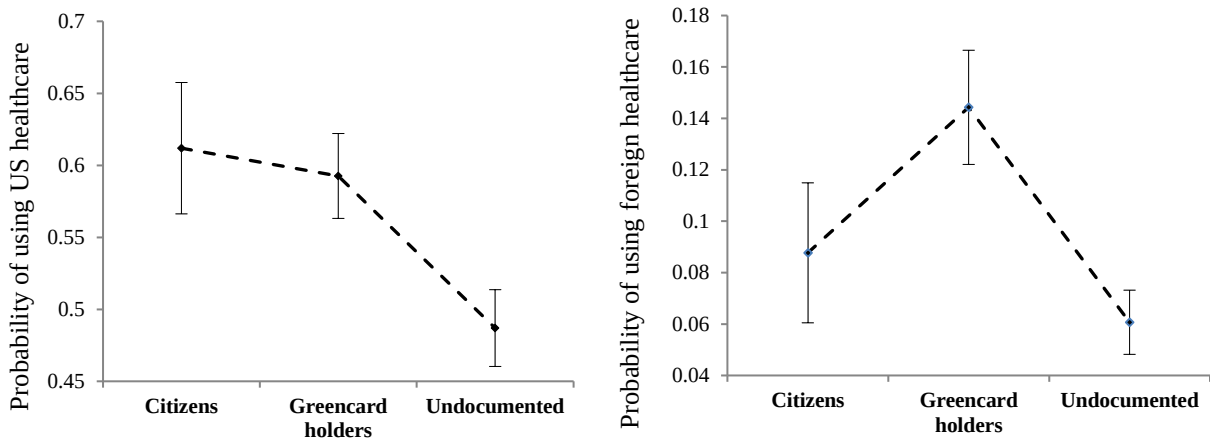

Figure 2.1: Probability of U.S. farm workers' health care utilization according to legal status

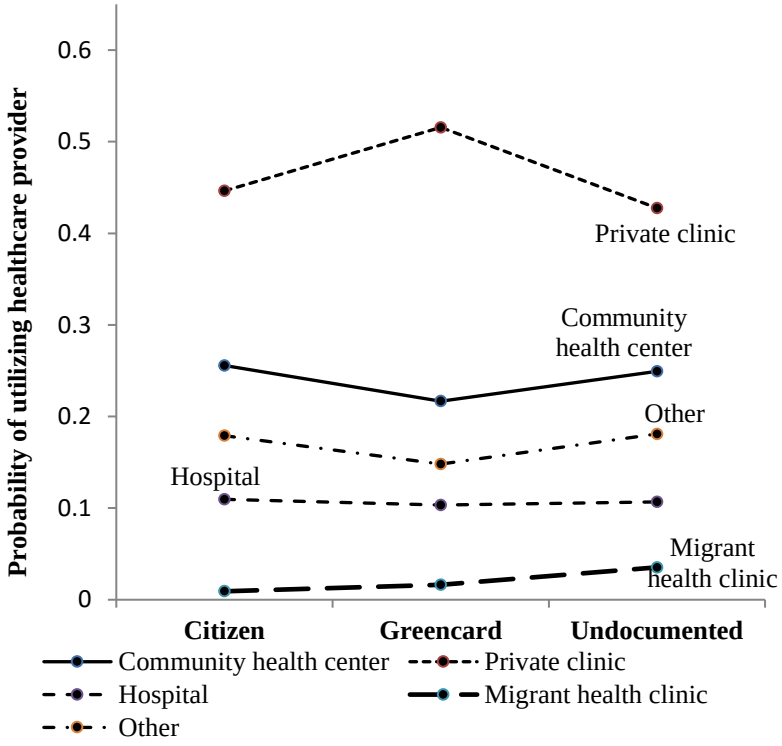

Figure 2.2: Probability of selection of healthcare providers for farm workers by legal status

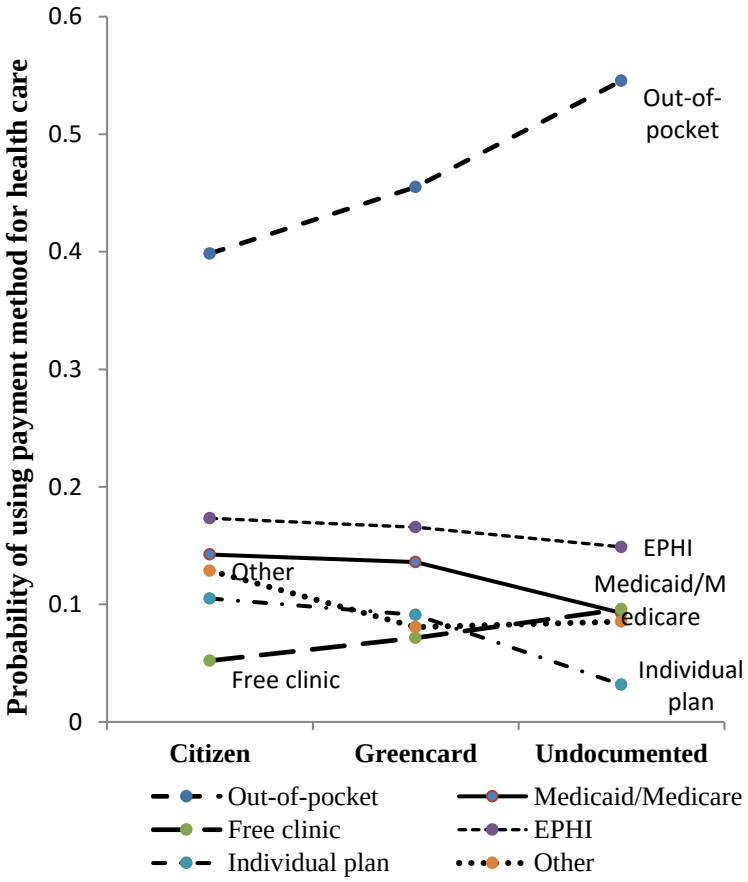

Figure 2.3: Probability of healthcare payment methods used by farm workers

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CHAPTER 3

EMPLOYMENT TIME ALLOCATION AND TENURE DECISIONS OF U.S. FARM WORKERS[5]

[5] Luo, Tianyuan and Cesar Escalante. Submitted to the Economic and Labour Relations Review. June 16, 2016.

Abstract

This paper investigates the employment time allocation choices of U.S. workers between farm and non-farm work alternatives using individual level data from the National Agricultural Workers Survey (NAWS). Green card farm workers are found to devote smaller share of working time to the farm sector than citizen and undocumented workers, which raises the concern that the legalization of immigrant status could possibly exacerbate farm labor shortage conditions. Language barrier and length of residence in the country are found to play important roles in the time allocation of farm workers between farm and non-farm employment. Moreover, external economic shocks could more easily induce citizen and green card farm workers to abandon farm employment while undocumented workers tend to remain in their farm jobs during such difficult times.

3.1 INTRODUCTION

One of the pressing concerns faced by the U.S. farm industry has been the sourcing and retention of reliable farm workers that could help sustain business operations year after year. The industry's high labor turnover rates can be attributed to several factors. Relative to employers in the manufacturing, service, and other non-farm industries, farm operations involve more physically demanding and taxing work under working conditions that usually pose serious health risks (Calvin and Martin 2010; Escalante, Yu, and Li 2015). Even with such work demands, farm workers do not receive commensurate compensation that could not even compete with the wage rates offered by non-farm businesses (Emerson 2007; Kandel 2008; Escalante, Perkins, and Santos 2011).

The farm labor turnover issue is further complicated by the industry's dependence on foreign labor inputs. The tacit understanding in the U.S. farm industry is that undocumented immigrants were relied upon to perform farm tasks usually relegated to unskilled farm workers. Martin (2016), for instance, claims that between 2007 and 2009 almost 30 percent of U.S. crop workers were born in the country while the remaining 70 percent were born elsewhere. Within the foreign-born category, about 55 percent were unlawfully residing in the U.S. and thus did not have the proper legal employment authorization. The stricter implementation of immigrant control policies resulted in the deportation of some, if not all, of the undocumented immigrants (Martin 2013; Escalante, Yu, and Li 2015).

The farm industry's concern about worker retention goes beyond the forced eviction of undocumented foreign workers as immigration control enforcement is further pursued by the U.S. government. A more compelling issue revolves around the need to sustain the interests of

prospective farm workers, regardless of legal status, in considering farm employment and remaining employed in the sector for longer periods of time.

This study contends that farm workers of varied legal statuses could consider different motivations for seeking and retaining farm employment. For instance, the predominance of undocumented workers in the farm industry, even under stricter immigration controls, could possibly be induced by economic necessity and the lack or absence of other employment alternatives. However, when the same workers are granted the proper work authorization (perhaps through an amnesty grant) to expand their employment options, it would be interesting to validate whether their employment decisions would also change.

This study is designed to provide empirical support to the legal status argument of farm labor decisions of potential farm workers. In this study, the general categories of documented and undocumented farm workers will be used to discern the determinants of these workers' employment choices and the resulting labor supply pattern of the U.S. farm workers. Specific sub-categories for documented workers will be considered to address two separate issues. This study's analysis of the employment time allocation decisions of green card holders, who are immigrants that successfully obtained permanent residence status, could shed light on the issue of whether farm employment decisions are primarily influenced by the job uncertainties and deportation risks faced by undocumented workers. In other words, this analysis seeks to determine if the elimination of such risks and uncertainty under permanent residence status would translate to abandoning farm employment in favor of more promising, lucrative opportunities in other sectors. This study's results for the sub-category of farm workers with citizenship status would be useful in discerning attitudes towards farm employment, especially during more difficult economic periods when job opportunities are scarcer.

By utilizing data compiled from the National Agricultural Workers Survey (NAWS), this article will provide empirical evidence that will deepen the understanding of the patterns of farm employment dynamics and identify factors that significantly influence the farm workers' labor allocation decisions in and out of the farm sector. This study's findings will be useful in forecasting the predictive labor supply of specific farm worker groups for the sake of more effective farm business planning and immigration policy formulation.

This study's empirical results provide an important qualification to the claim on the farm sector's reliance on foreign labor. Such dependence is validated only while certain farm workers are restricted in their social visibility, mobility, and employment options. In contrast, green card holders take advantage of their legal benefits under their permanent residence status. These workers are usually lured away from farm employment by better job opportunities in the non-farm sector and thus would usually maintain shorter farm work tenure rates. Citizens are even less reliable in remaining employed and keeping the agribusiness industry afloat during periods of economic difficulties and downturns.

The following section provides further details on the linkages between U.S. immigration policies and farm labor supply conditions. This study's empirical framework and its results are presented in the subsequent sections that lead to the final concluding section.

3.2 U.S. IMMIGRATION CONTROL AND FARM LABOR SUPPLY

When stricter immigration controls were implemented at the federal and state levels in the United States in recent years, there have been some heated discussions on whether such immigration policies have affected the farm industry's business viability. These debates primarily revolved around the policies' repercussions on farm labor supply conditions. The pro-

immigration proponents maintain that stricter policies could not possibly harm the farm industry as farm work positions vacated by evicted undocumented workers could be filled in by domestic residents in dire need of jobs, especially during the recession. Among the empirical studies that supported such claim, Pham and Van (2010) found that local immigration enforcement efforts generally resulted in just a small negative impact on unemployment, although they qualify that such effects could have heterogeneous impacts on different industries. Martin (2007) analyzed the resulting wage scenarios and found no evidence of the expected consequences of immigration-induced farm labor shortages, such as a sharp increase in farm wages and decreases in the production levels of labor intensive farm outputs. Emerson (2007) clarified that U.S. farms may effectively curb the negative effects of such farm labor shortage with their capability and capacity to adopt labor-saving technology and modify their crop choices by veering away from labor-intensive specialty crops.

On the other hand, some industry and academic analysts presented counterarguments linking the economic woes of farm businesses to agricultural labor shortages allegedly caused by immigration reforms that increased the rate of deportation since 2002 (Gonzales-Barrera and Krogstad, 2014; Seid, 2006; Levine, 2005). The U.S. Department of Agriculture (USDA) estimated about half of all hired crop farmworkers in the country did not possess proper work authorization documents (Calvin and Martin, 2010; Kandel, 2008). Farmers have reported difficulties in sourcing and hiring farm workers, especially those that provide seasonal part-time work (Burke, 2010). Farm business owners have expressed frustrations and disappointments in attracting potential farm workers among available, unemployed local residents. Fruit and vegetable growers in California, Oregon, and Washington, among many other similar situations elsewhere, have contended that prospective domestic farm workers usually shunned away from

the demanding, more strenuous farm work as these job seekers are often lured by offers of better pay and more favorable working conditions in other industries (Wozniacka, 2013; Wells, 2012). Farm labor productivity issues were also cited by pointing out that domestic workers who actually showed up for farm work often turned in productivity levels considered to be significantly below par relative to the usual outputs produced by foreign farm workers, who were labeled by farmers as their "more motivated workers" (Escalante, Perkins, and Santos, 2011). Farmer groups have argued that farm labor shortage in the U.S. farming sector could have serious effects that should not be underestimated and ignored, specifically citing evidence of high quantities of un-harvested crops due to labor sourcing problems (Preston, 2007). A 2011 study in Georgia provides further support by contending that majority of the study's respondent farms had labor sourcing problems that translated to about 5,244 unfilled positions and resulting in about $75 million crop losses in 2011 alone primarily due to high quantities of un-harvested products (McKissick and Kane, 2011).

The central argument in these discussions that posits the importance of undocumented foreign workers in stabilizing farm labor supply as domestic residents have shown less interest in farm employment deserves a more careful scrutiny. A deeper evaluation of the issue raises the question of whether or not the farm labor problem supply and productivity problems were related to the prospective farm worker's legal status or country of origin. This study's major contention supports the former (legal status) argument where "motivated farm labor" can only be supplied by those whose undocumented immigration status translates to a very limited set of employment options. Hence, these workers could be motivated enough to endure the more physically demanding work in the farm for the sake of survival.

A case in point is the recent executive order, Deferred Action for Parental Accountability (DAPA), proposed by President Barack Obama that is expected to prevent the deportation of approximately 5 million undocumented immigrants. The popular contention is that the presidential amnesty grant could only further undermine the progress of farm businesses as the newly legalized immigrants under the grant could more likely seek employment outside the farm sector as legalization of one's immigration status brings about flexibility in choosing among several possible employment alternatives (Wells, 2014; Daniels, 2015; Paletta, 2014).

3.3 DATA AND VARIABLE MEASUREMENT

This study's data were compiled from the National Agricultural Workers Survey, which is the only nationally representative cross-sectional survey of hired agricultural laborers in the United States. All farm workers interviewed in the survey provided individual and household information on their demographic attributes, income, and other structural characteristics. The NAWS uses worksite sampling method instead of residence sampling and is conducted three times a year to ensure the representativeness of its sampling of workers.

This article focuses on the data collected from 1993 to 2012 resulting in a sample size of 56,976 observations. The geographical affiliation of the respondents is categorized under 6 different regions: East, Southeast, Midwest, Southwest, Northwest, and California.[1] This analysis focuses on the employment time allocation of farm workers categorized as citizens, green card holders, and undocumented that account for 26%, 26%, and 46%, respectively, of the total observations. The random sampling method used in the survey produced a relative combined

abundance of responses from green card holders and undocumented farm workers. This only confirms the idea that farm work in the U.S. is mainly supplied by foreign workers as claimed by Martin (2016).

In order to investigate the employment time allocation decisions of U.S. farm workers, this article classifies a hired farm worker's aggregate available work weeks into three categories: farm employment weeks, non-farm employment weeks, and not working weeks. In addition, for the sake of the comparability of the time allocation decisions among classes of hired farm workers, the number of employment weeks for each work alternative is divided by the total weeks of residence in the U.S. to generate the share of an employment option for each legal status category.

The share of farm and non-farm workweeks used in this article could provide the same useful information as using the absolute magnitude of farm and non-farm workweeks. The absolute measure of employed weeks provides accurate figures of workweeks in farm and non-farm sectors, which are very informative indicators for quantifying the total amount of labor supplied to agriculture. However, this indicator may not be able to completely gauge the labor supply propensity of immigrant farm workers. For instance, if an immigrant resided in the U.S. for only three months and devotes such time to farm employment, then this immigrant contributes 100% of his/her working time to agriculture and does not turn over to other non-farm sectors. In absolute sense, this immigrant's work tenure in agriculture is less than that of another worker who has been employed for at least 4 months in the farm sector, even if this worker has not fully devoted his/her working time to agricultural employment.

This study addresses the concern of whether immigrant farm workers, especially green card holders, are more inclined to abandon their farm jobs in favor of job opportunities in the

non-farm sectors. The working time allocation approach allows for the verification of this empirical question. By using the ratios of employed weeks in farm and non-farm sectors, crucial information of the time allocation and utilization patterns of farm workers in the U.S. can be extracted that could help to quantify their labor supply propensity and generate practical implications for foreign labor hiring policies.

Panel (A) in Table 1 shows the dependent variables capturing the time allocation decisions for farm workers. Figure 1 presents a graphical representation of such allocation decisions made by different legal categories of workers.

As can be gleaned from Figure 1, undocumented farm workers devote the highest proportion of their employment time to farm work at approximately 83%, followed closely by green card holders at 79%. Citizen farm workers have the lowest allocation of time to farm work, but rank the first in registering more time spent in not working. Undocumented farm workers have the shortest period of not working. As for employment time allocated to non-farm work, citizens and green card holders record more time spent on non-farm jobs than undocumented farm workers. In addition to the patterns noted in general allocation of employment time, Figure 2 presents the intertemporal trends and disparities of the farm workers' time allocation between farm and non-farm jobs.

The contrasting trends in the left and right plots indicate the shifting of time allocation of farm workers between farm and non-farm sectors. Undocumented and green card holders in general have more stable labor time allocation trends over the years compared to citizens. Citizen farm workers registered a lower share of time devoted to farm work prior to 1998 (with the lowest point at 59.4% in 1995); thereafter the share started increasing to levels comparable to those of green card holders (with the highest point at 82.1% in 2006). The large increase in the

share of farm working time by citizen farm workers from 1995 to 2010 could be explained by the significant decline in the supply of foreign farm labor force that was caused by a surge in farm labor productivity in Mexico (Charlton and Taylor 2013). As fewer Mexican farm workers moved to farms in the U.S. particularly after 2000 (Martin and Jackson-Smith 2013), many citizens were somehow compelled to devote more time to farm works until 2007 when the U.S. economy was ushered into a period of recession and work time allocation leaned more towards non-farm employment.

The choice of explanatory variables in this article is guided by previous relevant research. Panel (B) in Table 1 shows the independent variables considered in this study. As suggested by Acquaye, Alston, and Pardey (2003), there are substantial differences in agricultural input requirements and productivity growth rates among regions in the U.S. such that labor demand and utilization patterns across regions could vary as well. To control for this regional variation in labor use, this article applies regional fixed effects, in addition to the inclusion of time (year) fixed effect.

Education is usually regarded as an important tool for promoting non-farm employment and thus enhancing income diversification opportunities for rural households (Yunez-Naude and Taylor 2001). Other studies have also emphasized the important role of education in farm and non-farm employment (Mishra and El-Osta 2016; De Janvry and Sadoulet 2001). The summary statistics show that citizen farm workers usually have higher educational attainment levels as majority of these workers have had more than 10 years of education experience. Undocumented workers have significantly lower educational attainment that, in turn, reflects on their ability to compete for non-farm jobs due to the language barrier arising from their low English speaking and reading proficiency levels.

This analysis also considers the possible effects of other demographic and structural attributes on the time allocation decisions of farm workers. Several previous studies have provided empirical evidence on the significant explanatory power of certain individual characteristics on off-farm labor supply decisions. Ahituv and Kimhi (2006) find that older and female workers would be less inclined to work on farms. Lien, Kumbhakar, and Hardaker (2010) suggest that younger and married individuals would exhibit a greater preference for off-farm employment. Notably, undocumented farm workers in our sample are predominantly male and generally 10 years younger than their documented peers.

The number of dependents among family members, such as children, is found to reduce a farm household's exposure to off-farm activities (Lien, Kumbhakar, and Hardaker 2010; Goodwin and Mishra 2004; Bjornsen and Biorn 2010). The responsibility of taking care of dependents could reduce the time allocated to non-farm work, but does not necessarily affect the time allocation to and performance of farm work as both tasks can usually be done together in a well confined farm business and household setting (Lien, Kumbhakar, and Hardaker 2010). As suggested by some studies, a variable measuring the number of years of residence in the U.S. is also added to capture the immigrant/foreign worker's cultural and social assimilation (Vargas 2016; Hamermesh and Trejo 2013). In terms of ethnic origins, 88.7% and 90.2% of green card holders and undocumented farm workers, respectively, are from Mexico. The predominance of a single source of foreign farm labor reduces the measurement error of characteristics across different immigration cohorts when analyzing the overall population (Vargas 2016).

As earlier mentioned, the representativeness of NAWS respondents is ensured by conducting the survey in three different seasons within a year so that farm workers who are temporarily employed at different times, assuming different farm tasks and working on diverse

crops could be accounted for and included in the surveys. Serra, Goodwin, and Featherstone (2005) indicate that the labor-intensive activities on farm could decrease the share of time allocated to non-farm sectors for farm households. For instance, fruit and vegetable farm workers would usually be required to devote more time at the work site than grain crop workers due to the labor-intensive nature of the former operations. Thus, work time allocation decisions even within the farm sector may also be differentiated according to the nature and type of farming enterprises.

In considering the income effect, this analysis utilizes expected individual income in lieu of actual individual income owing to the suspicion that individual income may be modeled endogenously with the time allocation between farm and off-farm activities. This article follows the approach proposed by El-Osta, Mishra, and Ahearn (2004) that uses the predicted value for the possible endogenous variable to address the endogeneity issues. In this article, the expected individual income is constructed as a function of a series of factors based on previous models (De Janvry and Sadoulet 2001; Atamanov and Van den Berg 2012; Ahearn, El-Osta, and Mishra 2013) and an exclusive covariate (country of origin). Adsera and Chiswick (2007) examine the impact of country of origin on the labor market outcome, including immigrants' work earnings, and find that there are significantly large differences among immigrants originating from various countries. This study does not expect to find any country of origin effect on the time allocation decisions of farm workers, except through changes in individual incomes. In the sample used in this analysis, undocumented farm workers have statistically lower incomes than documented workers (Table 1).

3.4 THE CONCEPTUAL AND EMPIRICAL FRAMEWORK

This article's model of farm and non-farm labor supply decisions of different classes of farm workers assumes the following utility function of individuals:

$$U_i = U_i(W_i, A_i|X) \quad (1)$$

where i=0,1,2,… represents the first to the Nth production sector. Given the characteristics of individuals X, utility is affected by such factors as the sectoral wage rate W_i and sectoral amenities A_i. In this article, farm workers maximize their utilities by choosing between farm and non-farm employment based on the comparison of the utility derived from working in these separate sectors. If the utility that can be derived from farm sector is higher than non-farm sector, such as

$$\Delta U = U_{FARM} - U_{NONFARM} \quad (2)$$

when $\Delta U > 0$, farm workers would continue to work on the farm; when $\Delta U < 0$, farm workers would transfer to non-farm sectors.

This study identifies factors that may influence the farm workers' decisions of allocation of time (measured in terms of weeks and referred to in this article as "workweek"[2]) for farm and non-farm employment alternatives. The work time allocation decisions of different classes of workers according to their legal stature will be scrutinized using different estimation techniques. Initially, this analysis will estimate a base ordinary least square (OLS) model of cross-sectional data assuming all independent variables are exogenous. The model will subsequently be extended to account for possible endogenous issues as the OLS model is replaced by a seemingly unrelated generalized linear modeling framework (SUR-GLM). A third modeling approach, fractional multinomial logit (FMLOGIT) estimation, is also employed given the model's suitability to this study's proportional response dependent variable.

The time spent in the U.S. within the last year before the interview for hired farm workers j = 1,2,…J is divided into three categories: farm work, non-farm work, and not working. The basic models are structured as follows:

$$\frac{FARMWEEKS_{jtr}}{US\ WEEKS_{jtr}} = \alpha_1 + X'_{jtr}\gamma + \rho_t + \varphi_r + \varepsilon_{jtr} \quad (3)$$

$$\frac{NONFARMWEEKS_{jtr}}{US\ WEEKS_{jtr}} = \alpha_2 + X'_{jtr}\mu + \rho_t + \varphi_r + \epsilon_{jtr} \quad (4)$$

$$\frac{NOWORKWEEKS_{jtr}}{US\ WEEKS_{jtr}} = \alpha_3 + X'_{jtr}\sigma + \rho_t + \varphi_r + e_{jtr} \quad (5)$$

where $FARMWEEKS_{jtr}$, $NONFARMWEEKS_{jtr}$, and $NOWORKWEEKS_{jtr}$ represent the number of farm work, non-farm work, and not working weeks devoted by individual j in year t and region r, respectively. $US\ WEEKS_{jtr}$ is the total number of weeks an individual spends in the U.S., which is the sum of farm employment, non-farm employment and not working weeks. The observed shares on the left side of equations (3), (4), and (5) have two common characteristics: (a) they are bounded between 0 and 1, inclusive, and (b) the sum of all three share components for any farm worker should be 1. ρ_t is the year trend effect while φ_r controls for regional fixed effects. The vector X'_{jtr} captures the demographic characteristics of farm workers as well as other covariates listed in Table 1.

This model can also be applied to separate samples of farm workers with different legal statuses by taking out the variable of current legal status. A linear model is often used due to its simplicity; however this model has its shortcomings and could be enhanced in some ways. First, the predicted value from a linear model may not lie between the boundary of 0 and 1. Second, when dependent variable takes a significant share of boundary values, linear regressions may have unreliable and biased estimates. Third, single linear regression also ignores the potential

correlations among the decisions of time allocation on not working, farm, and non-farm categories. Given the estimation issues listed as such, a fractional logit model that belongs to the generalized linear model (GLM) family suggested by Papke and Wooldridge (1996) is employed. To further take into consideration the correlation between the error terms of each dependent variable, a seemingly unrelated GLM equation system is constructed. Moreover, a fractional multinomial logit model that fits both the proportional nature of the dependent variable as well as the multiple choices is also utilized.

The fractional regression model is widely used in analyses involving proportional response variables such as financial asset portfolio shares (Mullahy 2015), time allocation (Mullahy and Robert 2010), share of output (Kawasaki and Lichtenberg 2013), and household television rating (Hausman and Leonard 1997). The fractional regression model, introduced by Papke and Wooldridge (1996), expands the generalized linear model (GLM) and combines it with a quasi-likelihood maximization econometric method to generate robust estimates and inferences for proportional responses. Moreover, in the application of the model to the analysis of the share of participation in 401(k) as dependent variable, Papke and Wooldridge (1996) show that such estimation technique would produce fully robust and relatively efficient results.

The univariate version of the fractional regression model is used as starting point for developing the multivariate fractional regression model. Under the fractional logit model, the share/proportional value of time allotted to each activity can be specified by the following functional form whereby the expectation of the share time allocation S_{jtr} is conditional on a series of covariates and fixed effects

$$E\left(S_{jtr}\middle|X_{jtr}\right) = G\left(X_{jtr}\beta\right) \tag{6}$$

where X_{jtr} are the covariates that would affect the time allocation decisions of farm workers. $G(\cdot)$ is the cumulative distribution function (cdf) that follows the logit cdf. To estimate the β parameters, the Bernoulli likelihood can be specified as follow and its log-likelihood can be maximized by using the quasi-maximum likelihood estimation methods:

$$L_j = \left[G\left(X_{jtr}\beta\right)\right]^{S_{jtr}}\left[1 - G\left(X_{jtr}\beta\right)\right]^{1-S_{jtr}} \quad (7)$$

The quasi-maximum likelihood estimation will produce consistent estimates of β even if the Bernoulli likelihood is incorrectly specified as long as the link function is in the correct form (Hausman and Leonard 1997). In addition, all GLM equations could be estimated in an equation system resembling a seemingly unrelated regression form in order to address the possible issue of correlated error terms associated with time allocation decisions for different activities.

In addition to the fractional regression model that separately estimates the share of time allocated to three activities, an extended model that accommodates both the proportional responses and multiple correlated choices can also be used. In this model, $S_{jtr} \in [0, 1]$, $\sum_{m=1}^{M} S_{jtrm} = 1$, where m represents the category on which the allocation share is calculated. Moreover, the probability of observing boundary solutions in outcomes (i.e. 0 and 1) is essential. Since all β cannot be estimated separately under multinomial quasi-likelihood methods (Mullahy 2015), normalization is used by setting the coefficient of Mth category to be zero. As a result, the expectation value of share dependent variable conditional on covariates can be constructed as the following form

$$E\left(S_{jtrn}|X\right) = \left[\frac{\exp(X_{jtr}\beta_n)}{1+\sum_{m=1}^{M-1}\exp(X_{jtr}\beta_m)}\right], n = 1, 2, \dots, M-1 \quad (8)$$

and

$$E\left(S_{jtrM}|X\right) = \left[\frac{1}{1+\sum_{m=1}^{M-1}\exp(X_{jtr}\beta_m)}\right] \quad (9)$$

The multinomial logit likelihood function is therefore defined as

$$L = \prod_{j=1}^{J} \prod_{m=1}^{M} E\left(S_{jtrm} \middle| X_{jtr}\right)^{S_{jtrm}} \quad (10)$$

The parameter could be estimated by maximizing the log-likelihood form of equation (10) and the multinomial logit quasi-maximum likelihood estimation will provide consistent estimates of β following the contention presented by Papke and Wooldridge (1996).

3.5 EMPIRICAL RESULTS

The three econometric approaches employed in this study (OLS, SUR-GLM, and FMLOGIT)[36] are applied to a total of six model versions. Three versions of the estimating equations are labelled as Employment Decision models that identify the determinants of farm workers' work time allocation decisions for farm, non-farm, or not working. These models accommodate demographic, structural, and economic factors that could influence the workers' work week allocation among the three employment scenarios. Predictive job allocation decision values calculated over time would also shed light on the tendency of workers to consider farm employment under more volatile economic conditions.

The other three versions correspond to Farm Worker Category models that allow for the validation of variations in labor supply decisions among all three types of agricultural workers, with specific attention given to the results for green card and undocumented farm workers. In other words, this analysis sheds light on the validity of the legal status argument whereby farm employment decisions are more influenced by necessity and limited options under greater legal risks and uncertainty.

[6] The OLS results are reported to illustrate the relative strengths of the SUR-GLM and FMLOGIT models.

3.5.1 Employment Decision Models' Results

The estimated marginal effects for the three employment decision models are reported in Table 2. Of special interest in these results are the estimates obtained for the legal status variables that could reflect the disparities of time allocation trends among citizens, green card holders, and undocumented farmworkers. In the farm work model, the SUR-GLM and FMLOGIT results (columns 2 and 3, respectively) indicate that citizen farm workers' work time allocation for farm employment is 5.1% to 5.6% higher than the allocation decision of green card holders. Undocumented farm workers also exhibit a relatively higher propensity to work in the farm sector than green card farm workers by devoting an incremental 4.4% to 4.6% of work time. In the non-farm work model, significant disparity in time allocation is obtained for citizen farm workers vis-à-vis the excluded category (green card holders) as these workers allocate 4.8% less time than the latter group of workers (columns 5 and 6).

The green card holders' apparent preference for non-farm employment may be motivated by economic reasons as the farm sector usually lags behind other sectors in terms of offering competitive compensation rates. Immigrants who have recently obtained permanent residence status may consciously take advantage of their newly acquired greater flexibility in exploring more financially rewarding employment options outside the farm sector. Undocumented immigrants, on the other hand, face strict legal restrictions that constrain their mobility, visibility, and ultimately their employment options. As a result, these workers would rather persist in performing more taxing, strenuous farm work for relatively lower wages and, at times, even under poor working conditions.

The not working model results provide further validation of such contentions. Undocumented farm workers tend to spend 3.7% less hours not working than green card holders. These workers seem to be more compelled to remain employed for economic reasons, perhaps even when their current employment conditions (such as farm work) are not ideal.

Figure 3 presents a comparison of the predicted farm and off-farm labor time allocation decisions among different types of farm workers. The right plot indicates that the predicted value of the proportion of non-farm work weeks for green card farm workers is statistically higher than the other two worker groups. The left plot, on the other hand, indicates that green card workers have the least inclination to work on the farm. Undocumented farm workers register a higher rate than green card holders in the predicted value of farm work week allocation at approximately 77% of their time. Citizen farm workers have the highest share of time allocated to farm work and the lowest share of time allocated to non-farm work at 81% and 4%, respectively. The plots in Figure 3 suggests that in the event that undocumented workers succeed in obtaining legal employment status (perhaps through permanent residence or amnesty grant), their devotion of time to farm work could possibly decrease as their flexibility to access and vie for off-farm employment increase. This possibility raises the concern of an impending labor shortage in the farm sector.

As for the demographic and structural variables, the significant result obtained for the age variable is consistent with earlier findings (Lien, Kumbhakar, and Hardaker 2010). Older farm workers usually are more drawn to being preoccupied with farm work, although the share of their farm work time would diminish in their more advanced ages. Results also indicate that female farm workers would tend to allocate 11.9% less time to farm work and 12.4% more time to not

working than their male counterparts. These trends are consistent with persistent societal roles (especially in more remote rural areas) whereby female household members are usually expected to be more responsible for performing household chores and child care that could indeed diminish their availability for farm work.

The number of children in a household has insignificant results in the farm and non-farm work models, yet it yielded a significant effect on the not working state. The farm work experience variable has been found to significantly affect the share of work time devoted to farm and off-farm employment. This suggests that as farm workers gain more years of farm work experience, they tend to increase the amount of time devoted to agriculture at the expense of a declining allocation of work time to non-farm work time.

This study also validates the influence of the nature and type of crop enterprise operations on employment time allocations. Specifically, horticulture farm workers were found to devote 7.2% more time and 3.5% less time to farm and non-farm work, respectively, than field crop farm workers. Those who work in farms growing vegetables and other crops also allotted less work time to non-farm jobs compared to farm workers employed in field crop farms. The overall trend of these results indicate that capital-intensive crops, such as field crops, that naturally have less demand for manual labor would employ workers who use their greater work time flexibility to seek jobs in the non-farm sector. On the other hand, the higher premium on manual labor in the production of such labor-intensive crops as vegetables and horticultural products would usually result in the employment of workers in such enterprises who tend to allocate more time to farm work than off-fam employment.

3.5.2 Farm Worker Category Models' Results

The marginal effects estimated for the three farm worker category models are reported in Table 3. Certain demographic and structural variables have varied effects on the different worker categories. In the green card worker model, work time allocation to non-farm jobs increases with higher educational attainment level as well as higher English speaking and reading proficiency levels. These variables, however, do not have any significant effect in the undocumented worker model. The age variable produced a consistently significant positive effect on farm work time allocation across all three worker category models. Such age effect, however, diminishes as the chronological age of the worker increases.

Previous studies on the role of assimilation in the time allocation decision trends of immigrants reinforce its importance in such decisions owing to its implications on welfare promotion and the economic integration of the immigrant population. Following Vargas (2016), this study uses the years of residence in the U.S. as an indicator of the immigrant farm workers' assimilation into the society. The findings in Table 3 suggest that, for both green card and undocumented farm workers, a longer tenure (more years of residence in the U.S.) would lead to a reduction in the share of time spent in farm work. Notably, undocumented farm workers with longer residence tenure in the U.S. would also increase their work time allocation to non-farm employment. It seems that a longer tenure of residence in the U.S. that translate to a higher level of social assimilation would tend to increase the undocumented workers' confidence and aggressiveness in seeking non-farm employment, even under the usual stricter enforcement of immigration controls.

Figure 4 shows the change in the predicted share of time allocated to farm and non-farm activities by farm workers arising from the impact of the length of residence in the U.S. The trend for green card farm workers indicates a slowly increasing trend whereby the workers' longer residence would result in a higher predicted proportion of weeks devoted to non-farm work. Correspondingly, there is a slowly decreasing trend in predicted farm work time allocation rates for green card holders as they accumulate tenure in their years of residence in the U.S. Notably, the slopes of the undocumented workers' predicted time allocation rates in both plots are much steeper than those for observed for green card farm workers. Undocumented farm workers experience larger changes in their predicted proportions of time allocations for farm and non-fam work as they stay longer in the U.S. As shown in Figure 4, undocumented workers would initially allocate a higher share of time to farm work compared to green card workers. However, as the residence of years in the U.S. increases, these workers' share of time allocated to farm work would decrease from 80% to 40% (in contrast to the green card workers' rates dropping to 66% at the end of the time horizon). In contrast, the undocumented workers' non-farm work time allocation rates after about 40 years of residence is predicted at about 40%, which is substantially higher than the comparable rate for green card holders at only 10%.

The number of children in each household has significant impacts on the time allocation decisions of citizen and green card farm workers, while undocumented farm workers are unaffected by this factor. Similarly, English speaking proficiency significant impacts the decisions of citizen and green card farm workers, but no such effect is noted for undocumented farm workers. Figure 5 shows the predicted values of time share allocations for different employment activities according to English speaking proficiency levels.

The plots in Figure 5 indicate that citizens would tend to increase the proportion of time allocated to farm work, but decrease their non-farm work time allocation, as their English speaking proficiency improves. In contrast, immigrant farm workers (undocumented or green card holders) have shown tendencies to decrease their farm work time allocation as their English speaking proficiency levels increase. This means that as immigrants have overcome the language barrier, their employment options expand with their increasing ability to handle jobs in the non-farm sector that require a good command of the English language, especially in terms of oral communications. Such non-farm jobs would include working in the food service and hospitality businesses. When these opportunities become available to them, their economic status would compel them to vie and assume these better paying positions in the non-farm sector. Among the classes of immigrant workers, green card holders enjoy the legal status that provides them the freedom and flexibility to consider these work positions.

Next we scrutinize the influence of economic fluctuations on the time allocation pattern of farm workers. The natural resilience of agriculture in weathering economic volatility has kept the sector growing at a decent rate during the 2008 financial crisis as it fared better during the period relative to other non-farm industries (the Economic Report of the President, 2013). It is of great interest to examine if the share of time allocated to farm work of farm workers would stay the same or even increase in response to the economic shocks during the recessionary period. The conjecture is that the proportion of time allotted to farms could increase as other non-farm sectors confront relatively more economically difficult and stressful conditions. Figure 6 shows how the predicted value of proportion of farm and non-farm employment weeks of farm workers varies over the sample years.

The trends shown in Figure 6 indicate that the predicted value of the farm work week proportion could be affected by economic fluctuation. Contrary to our expectation, the proportion of farm work weeks decreases and proportion of non-farm works increase at the onset of the financial crises for both citizens and green card holders. During the recent global recession that started in 2008, green card farm workers showed the largest decrease in the proportion of farm work weeks of approximately 22% from 2008 to 2009. Citizen farm workers also exhibit a downward trend in farm work time share yet the magnitude of the decrease is smaller. Meanwhile, green card farm workers also show a large increase in the share of time allocated to non-farm work, followed by citizen farm workers. These results indicate that citizen and green card farm workers are usually more responsive to the economic shocks as they seem to prioritize more adaptive work decisions for the sake of survival and recovery under the changing economic conditions. On the other hand, undocumented workers show more stable and consistent patterns of supplying agricultural labor even during period of economic fluctuation. Such behavior would then be beneficial in helping maintain a decent rate business growth in the farm sector, even when the rest of economy tends to falter under more volatile economic conditions.

3.6 CONCLUSION

This study has provided important empirical evidence on the determinants of employment decisions of farm workers under different legal immigration statuses. In general there seems to be a diminished interest in working in agriculture among workers with flexible employment options.

Specifically, the predicted value of proportion of weeks devoted to farm work indicates that green card holders tend to spend the least proportion of workweeks to agricultural

employment among all three farm worker categories. In contrast, undocumented workers have registered a higher workweek allocation rates in favor of farm work. This study's results indicate that the length of experience accumulated in farm work has influenced workers to remain employed in the farm and even increase their workweek allocation to farm jobs instead of switching to non-farm employment. Such retention effect, however, would diminish as the years of farm work experience accumulate. This result has been duplicated among groups of documented farm workers (citizens and green card holders). Moreover, the length of residence in the U.S. is found to increase the proportion of farm workweeks of green card holders over the years. Notably, the time allocation pattern for farm work registered by undocumented farm workers tends to be quite consistent over the years. However, this pattern can be disrupted, especially among citizen and green card workers, by external shocks, such as the recent economic recession.

This study's findings therefore clarify that the contention that the farm sector subsists primarily on foreign workers for its seasonal farm labor requirements should be made with caution and qualification. This study's findings suggest that such reliance only holds among farm workers whose undocumented status restricts their social visibility, mobility and job choices. In the absence of a more comprehensive dataset that traces the historical immigration path of foreigners granted permanent residence status (isolating those that previously held valid, unexpired visas from amnesty grantees and other illegal residents with undocumented status), this study's findings on the farm work allocation behavior noted among green card holders could lend some support to the legal status argument in farm workweek allocation behavior. These results can therefore imply that efforts to legalize the immigration status of undocumented aliens

(such as the recent presidential amnesty grant in 2014) could only possibly lead to a diminishing supply of labor for the farm sector.

The agricultural industry is naturally attuned to the changing landscape of the general economy that may arise due to significant external shocks, such as the most recent economic downturn. Evidence from this study suggests that citizen and green card farm workers tend to be more responsive to fluctuations in the general economic activity. Under unfavorable economic conditions, citizens and green card holders would devote fewer weeks to agricultural industries than undocumented farm workers, who, in contrast, are much less responsive to economic shocks as they tend to stick to their status quo labor allocation pattern through the years. More effective policies aimed at maintaining adequate and stable supply of farm labor should therefore take into account the need for tempering the effects of immigration status legalization with more employment retention efforts directed towards specific categories of farm workers.

Table 3.1: Summary statistics of dependent and independent variables

		Citizen		Green card holder		Undocumented	
Variable	Definition	Mean	Std.	Mean	Std.	Mean	Std.
	Panel (A): Dependent variables						
Farm work	Share of time allocated to farm works	0.712	0.307	0.792	0.239	0.83	0.231
Non-farm work	Share of time allocated to non-farm works	0.091	0.214	0.038	0.139	0.049	0.163
Not working	Share of time allocated to not working	0.198	0.258	0.17	0.209	0.12	0.181
	Panel (B): Independent variables						
Edu1_6[a]	If has 1 to 6 years of education=1, otherwise=0	0.134	0.341	0.641	0.48	0.585	0.493
Edu7_9	If has 7 to 9 years of education=1, otherwise=0	0.167	0.373	0.159	0.366	0.241	0.428
Edu10	If has more than 10 years of education=1, otherwise=0	0.686	0.464	0.128	0.334	0.115	0.319
Age	Age(years)	37.57	14.197	40.45	11.389	29.40	9.901
Years in U.S.	Years of residence in the U.S. (years)	25.55	10.409	19.11	9.404	6.767	7.007
Female	If female=1, otherwise=0	0.266	0.442	0.199	0.399	0.151	0.358
Married	If married=1, otherwise=0	0.525	0.499	0.785	0.411	0.521	0.5
Expected Ind_income	Level of expected individual income (categories)	7.853	2.42	7.332	2.147	5.251	2.011
Children: <6 years old	Number of children in a household who are less than 6 years	0.204	0.546	0.324	0.64	0.24	0.577
Children: 6-13 years	Number of children in a household who are between 6 to 13	0.301	0.696	0.583	0.916	0.204	0.599
Children: 14-17 years	Number of children in a household who are between 14 to 17	0.155	0.445	0.274	0.573	0.061	0.29
Mexican	If a Mexican=1, otherwise=0	0.132	0.338	0.887	0.317	0.902	0.297
Chicano	If a Chicano=1, otherwise=0	0.026	0.16	0.002	0.044	0.002	0.044
Other Hispanic	If other Hispanics=1, otherwise=0	0.024	0.153	0.026	0.16	0.064	0.244
Puerto Rican	If a Puerto Rican=1, otherwise=0	0.058	0.233	0	0.015	0	0.021
Not Hispanic or	If not a Hispanic=1, otherwise=0	0.59	0.492	0.033	0.178	0.012	0.107
English speaking[b]	Level of English speaking proficiency (categories)	3.607	0.83	1.931	0.88	1.518	0.71
English reading	Level of English reading proficiency (categories)	3.551	0.905	1.732	0.871	1.364	0.653
Farm work experience	Years of working in agriculture (years)	15.73	12.814	16.96	9.444	6.179	5.999
Harvest[c]	If farm task is harvest=1, otherwise=0	0.178	0.382	0.29	0.454	0.352	0.478

Postharvest	If farm task is post-harvest=1, otherwise=0	0.135	0.342	0.098	0.298	0.09	0.287
Semiskilled	If farm task is semiskilled=1, otherwise=0	0.253	0.435	0.313	0.464	0.209	0.407
Supervisor	If farm task is supervisor=1, otherwise=0	0.006	0.077	0.006	0.075	0.001	0.027
Othertask	If farm task is other=1, otherwise=0	0.212	0.408	0.118	0.322	0.135	0.342
Fruit[d]	If the crop at work is fruit=1, otherwise=0	0.168	0.374	0.458	0.498	0.395	0.489
Horticulture	If the crop at work is horticulture=1, otherwise=0	0.244	0.43	0.123	0.328	0.167	0.373
Vegetable	If the crop at work is vegetable=1, otherwise=0	0.223	0.417	0.251	0.433	0.262	0.44
Othercrop	If the crop at work is other crops=1, otherwise=0	0.08	0.271	0.049	0.216	0.054	0.226

Notes: [a] The baseline for education categorical variable is zero years of education. [b] Speaking and Reading are categorical variables that measure how well a farm worker speaks and reads English; proficiency categories are defined as follows: 1. Not at all, 2. A little, 3. Somewhat, and 4. Well. [c] The baseline for farm task categorical variable is pre-harvest task. [d] The baseline for the crops at farm work categorical variable is field crop.

Table 3.2: Marginal effects of the determinants of time allocation decisions for all hired farmworkers in the U.S. – Employment Decision Models (1993-2012)

	Farm work			Non-farm work			Not working		
	OLS	SUR-GLM[a]	FMLOGIT[b]	OLS	SUR-GLM	FMLOGIT	OLS	SUR-GLM	FMLOGIT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Citizen	0.054***	0.051***	0.056***	-0.044***	-0.048***	-0.048***	-0.01	-0.007	-0.008
	(0.013)	(0.014)	(0.015)	(0.010)	(0.014)	(0.014)	(0.013)	(0.011)	(0.011)
Undocumented	0.047***	0.044***	0.046***	-0.006	-0.008	-0.009	-0.041***	-0.037***	-0.037***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)
Edu1_6[c]	-0.005	0	-0.004	-0.006	0.01	0.01	0.011	-0.002	-0.006
	(0.019)	(0.016)	(0.017)	(0.015)	(0.014)	(0.014)	(0.016)	(0.013)	(0.013)
Edu7_9	-0.006	-0.002	-0.007	-0.001	0.017	0.018	0.007	-0.006	-0.011
	(0.020)	(0.018)	(0.018)	(0.016)	(0.015)	(0.015)	(0.017)	(0.014)	(0.014)
Edu10	-0.036	-0.024	-0.028	0.004	0.022	0.023	0.031	0.01	0.005
	(0.028)	(0.024)	(0.024)	(0.024)	(0.019)	(0.019)	(0.024)	(0.019)	(0.018)
Age	0.009***	0.009***	0.008***	0.002	0.004**	0.004**	-0.011***	-0.011***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age2	-0.000***	-0.000***	-0.000***	0	-0.000**	-0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years in U.S.	-0.008***	-0.006***	-0.006***	0.005***	0.003***	0.003***	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	0.000	(0.001)	(0.001)	(0.001)
Female	-0.149***	-0.141***	-0.119***	0.023	-0.008	-0.005	0.126***	0.116***	0.124***
	(0.040)	(0.031)	(0.031)	(0.034)	(0.024)	(0.024)	(0.035)	(0.025)	(0.024)
Married	0.003	0.007	0.005	-0.027**	-0.015	-0.015	0.024*	0.013	0.01
	(0.015)	(0.013)	(0.013)	(0.013)	(0.010)	(0.010)	(0.013)	(0.010)	(0.010)
Children: <6 years old	-0.032	-0.022	-0.027*	-0.021	-0.005	-0.003	0.053***	0.034***	0.030**
	(0.020)	(0.016)	(0.016)	(0.017)	(0.013)	(0.013)	(0.017)	(0.012)	(0.012)
Children: 6-13 years old	-0.018	-0.014	-0.017*	-0.009	0.001	0.001	0.027***	0.018**	0.016**
	(0.012)	(0.009)	(0.010)	(0.010)	(0.007)	(0.008)	(0.010)	(0.008)	(0.007)
Children: 14-17 years old	-0.009	-0.006	-0.009	-0.015	-0.004	-0.004	0.024*	0.016*	0.013
	(0.015)	(0.012)	(0.013)	(0.014)	(0.012)	(0.012)	(0.013)	(0.009)	(0.009)
English speaking	-0.019	-0.011	-0.016	-0.011	0.009	0.009	0.03	0.012	0.007
	(0.024)	(0.019)	(0.019)	(0.020)	(0.014)	(0.014)	(0.021)	(0.015)	(0.014)
English reading	-0.016**	-0.011	-0.013*	0.005	0.004	0.004	0.011*	0.008	0.008

	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Farm work experience	0.011***	0.011***	0.010***	-0.011***	-0.007***	-0.007***	0	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Harvest[d]	0.007	0.007	0.006	0.012	0.013*	0.013*	-0.018***	-0.019***	-0.020***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Postharvest	0.004	0.006	0.006	-0.009	-0.001	-0.001	0.006	-0.004	-0.006
	(0.013)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)
Semiskilled	0.015	0.022	0.017	-0.023	-0.006	-0.005	0.008	-0.007	-0.011
	(0.022)	(0.017)	(0.018)	(0.019)	(0.014)	(0.014)	(0.019)	(0.014)	(0.014)
Supervisor	0.044	0.061	0.038	-0.076	-0.008	-0.006	0.033	-0.016	-0.032
	(0.086)	(0.071)	(0.074)	(0.075)	(0.069)	(0.070)	(0.077)	(0.061)	(0.061)
Othertask	0.008	0.016	0.009	-0.024	-0.003	-0.002	0.015	-0.002	-0.007
	(0.023)	(0.020)	(0.019)	(0.020)	(0.015)	(0.015)	(0.020)	(0.015)	(0.015)
Fruit[e]	-0.001	-0.005	-0.015	-0.029**	-0.024**	-0.024**	0.030**	0.040***	0.040***
	(0.016)	(0.013)	(0.013)	(0.014)	(0.010)	(0.010)	(0.012)	(0.011)	(0.011)
Horticulture	0.082***	0.088***	0.072***	-0.064***	-0.036***	-0.035***	-0.017	-0.030**	-0.036**
	(0.020)	(0.019)	(0.017)	(0.019)	(0.013)	(0.013)	(0.016)	(0.015)	(0.014)
Vegetable	0.031**	0.029**	0.016	-0.046***	-0.040***	-0.041***	0.015	0.025***	0.025***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.008)	(0.008)	(0.010)	(0.009)	(0.009)
Othercrop	0.050**	0.060***	0.039**	-0.076***	-0.045***	-0.043***	0.026	0.011	0.005
	(0.023)	(0.020)	(0.020)	(0.020)	(0.015)	(0.015)	(0.019)	(0.016)	(0.016)
Expected Ind_income	0.008	-0.003	0.005	0.035	0.009	0.007	-0.043	-0.019	-0.013
	(0.031)	(0.024)	(0.025)	(0.026)	(0.018)	(0.019)	(0.027)	(0.020)	(0.019)
N	34320	34320	34320	34320	34320	34320	34320	34320	34320
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates[f]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1751			0.0955			0.2047		
McFadden's R^2		0.394248	0.411383		0.454587	0.411383		0.407107	0.411383
$\chi 2$		2217.084	3581.14		1628.922	3581.14		2137.461	3581.14

Notes: [a] SUR-GLM denotes the seemingly unrelated regression of generalized linear model. [b] FMLOGIT denotes the fractional multinomial logit model. [c] The baseline for education categorical variable is zero years of education. [d] The baseline for farm task categorical variable is pre-harvest task. [e] The baseline for the crops at farm work categorical variable is field crop. [f] Other covariates include the Hispanic origins including Mexican, Chicano, other Hispanic, Puerto Rican, and not Hispanic or Latino. Huber-White robust standard errors are reported in parentheses. Models are weighted by the sample weight provided by NAWS. *p ‹ 0.10; **p ‹ 0.05; ***p ‹ 0.01.

Table 3.3: Marginal effects of the determinants of time allocation decisions for U.S. hired farmworkers by legal status – Farm Worker Category Models (1993-2012)

	Citizen			Green card holder			Undocumented		
	Farm work (1)	Non-farm work (2)	Not working (3)	Farm work (4)	Non-farm work (5)	Not working (6)	Farm work (7)	Non-farm work (8)	Not working (9)
Edu1_6[a]	-0.129***	0.077	0.051	-0.048	0.057**	-0.009	-0.001	-0.004	0.006
	(0.050)	(0.060)	(0.041)	(0.030)	(0.026)	(0.022)	(0.041)	(0.033)	(0.025)
Edu7_9	-0.094*	0.063	0.032	-0.060*	0.063**	-0.003	-0.003	0.004	-0.002
	(0.051)	(0.060)	(0.042)	(0.033)	(0.028)	(0.024)	(0.042)	(0.033)	(0.026)
Edu10	-0.110**	0.1	0.01	-0.119***	0.080**	0.039	-0.014	0.012	0.002
	(0.053)	(0.063)	(0.044)	(0.042)	(0.035)	(0.029)	(0.062)	(0.049)	(0.039)
Age	0.015***	0.016***	-0.032***	0.009***	0.011***	-0.020***	0.007**	0.001	-0.008***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Age2	-0.000***	-0.000***	0.000***	-0.000***	-0.000***	0.000***	-0.000***	0	0.000***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Years in U.S.				-0.003***	0.001	0.002***	-0.008***	0.005***	0.003***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.015	-0.031	0.016	-0.037	-0.112***	0.149***	-0.095	0.012	0.083
	(0.037)	(0.038)	(0.032)	(0.048)	(0.034)	(0.032)	(0.097)	(0.076)	(0.060)
Married	0.015	0.018	-0.032*	-0.013	0.011	0.002	-0.002	-0.023	0.024
	(0.018)	(0.018)	(0.018)	(0.020)	(0.015)	(0.014)	(0.035)	(0.027)	(0.022)
Children: <6 years old	-0.040**	0.011	0.029	-0.060**	0.042**	0.018	-0.036	-0.012	0.048
	(0.020)	(0.019)	(0.018)	(0.024)	(0.017)	(0.016)	(0.048)	(0.038)	(0.029)
Children: 6-13 years old	-0.039***	0.003	0.035***	-0.048***	0.030***	0.018*	-0.017	-0.009	0.026
	(0.013)	(0.014)	(0.012)	(0.014)	(0.010)	(0.010)	(0.028)	(0.022)	(0.017)
Children: 14-17 years old	-0.031*	-0.017	0.048***	-0.047***	0.025*	0.022*	-0.016	0	0.016
	(0.018)	(0.020)	(0.018)	(0.018)	(0.013)	(0.012)	(0.036)	(0.031)	(0.022)
English speaking	-0.130***	0.060**	0.070***	-0.068**	0.071***	-0.003	-0.025	-0.006	0.031
	(0.026)	(0.029)	(0.023)	(0.029)	(0.021)	(0.020)	(0.057)	(0.044)	(0.035)
English reading	0.019	-0.01	-0.009	-0.021*	0.016*	0.005	-0.013	0.003	0.01
	(0.019)	(0.022)	(0.015)	(0.011)	(0.009)	(0.009)	(0.013)	(0.010)	(0.009)
Farm work experience	-0.001	-0.003	0.004	-0.001	0.003	-0.002	0.012	-0.011*	-0.001

	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.008)	(0.006)	(0.005)
Harvest[b]	-0.022	0.012	0.011	-0.02	0.005	0.015	0.013	0.023***	-0.036***
	(0.018)	(0.018)	(0.018)	(0.014)	(0.012)	(0.011)	(0.010)	(0.009)	(0.007)
Postharvest	-0.073***	0.051**	0.022	-0.054***	0.028*	0.026*	0.02	-0.008	-0.012
	(0.020)	(0.020)	(0.018)	(0.019)	(0.016)	(0.014)	(0.022)	(0.018)	(0.015)
Semiskilled	-0.018	0.002	0.016	-0.021	0.044**	-0.023	-0.004	-0.012	0.016
	(0.025)	(0.027)	(0.023)	(0.027)	(0.020)	(0.020)	(0.052)	(0.041)	(0.032)
Supervisor	-0.063	-0.105	0.168**	-0.077	0.225***	-0.148*	0.643***	-0.859***	0.217*
	(0.114)	(0.130)	(0.081)	(0.098)	(0.079)	(0.083)	(0.191)	(0.145)	(0.124)
Othertask	0.011	0	-0.011	-0.032	0.042*	-0.01	-0.005	-0.01	0.016
	(0.026)	(0.027)	(0.024)	(0.030)	(0.023)	(0.023)	(0.051)	(0.040)	(0.031)
Fruit[c]	0.053**	-0.022	-0.031	0.008	-0.051***	0.044**	-0.01	-0.02	0.03
	(0.022)	(0.025)	(0.023)	(0.021)	(0.014)	(0.018)	(0.031)	(0.024)	(0.020)
Horticulture	0.03	-0.019	-0.011	0.066**	0.022	-0.088***	0.056	-0.054*	-0.002
	(0.023)	(0.022)	(0.022)	(0.030)	(0.021)	(0.024)	(0.041)	(0.032)	(0.026)
Vegetable	0.015	-0.013	-0.002	0.039**	-0.058***	0.019	0.018	-0.038**	0.019
	(0.018)	(0.017)	(0.018)	(0.020)	(0.013)	(0.017)	(0.024)	(0.018)	(0.015)
Othercrop	-0.065**	0.032	0.033	0.028	0.022	-0.050**	0.028	-0.064*	0.036
	(0.028)	(0.025)	(0.024)	(0.032)	(0.023)	(0.025)	(0.049)	(0.038)	(0.031)
Expected Ind_income	0.077***	-0.024	-0.053**	0.083**	-0.079***	-0.004	0.012	0.029	-0.041
	(0.027)	(0.028)	(0.024)	(0.037)	(0.026)	(0.025)	(0.077)	(0.060)	(0.048)
N	10148	10148	10148	11391	11391	11391	21459	21459	21459
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
McFadden's R^2		0.215			0.134			0.110	
$\chi 2$		2069.837			1872.424			2786.399	

Notes: [a] The baseline for education categorical variable is zero years of education. [b] The baseline for farm task categorical variable is pre-harvest task. [c] The baseline for the crops at farm work categorical variable is field crop. [d] Other covariates include the Hispanic origins including Mexican, Chicano, other Hispanic, Puerto Rican, and not Hispanic or Latino. Huber-White robust standard errors are reported in parentheses. Models are weighted by the sample weight provided by NAWS. *p ‹ 0.10; **p ‹ 0.05; ***p ‹ 0.01.

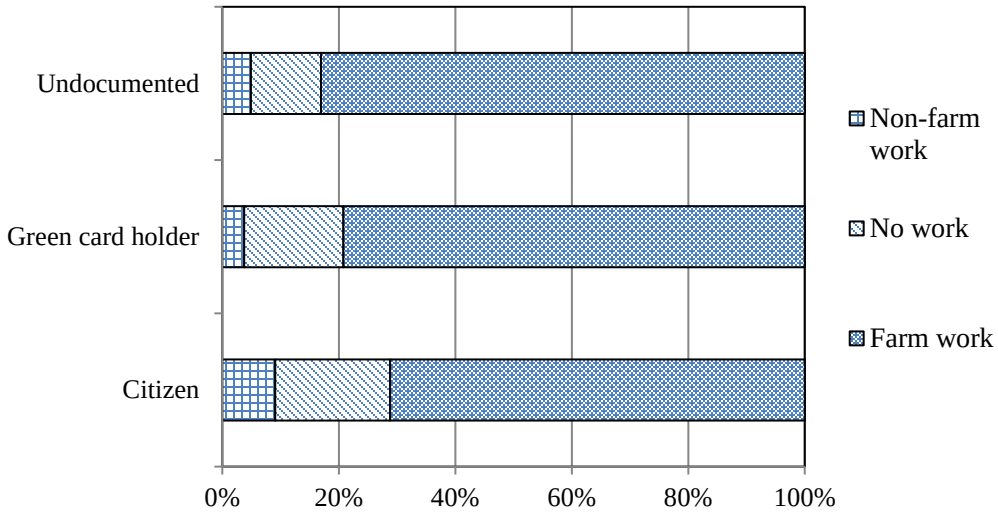

Figure 3.1: Hired farm workers' sample time allocation patterns according to legal status

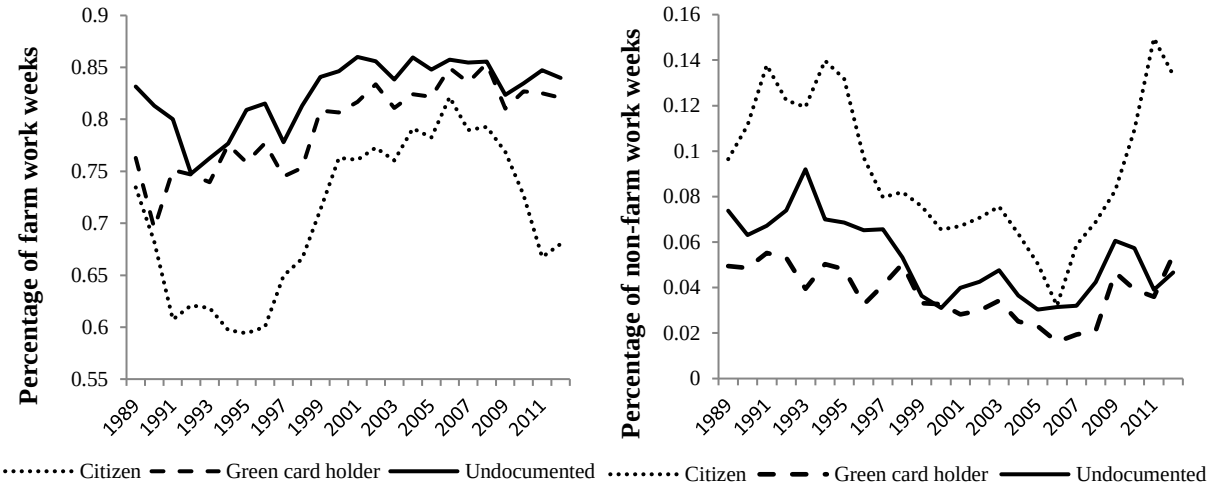

Figure 3.2: Work time allocation trends among farm workers of different legal statuses

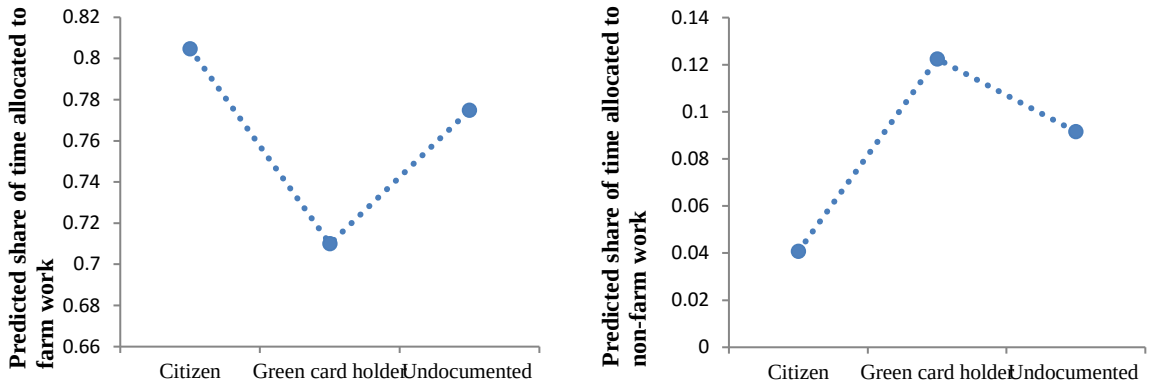

Figure 3.3: predicted share of time allocated by farm workers to farm and non-farm work

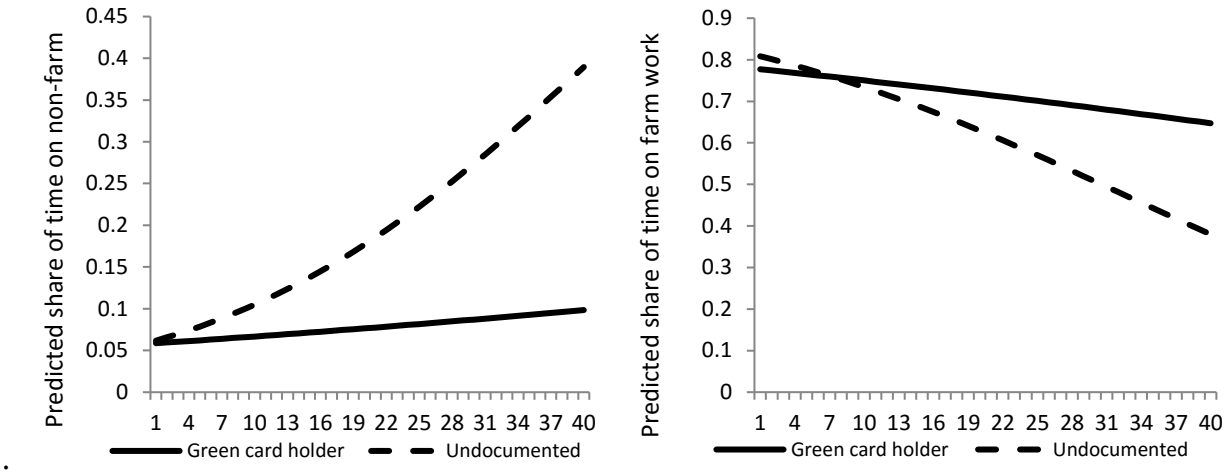

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Figure 3.4: Predicted share of time allocated by farm workers to farm and non-farm work by the length of residence in the U.S.

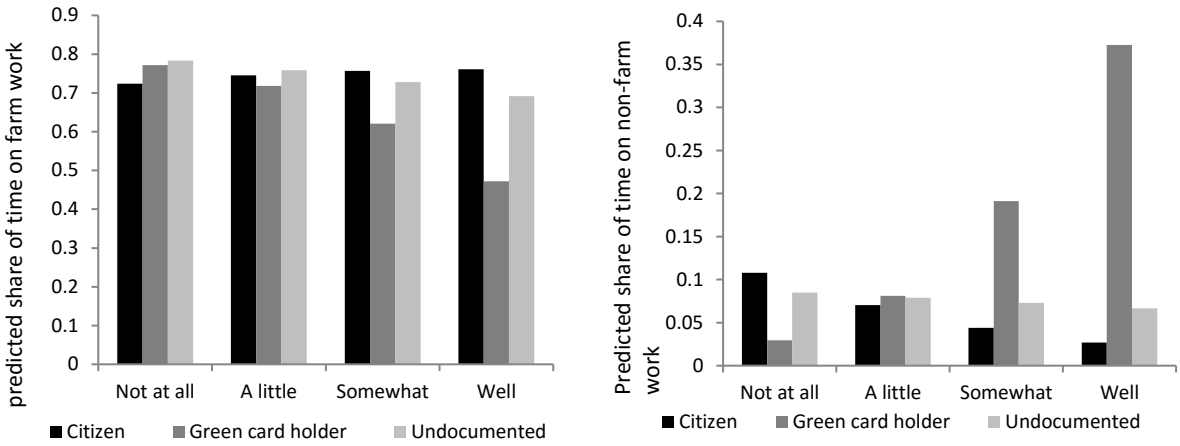

Figure 3.5: Predicted share of time allocated by farm workers to farm and non-farm work according to levels of English speaking proficiency

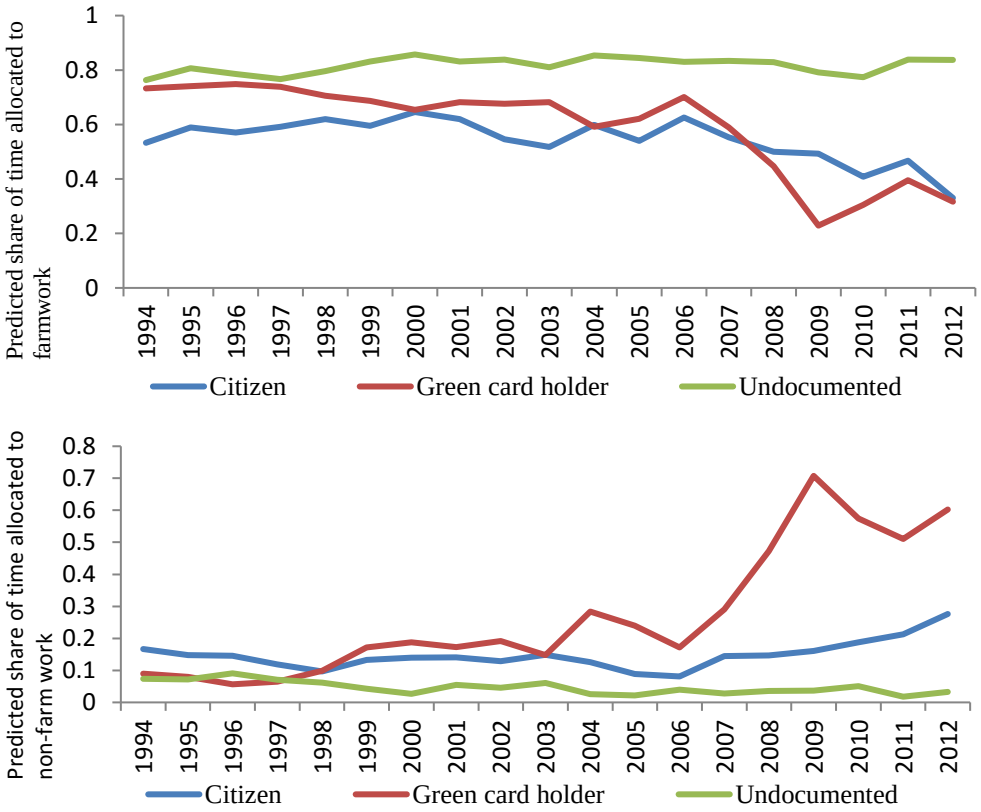

Figure 3.6: Trend of predictive shares of time allocated to farm and non-farm works

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CHAPTER 4

THE IMPACTS OF E-VERIFY MANDATES ON WAGES OF NATIVE AND IMMIGRANT WORKERS[7]

[7] Luo, Tianyuan and Genti Kostandini. Submitted to Industrial and Labor Relations Review, April 17, 2017.

Abstract

This paper analyzes the impact of undocumented immigrants' emigration caused by E-verify on the wages of the natives and immigrants in the adopting states. Using data from the Current Population Survey for the 2000-2014 period, we examine the heterogeneous wage effects on non-migrant natives and immigrants by industrial and educational group. Immigrants and natives who work in manual industries are found to experience decreases in their wages, while other industries are more likely to witness wage increase. The wage effects of E-verify on natives are found to be smaller and insignificant.

4.1 INTRODUCTION

Employment verification mandate (E-verify) gained much popularity among state government across the U.S. as a way to curb the undocumented immigration trend. As suggested by numerous previous studies, E-verify is quite efficient in reducing undocumented immigrants, even though there may exist issues such as identity fraud and firm noncompliance (Amuedo-Dorantes and Bansak 2012; Meissner and Rosenblum 2009; Nowrasteh 2012). For example, Lofstrom, Bohn, and Raphael (2011) find that the number of non-citizen Hispanic immigrants in Arizona dropped by about 92,000 persons due to the E-verify mandate during 2008-2009 period. Bohn and Lofstrom (2013) find a decline of 11% in the rate of formal employment for unauthorized workers in Arizona. Orrenius and Zavodny (2016) examine the impact of E-verify in a more general case (for seven E-verify adoption states) and suggest that the number of recent immigrants in states that adopted universal employment verification mandates falls by approximately 40%. Additionally, there are more studies that reach similar conclusions (Bohn, Lofstrom, and Raphael 2014; Amuedo-Dorantes and Bansak 2012; Amuedo-Dorantes and Lozano 2015).

In addition to the goal of deterring the hiring of undocumented workers, E-verify mandate is also expected to improve the labor market opportunities for natives and legal immigrants who compete with undocumented immigrants for jobs in the U.S.(Orrenius and Zavodny 2015). However, not all natives and legal immigrants in the U.S. directly compete with undocumented workers. This is more often the case for these who have relatively low educational attainment[8] or working in immigrant-concentrated industries. Therefore, to verify if there is indeed an improvement in the employment opportunities and wages of U.S. natives and

[8] A large share of undocumented immigrants has an education less than high school graduation (Cohn and Passel 2009).

legal immigrants, the impact of E-verify adoption should be examined by education and industry. With a similar concern, Amuedo-Dorantes and Bansak (2012) study the impact of E-verify mandates on the employment of likely undocumented workers across industries and find that agriculture and construction industry would experience an inflow of likely undocumented workers while industries such as private households service and retail trade would see a significant loss of likely unauthorized immigrant women or men. As a result, natives and legal immigrants in agriculture and construction may face higher pressures of job competition from the inflow of undocumented workers and even experience a decrease in their wages. In addition, by using data from Quarterly Workforce Indicator (QWI), Orrenius, Zavodny, and Gutierrez (2016) show that industries such as construction and traveler accommodation experience a decrease in their employment rates after the universal E-verify mandates while industry of dwelling services witness an insignificant change. With the knowledge that E-verify affects the distribution of undocumented workers across industries (Amuedo-Dorantes and Bansak 2012; Orrenius, Zavodny, and Gutierrez 2016), it is interesting to know the changes in the wages of natives and immigrants, particularly for those who directly compete with undocumented workers. This article evaluates whether E-verify has completed the goal of supporting native and legal workers through changes in their wages, and if so, who, in which industry and by how much?

By applying a Difference-in-Differences (DID) framework, this article uses micro level individual data provided by the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) from 2000-2014 and examines the impact of E-verify mandates on the wages of U.S. natives and immigrants by industry and educational attainment. Previous studies examining the wage impact of E-verify or other immigration enforcements on general population

provide mixed results. Some find that tougher immigration enforcement could decrease the earnings of natives (Orrenius and Zavodny 2009; Stark and Jakubek 2012), others provide contrary evidence and find a growth of earnings for natives and other immigrants (Bohn, Lofstrom, and Raphael 2015; Orrenius, Zavodny, and Gutierrez 2016). Additionally, more previous studies find no impact of immigration enforcement, including E-verify, on the earnings of natives and other legal immigrants (Orrenius and Zavodny 2015; Hotchkiss and Quispe-Agnoli 2013; Amuedo-Dorantes and Bansak 2014). To contribute to the body of similar literature, this article explores the wage impact of E-verify by industry and education to examine if natives and immigrants in certain industries are actually affected to a significant extent but could not be discerned at an aggregated level investigation. Moreover, this study could also provide industry-specific E-verify impact on wages for policymakers in states who pay more attention to certain industries.

The pattern of states that adopted E-verify in the U.S. raises our concern on the exogeneity of E-verify law enactment. The states which adopted E-verify may be also these experienced a significant change in the wages of their native and immigrant population. To examine this possible endogenous issue that may bias estimates, we conduct a series of placebo test on the policy exogeneity and are able to provide consistent evidence to show that there is no systematic difference among states in wages as well as the wage affecting policies that may bias the results. Another factor that may reduce the reliability of our results is the migration of natives in response to the removal of undocumented workers. To verify the migration pattern of natives after the adoption of E-verify, we apply a displacement model suggested by (Card and DiNardo 2000) and find that natives show limited response to a reduction in the number of undocumented

immigrant. The results of both tests together with the ones from DID parallel pre-trend assumption test are shown and discussed in the section after the main results.

We provide four important findings: First, some industries such as manual industry experiences an inflow of undocumented immigrants while other industries, service and trade industries, experience a reduction and insignificant change in undocumented population, respectively. Second, immigrants who are high school dropout and work in manual industry experience a decrease in their wages while other immigrants who are high school graduates in service and trade industry have a higher wage in E-verify adoption states. The benefits of the disadvantaged immigrant cohort that has lower education and works in a more hostile environment (agriculture and construction) are further pronounced. Third, natives experience no change in their wages from the adoption of E-verify, even when examined by industry and educational attainment suggesting that E-verify did not work as policymakers had hoped for. Fourth, we find the wage impact of E-verify to be temporary and fade away quickly after two years after adoption. The local economic adjustment quickly absorbed the shock caused by E-verify in the states' labor market.

The remainder of this article is organized as follows: Section II provides a detailed background on the federal E-verify system and an analysis of the educational and industrial distribution of U.S. immigrants and natives. Section III describes the data. Section IV analyzes the empirical results while section V provides results of the test for parallel pre-trends, displacement effect and policy exogeneity. Section VI concludes.

4.2 BACKGROUND AND LITERATURE REVIEW

E-verify is a free federal online program that provides employment eligibility information for newly hired employees to employers in the U.S. It was first established as a voluntary pilot program by the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 and was used voluntarily by firms in all 50 states in 2003 (Amuedo-Dorantes and Bansak 2012). However, a lack of stringent mandated enforcement of E-verify has undermined the effectiveness of ending unauthorized immigration intended by the federal government. The lax implementation of federal level immigration enforcement and the slow progress of national level immigration reform since 1996 has spurred an extraordinary wave of state-level immigration legislations during the recent decades. E-verify mandate became the most widely adopted immigration enforcement at the state level. The Legal Arizona Workers Act (LAWA), which took effect in 2008 in Arizona, became the first and, arguably, the most restrictive legislative action of adopting E-verify at the state level (Bohn, Lofstrom and Raphael 2015). Under LAWA, all employers are required to verify the employment eligibility of newly hired workers through E-verify system. After Arizona, states such as Georgia, North Carolina and Mississippi also adopted comprehensive E-verify systems to impede the immigration of unauthorized workers. Table 1 presents the states and the dates of implementing universal E-verify mandates. Some states, such as Georgia, Mississippi and North Carolina, phased into the adoption of E-verify by starting with requirements solely on public agencies or government contractors in the initial stage.[9]

A series of studies evaluating the impact of E-verify adoption suggest that the states which adopted immigration reform have experienced significant changes in their labor market

[9] For more information about the E-verify and its implementation across states, please refer to http://www.uscis.gov/e-verify.

structure, such as a notable decrease in the undocumented workers (Bohn et al. 2014; Amuedo-Dorantes and Bansak 2012; Nowrasteh 2012) and an increase in the earnings of native workers (Orrenius and Zavodny 2015). Amuedo-Dorantes and Bansak (2012) also document a decline of employment for general unauthorized workers due to E-verify implementation and an increase in unauthorized employment in agriculture and construction industry. Amuedo-Dorantes and Lozano (2015) uses the Synthetic Control Method and find that the adoption of E-verify removes undocumented workers significantly more than other tough immigrant enforcements in Arizona. Finally, E-verify mandates are also found to dampen deportees' intention of reentering the U.S. in the future (Amuedo-Dorantes, Puttitanun and Martinez-Donate 2013).

The studies mentioned above uniformly suggest that the population of unauthorized workers decreases due to the adoption of E-verify system. According to traditional economic theory of labor supply and demand, labor supply reduction in certain industries and increase in others would affect wages differently. If the demand for labor remains the same, industries that experience labor supply increase would witness a decrease in wages. However, this outcome would change if employers alter their demand for labor. E-verify has changed the labor demand as well as the supply in market. On demand side, E-verify requiring employers to verify the legal identity of newly hired employee would impose higher hiring cost and high penalty for business. On supply side, workers without proper employment documents would flee to other states and new unauthorized workers would avoid entering the E-verify adoption states. Consequently, the wage would be subject to the influence from both labor demand and supply changes caused by E-verify adoption.

Orrenius and Zavodny (2009) find that natives who are white and Hispanics experienced a decrease in their hourly earnings compared to immigrants from Latin America after the tougher

enforcement due to 9/11 terrorist attack in 2001. Bohn. Lofstrom, and Raphael (2015) examine the impact of E-verify mandates on the wages of low-skilled natives and find an evident increase in wages for low-skilled native white men after E-verify adoption in Arizona. They suggest that the constriction of low-skilled labor offset the impact of decreasing labor demand and thus improved the outcome for low-skilled white men. Their findings are also supported by those of Orrenius, Zavodny, and Gutierrez (2016), who also demonstrate an increase in the monthly earnings for non-Hispanic whites and non-Hispanic blacks. Orrenius and Zavodny (2015) look at the impact of E-verify adoption in all seven states and only find a significant increase in the hourly earnings among the U.S.-born Hispanic population but not among the Mexican-born naturalized citizens and U.S.-born white population. They attribute the insignificant change in the hourly earnings of non-Hispanic U.S. natives to the little competition between natives and unauthorized immigrants. Our finding for wages of natives is broadly in line with that from Orrenius and Zavodny (2015) and we explain that immigrants, who would be closer substitutes for undocumented immigrants, has absorbed the wage impact of E-verify adoption. Consequently, natives would be affected to a less or negligible level.

By building a theoretical model that examines the response of a firm that optimize its profit to the employer sanctions of different enforcement levels, Stark and Jakubek (2012) demonstrate that a firm's response could result in a reduction in the labor wages and the employer sanction may hurt the employment benefit of natives in the scenario of high enforcement level. To answer the question of whether state immigration legislation would affect the wages of documented workers after removing undocumented immigrants, Hotchkiss and Quispe-Agnoli (2013) examine the observed wage differential between unauthorized and authorized workers in Georgia. They find that the wage disparities between undocumented and

documented workers are mainly due to the lower productivity not the willingness to accept lower wages of the former workers. In other words, they state that the removal of undocumented workers would hardly raise the wages of natives as much as expected. Amuedo-Dorantes and Bansak (2014) demonstrate that the wage impact on natives varies by gender. They find that, in general, the enactment of E-verify mandates have little impact on naturalized Hispanics as well as non-Hispanic natives. However, the non-Hispanic men experience an increase in their wages by 2.9% after the universal E-verify law enactment but the estimate is significantly only at 10% level.

As aforementioned, the impact of E-verify is generally examined at the aggregate economy level. This study examines the impact by various educational and job experience backgrounds due to the different degrees of responsiveness to labor supply shock in these groups (Borjas 2003; Orrenius and Zavodny 2007). This is particularly true in examining the wage effect of E-verify that aims to reduce unauthorized immigrants. We expect that certain cohorts (such as workers with low skills or limited educations) are more likely to be affected and experience a higher adjustment in their wage. As Card (2005) points out, immigrants in the U.S. in general have lower educational attainment compared to natives. For example, 38.2% of immigrants are high school dropouts compared to 14.7% among natives. Moreover, unauthorized immigrants of ages 25-64 have very low education levels, and nearly 50% of unauthorized immigrants are high school dropouts (Passel and Cohn 2009). As a result, a significant reduction of unauthorized immigrants, the majority of who are low-educated workers, could affect the wage of the competitive low-skilled native cohort to a greater extent.

In addition to the flow of undocumented workers, the stock or amount of undocumented workers also determine the wages in different indutries. As pointed out by Hotchkiss and

Quispe-Agnoli (2013), the wage of an industry could be affected by the willingness of undocumented workers to accept low wages. Employers could exercise monopsony power on undocumented workers and thus reduce their wages. The adoption of E-verify could enhance the monopsony power of employers by making it harder to find jobs elsewhere and also by requiring that E-verify screen only need to be applied to newly hired employees. To avoid the E-verify screen, formerly hired undocumented workers have to stay in the same job and could be more vulnerable to the exploitation of employers. Orrenius and Zavodny (2015) and Bansak and Raphael (2001) provide evidence that the immigration enforcement reduced earnings of likely unauthorized immigrants, most of whom are high school dropouts. Furthermore, immigration enforcement such as E-verify could also produce job market discrimination against the green card holders and naturalized citizens who look foreign-born (Bansak 2005), thus depressing their wages. If the wage depressing impact (higher monopsony and discrimination) of immigration enforcement is added up to the wage decreasing impact from larger labor supply, certain industry would experience a significant decrease in wages. To sum up, we expect that: First the wages in industries that have a high proportion of undocumented immigrants (even after the adoption of E-verify) and experience an inflow of undocumented labor would decrease. Second, the wages in industries that have a modest concentration of undocumented population but experience an out-migration of unauthorized labor are undetermined.

As shown in Figure 1, agriculture and construction have the highest share of undocumented immigrants, followed by the leisure and hospitality industry. In the extreme case, if E-verify had completely eliminated undocumented workers, agriculture would lose 16% of its labor force and construction would lose 12% in 2012, meanwhile manufacturing would

experience a decline of 6% in labor supply.[10] As a result, keeping everything else constant, a larger percentage decrease of unauthorized immigrants could impose a greater upward pressure on the wage level in agriculture and construction. In addition, the labor-intensive characteristic and relatively low educational attainment requirements of agriculture and construction (Bureau of Labor Statistics 2012) could further amplify the wage impact of the labor force shrinkage.

So far, we have shown that the share of unauthorized immigrants varies across industries. Moreover, we also point out that unauthorized immigrants are more likely to be in the lower end of education or skill distributions. As a result, the cohort that experiences the largest impact of E-verify would be the competing legal workers (both natives and legal immigrants) with limited skills in the industries that have a higher dependence on unauthorized workers. Table 2 displays the percentage of immigrants and natives across educational levels and industries. We show the statistics between 2000 and 2007 because the state level adoption of E-verify, which was initiated by Arizona in 2008, may have changed the educational distribution afterwards.

Table 2 shows that the percentage of immigrants working in agriculture who are high school dropouts is 68.06%, the highest among all industries. Construction and personal service also have relatively high proportions of immigrant high school dropouts, which are 49.54% and 35.21%, respectively.[11] For natives working in agriculture and construction, the percentage of workers who are high school dropouts are 12.16% and 10.98% respectively, which are much lower than those of immigrants. Moreover, the shares of high school dropouts among immigrants in business and repair industries are quite small compared to those in agriculture and

[10] Martin (2009) points out that approximate 55% of the foreign-born farm workers are undocumented, which is higher than the estimate from Pew Research Center. We report the estimates of number of undocumented workers calculated by the Pew Research Center because it is the only source we know that investigates and compares the number of undocumented workers across industry.

[11] We do not know whether these immigrants are legal or not through CPS.

construction. Based on the educational composition for each industry in Table 2, it seems that immigrants in the manual industry would be largely affected by the adoption of E-verify.

4.3 DATA

4.3.1 Annual Social and Economic Supplement Dataset 2000-2014

We use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) during the 2000-2014 period to investigate the impact of E-verify adoption on the wages of native and immigrant workers. The ASEC is a nationally representative large-scale survey conducted by the U.S. Census Bureau and contains a wealth of information on labor market outcomes of individual interviewees. We focus on examining the impact of E-verify among different industrial and educational groups because of the disparities in the degree of substitution between natives and immigrants as well as the scale of reduction in immigrants across industrial groups. Following Borjas (2003), an immigrant is defined as an individual who is foreign-born and is either a naturalized citizen or noncitizen; then the rest are defined as natives.

The hourly wage data is obtained by dividing the yearly wage and salary income by the total hours worked per year. All the hourly wage data are deflated using the Consumer Price Index (CPI) provided by the Federal Reserve Economic Data. We note that a potential impact of E-verify is its ability to increase self-employment among unauthorized immigrants, which could lead to an underestimation of the adverse effects on wages (Orrenius and Zavodny 2015).

We focus on individuals of ages between 18 and 65 and define the educational levels as high school dropouts (less than 12 years education), high school graduates (12 years of education), workers with some college (13-15 years of education) and college graduates (16

years of education or more). To eliminate the influence of outliers, following Card (2009), we "Winsorized" hourly wage in sample years at a lower value and upper value which are 0.75 times and 50 times the federal minimum wage, respectively.

Table 3 presents descriptive statistics for both natives and immigrants on their characteristics for the 2000-2014 period. Immigrants have a larger family size and are more likely to be male and married. Natives have higher mean hourly earnings of $42.07 while immigrants have a mean hourly wage of $37.73. Natives also have a higher educational level than immigrants. The most significant gap between immigrants and natives is the share of Hispanic population, 51% of immigrants are Hispanics whereas only 8% of natives are Hispanics.

4.4 EMPIRICAL METHODS

4.4.1 Likely Undocumented Workers Industrial Distribution Model

The adoption of E-verify changes the wages of immigrants and natives mainly through the channel of undocumented workers migration. Workers without legal working permits may move to other non-adoption states or move to industries that are subject to a lower level of immigration enforcement effort. There are two possibilities that an industry in an E-verify adoption state would attract more undocumented workers: first, the higher dependence on labor that induces a rigid demand for workers, particularly undocumented workers, could lead to the firms' violation of E-verify laws and attract undocumented workers from other industries. Second, the E-verify mandates in some states that excluded certain industries could also affect the distribution of undocumented workers across industries. For instance, even the arguably strictest immigration enforcement in Arizona, Legal Arizona Workers Act (LAWA), exempted the businesses that hire

withholding-exempt employees such as seasonal workers and domestic help (Bohn and Lofstrom 2012). To lessen the labor shortage tension caused by E-verify adoption, an employee who has duration of employment less than nine months in a calendar year does not has to be screened by E-verify in North Carolina (Feere 2012). The different E-verify enforcement level across industries could reshuffle the labor allocation and transfer undocumented worker to enforcement exempted or lax industries.

However, it is not accurate to evaluate the impact of E-verify on the share of likely undocumented workers based on the unadjusted sample means because there could be some other cofounding factors that affect the share of likely undocumented workers such as time and state unobservable trends. To isolate the impact of E-verify on the probability of entering certain industry for likely undocumented workers, we construct the empirical model as follows:

$$Industry\_choice_{ist} = \alpha + \beta_3 EVerify_{st} + X_{ist}\lambda + \gamma_t + \rho_s + \gamma_t\rho_s + \mu_{ts} + \phi_{ist} \qquad (1)$$

where $Industry\_choice_{ist}$ indicates if a likely undocumented worker is working in one the four industries examined in this article. $EVerify_{st}$ indicates if a likely undocumented worker is in the state that has E-verify after the year of adoption. X_{ist} include covariates as in Table 3. Additionally, equation (1) also includes year and state fixed effect, state specific time trend, and year by state effect. ϕ_{ist} is error term.

4.4.2 E-verify Mandates Wage Effect Model

We exploit the effect of E-verify mandates on hourly wage for four different industrial groups (manual industry, service industry, manufacture industry, and trade industry). Manual industries include agriculture, construction and mining; service industries include personal services, business, and repair services; trade industries include grocery stores, drug stores, and restaurants; professional industries include hospitals, schools, universities, and government sectors.

Furthermore, the wage impact of E-verify is also examined across three educational levels: high school dropouts, high school graduates, and at least some college. Results in this section is different from that in previous section: the dependent variables in previous section are dummy variables indicating if an likely undocumented workers choose to work in a certain industry while the dependent variable in this section is the log wage of immigrants and natives who are categorized by their educational attainment and employed industry. Specifically, we run the regression with a basic form as follows:

$$Lnwage_{ist} = \alpha + \beta_1 EVerify_{st} + X_{ist}\lambda + \gamma_t + \rho_s + \gamma_t\rho_s + \mu_{ts} + \phi_{ist} \quad (2)$$

where $Lnwage_{ist}$ indicates the logged hourly wage of individual i, in state s and year t. $EVerify_{st}$ is a dummy variable indicating if a state s has implemented a comprehensive E-verify mandate. X_{ist} includes individual level characteristics that may affect the wage of natives and immigrants, which are shown in Table 3. γ_t and ρ_s represent the year and state fixed effects that control for unobservable year and state-specific factors that affect wages. μ_{ts} is the year by state effect. In addition, we also include state-specific time trends ($\gamma_t\rho_s$) to control for the longer-run changes in states over time, which further eliminates the omitted variables bias. ϕ_{ist} is the error term. However, due to the fact that adoption of E-verify coincides with economic recession in many states (Orrenius and Zavodny 2015), we note that the state-specific time trends term may also absorb and thus underestimate the impacts of E-verify mandates in certain states. As pointed out by Bertrand, Duflo and Mullainathan (2004), the state level serial correlation in DID models may produce downward-biased standard errors. Therefore, this article uses robust estimation by utilizing Huber-White standard errors clustering at the state level.

4.5 EMPIRICAL RESULTS

We first explore the impact of E-verify on distribution of undocumented workers across industries and then we examine the hourly wage of natives and immigrants across different industrial groups and educational levels.

4.5.1 DID Estimation: Industrial Distribution of Likely Undocumented Workers

As mentioned, the ASEC data does not identify if individuals are undocumented yet likely undocumented workers can be defined based on the characteristics of unauthorized population found by other literatures. Previous studies that examine the labor market outcomes of immigrants also provide their definition of likely undocumented workers. Orrenius and Zavodny (2015) define likely undocumented workers are those immigrants who are not naturalized citizens and are from Mexico with at most high school education. Amuedo-Dorantes and Bansak (2012) define the likely undocumented workers to be immigrants who are 16-45 years old, Hispanic noncitizens with an educational level of high school or less. We defines likely undocumented workers as immigrants who are 16-60 years old, high school dropouts and are Hispanic noncitizens with an immigration experience 10 years or less. Figure 2 presents the trends of the percentage of likely undocumented workers across industrial groups in E-verify adoption and non-adoption states.

Trends in Figure 2 indicate that the percentages of likely undocumented workers in manual industries are approximately 5% before 2008, which is more than twice as much as those in other industries. After the first universal adoption of E-verify in Arizona in 2008 (LAWA), the proportion of likely undocumented workers in manual industry shows a slightly increase in E-verify adoption states (solid line with square marker) compared to the non-adoption states (dashed line with square marker). The likely undocumented worker group in manual industries

would expect a large decrease in their wage because of a larger proportion of likely unauthorized workers in this industry and also an inflow of likely undocumented workers. Another industry that could observe a wage decrease is services. As can be seen from the graph above in Figure 2, the share of likely undocumented workers in the services in E-verify adoption states (presented by the solid line with triangle marker) displays an evident decrease relative to (the dash line) non-adoption states in 2011. The timing of this decrease in service industry in E-verify adoption state broadly matches the time when Georgia, North Carolina, South Carolina, and Alabama took their E-verify system into effective. In addition to the industries that could be affected by E-verify adoption to a larger extent, such as manual and service, some other industries may experience a little change in the share of likely undocumented workers and thus the industrial wages. This can be seen from the trade industry where there is little difference in the trends between E-verify adoption and non-adoption states over the entire sample period even though it has the similar share of likely undocumented workers as service industry (the scale of trend in trade industry in the above graph is modified to isolate it from the trends of service).

As can be seen, likely undocumented immigrant men would increase their probability of working in manual and service industry by 3.1% and 2.7%, respectively. As a result, the wages in these two industries would decrease due to the higher labor supply from relatively low-skilled workers. Likely undocumented immigrant women decrease the probability of working in service industry by 10%, which could offset the impact from the increase of likely undocumented immigrant men in service. Finally, industries of trade and professionals have insignificant impacts which are in line with the unadjusted trend shown in Figure 2.

4.5.2 DID Estimation: E-verify Wage Impact on Natives and Immigrants

Panel (A) in Table 5 presents the wage impact of E-verify on the population of immigrants. Results at the aggregate level (first column) suggest that high school graduates experience an increase in their wages by 5.9% and the effect are statistically significant at the 1% level. On the other hand, immigrants in other educational categories do not experience wage changes. Moreover, the adoption of E-verify has different impacts across the four industrial groups. Immigrants that dropped out of high school and work in manual industry (e.g. farm work, construction, see column 2) in E-verify adopting states experience a 5.5% decrease in their wages. The inflow of likely undocumented workers into manual industry jobs together with the high percentage of undocumented workers would decrease the wages. The adoption of E-verify system may enhance the monopsony power of employers in manual industries and impose a downward pressure on the wages of high school dropout immigrants. The states that adopted E-verify are not likely to eliminate all the undocumented immigrants. In fact, the employment of undocumented immigrants could be unaffected because of identity fraud and firms noncompliance (Amuedo-Dorantes and Bansak 2012; Meissner and Rosenblum 2009; Nowrasteh 2012). As a result, some proportion of unauthorized workers would stay in the states but suffer from a lower wage paid by employers due to the higher monopsony power caused by E-verify adoption. Undocumented workers may accept a lower payment level in order to be employed. Due to the higher risk of hiring undocumented workers and knowing that undocumented workers have limited mobility, employers are only willing to pay a lower wage to undocumented workers. This finding is in line with that of Orrenius and Zavodny (2015) and Bansak and Raphael (2001) who provide evidence that the immigration enforcement reduced earnings of likely unauthorized immigrants, most of whom are high school dropouts.

Service (column 3 in Table 5) is the other industrial group which is expected to be affected by the adoption of E-verify. As shown by Figure 2, service rank the second which has a higher proportion of likely undocumented workers. High school graduates who are immigrants and work in service experience increases of 21.3% in their hourly wage. To further verify the large increase in the wages for these cohorts in the service industry, we examine the trends of hourly wage for high school graduates and find that the mean wage for high school graduate in service industries before and after E-verify are 18.8$ and 31.2$, respectively. The increase in the wage of high school graduates cohort in the service industry is a surprising 65.9% during the post-treatment period. In contrast to manual industry, the adoption of E-verify in the service industry has significantly increased the wages for those with high school education but not with other education cohorts. The increase in the wage of immigrants in service industry can be explained by the 10% decrease in the population of likely undocumented immigrant women shown in Table 4, even though there is a modest inflow of likely undocumented immigrant men into service industry, however, such an impact may be offset by the out-migration of likely undocumented immigrant women.

As shown in panel (B) of Table 5, native workers who are employed in all four industries experience insignificant change in their hourly wages in the E-verify adopted states. First of all, compared to natives, other immigrants, documented or undocumented, would be closer substitutes for these undocumented workers who leave the state or industry. As a result, immigrant cohorts are more sensitive to the change in the number of undocumented workers than native population. Hotchkiss and Quispe-Agnoli (2013) study the impact of state immigration legislation on the labor market outcomes of documented and undocumented workers and provide evidence that there is less substitutability between documented and undocumented workers.

Secondly, even though there is a labor supply decrease shock in some industries, however, the adoption of E-verify could also decrease the labor demand due to higher production cost. If the labor supply decrease matches with labor demand decrease, then the wages are more likely to be unchanged. Moreover, even though there is monopsony power in the labor market that could depress the average wage of undocumented workers thus the wages of other legal workers. However, Hotchkiss and Quispe-Agnoli (2013) suggest that the lower wage of undocumented workers is not because their willingness to accept lower wages (more sensitive to monopsony) but due to their lower productivities. Consequently, the removal of undocumented workers would neither change the employment nor the wages of documented worker.

Our findings further support the results of previous research. Orrenius and Zavodny (2007) use occupation as a proxy for skills and examined the effect of large scale immigration on the wages of natives in manual, service and professional groups. They find that the wages of blue collar workers are adversely affected; however, the effect on the wages of skilled occupation workers is not statistically significant. Camarota (1997) also finds similar negative effects of immigration on low-skilled occupations. To address the potential endogenous problems caused by the cross-regions comparison, Borjas (2003) investigates the wage impact of immigration at the national level and uses education and experience groups as proxies for skill. Amuedo-Dorantes and Bansak (2014) find that universal mandate have insignificant impact on the log real hourly wages of naturalized Hispanics and non-Hispanic natives. Orrenius and Zavodny (2015) compare the impact of E-verify mandates on the real hourly earnings of likely undocumented workers to Mexican-born naturalized citizens and U.S.-Born white non-Hispanics and verify that the hourly earnings of the latter groups remain unaffected after E-verify mandate comes into effect. They suggest that it seems there is little compete between white non-Hispanic U.S.

natives and undocumented immigrants, which could also explain our findings that only immigrant workers are affected while the log hourly wages of natives are not affected. Moreover, our findings provide additional evidence to support the arguments by suggesting that the workers in particular industries are more likely to be affected by the migration of unauthorized population. Furthermore, we also point out that the cohorts that experienced the largest changes are more likely to be low-educated cohort.

Finally, we consider the change of estimates by how the adoption year is defined in this study since some states adopted E-verify in the mid-year. Results in Table 5 are generated based on rules that the event variable is defined as the year E-verify was adopted, even for state such as North Carolina which adopted E-verify in October. To examine if the results depend on the definition of policy years, we redefine the event variable by delaying one year for the states which adopted E-verify after the June in adoption year. As expected, the regenerated results are not statistically different from the estimates in Table 5.

4.6 FALSIFICATION AND ROBUSTNESS TEST

As discussed by Borjas, Freeman and Katz (1997), there are some potential challenges associated with the empirical strategy in the immigration and wage literature. For reasons explained below, the estimates of wage impacts of migration could be unreliable. Even though this article investigates the wage impact of labor outflow (emigration) rather than labor inflow (immigration), these identification caveats still apply.

First, Difference-in-Differences estimation requires that the trends of outcomes in treated and control units to be parallel so that we can safely conclude that the deviation of trend of outcome in treated groups is caused by the adoption of E-verify. However, if parallel pre-trends

assumption failed to hold, the estimates of DID would be no longer reliable because there are large deviations of treated trend from the controlled trend before and after the intervention, it is difficult to isolate the impact of E-verify adoption from other policies.

Secondly, the unobserved factors that lead to emigration may also have an impact on the wages of local population, thus leading to biased estimates. The population that emigrates is not randomly selected. The widespread E-verify adoption in the U.S. provides an appropriate quasi-natural experiment for investigating the wage impact of emigration, particularly in the case of out-migration of low-educated workers. Since the adoption of E-verify can be regarded as an exogenous shock to emigration, a Difference-in-Differences (DID) model would eliminate the estimation bias induced by the nonrandom selection of the emigrant population. However, if certain unobserved factors that determine the adoption of E-verify also affect the wage of workers, the DID estimates could be biased.

The final caveat is that native workers may respond to the outflow of illegal immigrants by moving into E-verify adopting states. Large outflows of undocumented workers could result in abundant job vacancies and perhaps higher wage rates. As a result, natives would migrate into those states and take the jobs that were held by undocumented workers. If there is a displacement effect, the model may not be able to capture the full impact of E-verify adoption on the wages of natives and immigrants who stayed. However, if the scale of inflow of native workers in response to the E-verify is small or negligible, regressions would provide at least informative lower bound estimates on the wage impact of immigration enforcement.

We first test the parallel pre-trend assumption of DID estimation, then examine if natives move into E-verify adoption following the reduction of undocumented worker using displacement effect model, and at last verify the exogeneity of E-verify adoption across states.

4.6.1 Pre-trends Assumption Test

The most crucial assumption for applying DID strategy is that the time trends of the outcome variable of treated group should not evolve differently compared to controlled groups in the absence of the policy treatment. The validity of this assumption could be verified by examining the unadjusted sample means of outcome variables in graphs and conducting the dynamic statistical test by including leads and lags in the model.

Figure 3 in present the log hourly wage trend of immigrant and citizen population in the U.S. between E-verify adoption and non-adoption states. The graphs presented on the left side of Figure 3 show the log hourly wage trends for immigrants in the U.S. It can be seen that the log hourly wage of immigrant fluctuates to a larger extent in treated states compared to that of citizens. Meanwhile, the pre-trends between treated and control states for immigrant population show a less level of match compared to that of citizens. However, this perhaps is caused by the inner trend within the E-verify adoption states and state-specific time trend can be included to adjust for the slightly deviation of pre-trends among immigrant group. In general, by examining the unadjusted sample mean of log hourly wage for all seven E-verify adoption states between 2000 and 2014, we observe that E-verify imposed a larger impact on the wages of immigrant cohort. Moreover, the graphs on the right side of Figure 3 show little evidence on the existence of the spillover impact of reduced undocumented immigrants from E-verify adoption on U.S. citizens.

Equation (2) provides estimates for β_1, which is the impact of E-verify on natives and immigrants when comparing the changes of wages in E-verify adopting states to the changes in states that do not adopt E-verify. The E-verify adoption decision made by each state is independent to unobservable factors that may affect the wage of workers, controlling for other

observables and a battery of state and time fixed effects. This assumption is also known as the parallel-trends assumption, which implies that treatment and control group would follow similar trends in the absence of treatment.[12]

Table 6 displays the estimated coefficients of the dynamic models during the years before E-verify adoption, the year of adoption and the years after adoption. Specifically, the natural log of hourly wage is regressed on year fixed effects, state fixed effects, state specific time trend, other covariates, and the event time indicators (leads and lags) of 12 years prior to and 6 year post to the year of E-verify adoption.

Figure 4 show the graphs of estimates in Table 6. As can be seen from panel (A) Figure 4, which presents the dynamics of E-verify impact on immigrants, none of the coefficient of pre-adoption years is statistically different from zero, indicating that there is no statistical difference in log hourly wage between treated and control states and the pre-trends match well.

As shown by panel (B) Figure 4, which displays the results for natives, none of the coefficient estimating the dynamic impact of E-verify during pre-treatment period is statistically significant, which implies that there is no different pre-trend during the pre-law periods. In the post-treatment period, the dynamic effect in the 3 years post E-verify is statistically significant at the 10% level. These preliminary findings are examined in more detail by the results of DID model on the hourly wages of natives in the next section.

4.6.2 Displacement Effect Model

Studies that empirically examined natives' location decisions in the wake of immigration shocks found scarce evidence of notable displacement effects. Card and DiNardo (2000) found that increases in immigrant population for specific skill groups would cause a small increase in the

[12] For more details on the dynamic model of parallel-trend test, please see Autor (2003) and Kostandini, Mykerezi, and Escalante (2014).

population of native-born individuals with similar skill level. Other research by Card (2001) further supported this finding. One earlier study by Wright, Ellis, and Reibel (1997) also indicated there is no correlation between immigration and native population flows. Some studies found that the displacement effect exists, but at a low rate. In an investigation of native workers location responses to the entry of Vietnamese manicurists in California, Federman, Harrington, and Krynski (2006) found that two non-Vietnamese would be displaced for every five Vietnamese entering the manicure market. Cortes (2008), using immigration network as an instrument, found that natives moved away in the wake of immigration. However, the author asserted that such displacement effects are not influential enough to eliminate the wage and price impact of immigration. Borjas (2006) estimated that two fewer natives would choose to reside in a certain state for every ten new immigrants in that state. This effect is even larger when investigated at the metropolitan level.

To ensure the accuracy of the wage impact of E-verify adoption, we apply the following specification based on Card and DiNardo (2000) to examine the displacement effect caused by the adoption of E-verify:

$$\frac{LowskilledNatives_{st}}{HighskilledNatives_{st}} = \tau + \theta_1 EVerify_{st} + \mu_s + \omega_t + \mu_s\omega_t + \mu_{ts} + \varepsilon_{st} \quad (3)$$

where $LowskilledNatives_{st}$ and $HighskilledNatives_{st}$ are the numbers of low-skilled and high-skilled native-born individuals who participate in labor market in state s and year t. $EVerify_{st}$ is a dummy that indicates if a state has adopted E-verify. μ_s is state fixed effect, ω_t is year fixed effect, $\mu_s\omega_t$ is the state-specific year effect, μ_{ts} is the year by state effect, and ε_{st} is the error term. Following Cortes (2008), low-skilled workers are defined as high school dropouts and high-skilled workers are defined as those who complete at least high school.

States that adopted E-verify are expected to experience a drop in the population of undocumented workers, who have a 50% high school dropout rate (Passel and Cohn 2009). As a result, low-skilled native workers, who are close substitutes for undocumented workers, may migrate into the state, increasing the labor supply and offsetting the effect of emigration of undocumented workers caused by E-verify adoption. Meanwhile the population of high-skilled workers is expected to remain unaffected. If there is no displacement effect, which means that the natives do not respond to the undocumented workers emigration caused by E-verify, then the coefficient of Everify is equal or close to zero. Table 7 presents the results of displacement effects caused by E-verify. The second column shows the estimates of regressions weighted by the size of the state labor force.

Estimates in both columns are similar and are statistically significant at the 5% level. $\hat{\theta} = 0.0071$ suggests there is a displacement effect due to the adoption of E-verify, however, the magnitude of the E-verify displacement effect is quite small: the states that adopted E-verify experience a slight increase by about 0.0071 in the ratio between low-skilled and high-skilled natives. This suggests that low-skilled natives are not likely to move to states that adopted stringent immigration enforcement.

4.6.3 Policy Exogeneity of E-verify Adoption

If the states that have a higher wage level would be more likely to adopt E-verify, then the estimate of the wage impact would not be reliable. The seven states that adopted E-verify generally concentrate in southern region and experienced large wave of immigrant influx from 1990s to 2000s (Orrenius and Zavodny 2016). However, there are other states also experienced large wave of immigration during the same period but did not adopt E-verify, such as California and New Mexico. The exogeneity of E-verify adoption policy raises concerns among scholars

who conduct the similar studies (Orrenius and Zavodny 2016; Orrenius, Zavodny, and Gutierrez 2016) and requires a more careful scrutiny. This article does not focus on verifying the exogeneity of E-verify adoption across states for it is well beyond the scope of this research. However we make an effort to demonstrate that even though the E-verify adoption states appear to be similar in some aspects, when it comes to wages, and more importantly the policies that affect wages, there is no systematic difference biasing the results.

In Figure 5, states that adopted E-verify are presented by black dots while other control states are presented by gray dots. There is no obvious pattern indicating that states that have adopted E-verify had higher or lower hourly wage than the other states that have not adopted E-verify. The hourly wages in Arizona and Georgia are located above the average trend line and the hourly wages in other E-verify-adopted states stay below but very close to the average trend line. The scattered pattern shows that before the widespread adoption of E-verify across states, there is weak evidence suggesting that the states with lower or higher hourly wages are more likely to adopt E-verify.

In addition to Figure 5, we conduct a placebo test to further justify the assumption of policy exogeneity. If the states that adopted E-verify are not randomly selected, which means there may be unobservable characteristics that affect the adoption of E-verify and the wage simultaneously, then the significant differences in wages between E-verify adoption and non-adoption states could be found no matter if there is an actual policy change or not. As a result, the randomly chosen placebo year of policy change for seven E-verify adoption states would have statistically significant impact on wages, and therefore suggesting that there is systematic difference for these seven E-verify adoption states that would bias the results. However, ceteris

paribus, if there is no statistically significant impact found in these placebo years, then the policy endogeneity would be less of a concern.

We choose the period between 2000 and 2007 to avoid the effect of actual policy adoption. Meanwhile, we choose a subsample of immigrants who work in the service industry because as shown in Table 5, we found statistically significant impacts of E-verify adoption on this cohort. If we find no statistically significant marginal effect from placebo years for the same cohort, then it can be more convincingly concluded that the significant impact on wages is due to the adoption of E-verify but not the systematic differences between adopting and non-adopting states.

As can be seen from Figure 6, none of the marginal effects, except for the first one which is the real policy intervention impact, is statistically different from zero. Figure 6 suggests that there is little evidence to show that there are intrinsic characteristics that would affect both the adoption of E-verify and the wage in a state. We also repeat this placebo test for the cohort of immigrants who work in manual industry and draw a similar conclusion.

Finally, this article examines whether the wages of immigrant and citizen population cause a state to adopt E-verify. Orrenius and Zavodny (2016) examine if the size of the likely undocumented immigrant population would affect the E-verify adoption decision of a state. Based on the results of empirical estimation, they find that a larger size of likely unauthorized immigrants imposes little impact on the adoption of E-verify and some other politic factors may play more important roles. In fact, researchers in political science have studied the determinants of immigration policy including E-verify adoption, and find that factors such as regional demographic and economic indicators are of little influence.[13] Following Orrenius and Zavodny

[13] Ramakrishnan and Wong (2010) examine the factors on restrictionist ordinances across county and suggest that the proportion of Republicans and Democrats in a county is the most significant determinant. Meanwhile, labor

(2016), this study runs a regression with a dummy dependent variable indicating if a state has adopted universal E-verify that year. The independent variables of interest are lagged wages of immigrant and citizen cohort before the year of E-verify adoption. To control for other cofounding factors, the model also include lagged variables of economic indicators, state and year fixed effects, and state-specific time trend.

Results shown in Table 8 suggest that the states with lower wage of immigrant or citizen population are not more likely to adopt E-verify in later years. This result is in line with the conclusions of studies mentioned above that examine the determinants of immigration policy adoption (Ramakrishnan and Wong 2010; Lewis et al. 2012; Wong 2012) and implies that labor market outcomes play little role in the changes of E-verify adoption across state. Finally, the local partisanship, which is a suggested prominent factor determining the adoption of E-verify, was built over long time period and therefore connects the passage of E-verify to the history of a state instead of contemporary conditions, further adding to the evidence of E-verify policy exogeneity.

4.7 CONCLUSIONS

The widespread adoption of the federal E-verify system across several U.S. states has attracted a lot of attention. In addition to efficiently reducing the population of undocumented immigrants (Bohn, Lofstrom and Raphael 2014), E-verify is also expected to affect other cohorts, such as natives and legal immigrants, in terms of their employment opportunities and wages. Previous

market outcomes and demographic changes are not associated with higher probability of passing restrictionist legislations. Lewis et al. (2012) explore why city police departments enforce federal immigration control and also find that voter partisanship affects local police immigration enforcement. Finally, Wong (2012) further present evidence that the partisanship of a county determines the adoption of 287(g), which is another joint immigration enforcement by federal and local governments.

literature has studied the impacts of E-verify on the labor market outcomes of natives and immigrants at an aggregate level (Bohn, Lofstrom and Raphael 2015; Hotchkiss, Quispe-Agnoli and Rios-Avila 2015; Orrenius and Zavodny 2015). This paper contributes to the literature by estimating the impact of E-verify on wages of natives and immigrants by industrial groups and educational levels, providing evidence of the wage changes for the groups (low educational and skilled natives and immigrants) that directly compete with undocumented workers.

Findings of this article suggest that, on average, immigrants are more responsive to the adoption of E-verify than their native counterparts. Specifically, immigrants who are high school dropouts in manual industry experience a significant decrease of approximately 5.5% in their wage. On the contrary, the wages of immigrants who are high school graduates and work in service and retail trade industry increase after the adoption of universal E-verify mandates. However, the wage impact on immigrant population quickly fades away in two years after E-verify was adopted. Our findings provide evidence that the wage impacts of E-verify vary across industrial and educational groups, and have different responses according to the complementarity and substitutability between the population of undocumented immigrants and other cohorts, as well as the degree of dependence on undocumented immigrants of a particular industry. However, this article does not find significant wage impact of E-verify imposed on native workers in the U.S., even for natives who work in manual and service industry who are expected to be affected to a larger extent.

Table 4.1: States with universal mandate of E-verify

State	Universal E-verify Adoption Date
Arizona	Jan-08
Mississippi	Jul-08
Utah	Jul-10
Georgia	Jan-12
South Carolina	Jan-12
Alabama	Apr-12
North Carolina	Oct-12

Source: http://www.lawlogix.com/e-verify.

Table 4.2: Share of immigrants with different educational levels across industries

	High school dropout	High school graduate	Some college	College graduate
Immigrants(%)				
Agriculture	68.06	21.62	5.21	5.11
Construction	49.54	32.26	10.94	7.27
Personal service	35.21	35.67	16.18	12.94
Retail trade	29.23	36.00	19.14	15.46
Business and repair	26.00	25.98	16.81	31.48
Transportation	16.39	30.26	25.32	28.02
Professional	7.93	17.00	22.05	52.72
Natives(%)				
Agriculture	12.16	40.61	28	18.97
Construction	10.98	47.82	29.61	11.58
Personal service	10.74	41.29	34.4	13.56
Retail trade	10.37	40.98	34.68	13.98
Business and repair	5.88	32.14	31.73	30.25
Transportation	5.00	39.00	36.00	20.06
Professional	2.78	19.44	29.43	48.37

Notes: Tabulations from Annual Social and Economic Supplement (ASEC) data 2000-2007

Table 4.3: Summary statistics for natives and immigrants samples (2000-2014)

	Natives		Immigrants	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Family size	3.00	1.51	3.48	1.85
Age	40.10	11.99	39.69	11.17
Male	0.51	0.50	0.58	0.49
White	0.87	0.34	0.68	0.47
Black	0.11	0.32	0.09	0.28
Married	0.60	0.49	0.66	0.47
No school	0.00	0.02	0.01	0.10
High school graduate	0.31	0.46	0.28	0.45
Some college	0.32	0.47	0.18	0.39
Bachelors degree	0.21	0.41	0.18	0.38
Hispanics	0.08	0.28	0.51	0.50
Household head	0.52	0.50	0.49	0.50
Spouse	0.29	0.45	0.28	0.45
Child	0.10	0.30	0.06	0.23
Union status	0.02	0.16	0.02	0.12
Hourly wage	42.07	35.41	37.73	34.87
Observations	1,024,481		199,543	

Notes: Tabulations from Annual Social and Economic Supplement data 2000-2014. For the sake of brevity, Table 3 reports the summary statistics of variables of greater interests. The summary statistics of full set of control variables used in regression are available upon request

Table 4.4: Impact of E-verify on the probability of working in manual, service, trade, and professional industry of likely undocumented workers

Dependent variables	**Manual**	**Service**	**Trade**	**Professional**
		Panel A: Male		
E-verify	0.031**	0.027**	-0.022	0.008*
	(0.015)	(0.013)	(0.020)	(0.004)
N	11610	11610	11610	11610
		Panel B: Female		
E-verify	-0.022	-0.100**	0.049	0.006
	(0.020)	(0.050)	(0.034)	(0.022)
N	4395	4395	4395	4395
Year fixed effect	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes
State-specific time trend	Yes	Yes	Yes	Yes
Year by state effect	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes

Notes: Column (1) to (4) report estimates from the model as shown by equation (8): The dependent variable is a dummy variable which indicates if a likely undocumented worker is employed in one of the industries listed in the first row of table. a set of covariates including family size, age, age square, race, marital status, educational level, household status, occupations, Hispanic origin, union status. The entire sample is divided into two subsamples by gender. Individual-level weight suggested by ASEC data is used in all regressions. Robust standard errors clustered at state level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.5: Effects of E-verify adoption on log hourly wage of immigrants and natives by educational levels and industrial groups in E-verify adopting states, 2000-2014

	Total	**Manual**	**Service**	**Trade**	**Professional**
			Panel A: Immigrants		
High school dropout	0.022	-0.055**	0.067	-0.008	0.020
	(0.014)	(0.022)	(0.061)	(0.038)	(0.075)
N	50692	14271	8102	10051	3205
High school grad	0.059***	0.061	0.213***	0.068**	0.011
	(0.014)	(0.058)	(0.065)	(0.031)	(0.068)
N	55039	8106	8727	12903	7774
Somecol or more	-0.018	-0.308*	0.051	0.121*	-0.039
	(0.031)	(0.172)	(0.066)	(0.067)	(0.037)
N	93812	4441	11877	12760	35299
			Panel B: Natives		
High school dropout	0.029	-0.009	-0.027	0.055	0.052
	(0.022)	(0.049)	(0.083)	(0.048)	(0.059)
N	54617	8904	6197	15638	8009
High school grad	0.014	0.018	0.038	-0.03	0.032
	(0.010)	(0.038)	(0.042)	(0.025)	(0.022)
N	317376	40396	28891	65528	67961
Somecol or more	0.000	-0.056	0.005	0.041*	0.011
	(0.007)	(0.034)	(0.022)	(0.022)	(0.013)
N	652488	38328	51036	82508	283106
Year fixed effect	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes
State-specific time trend	Yes	Yes	Yes	Yes	Yes
Year by state effect	Yes	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes	Yes

Notes: Column (1) to (5) report esmates from the model as shown by equation (6): The dependent variable log hourly wage is regressed on a set of covariates including family size, age, age square, gender, race, marital status, educational level, household status, occupations, industries, Hispanic origin, union status. Educational categories are created according to the years of education: Dropout (less than 12 years education), High school graduates (12 years of education), and some college or more (more than 13 years of education. Individual-level weight suggested by ASEC data is used in all regressions. Robust standard errors clustered at state level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.6: Dynamic impacts of E-verify adoption

Lnwage	**Immigrants**	**Natives**
6 Years Prior	0.017	-0.004
	(0.019)	(0.011)
5 Years prior	0.026	-0.011
	(0.028)	(0.012)
4 Years Prior	0.029	-0.013
	(0.032)	(0.014)
3 Years Prior	0.026	-0.001
	(0.041)	(0.008)
2 Years Prior	0.031	-0.008
	(0.022)	(0.006)
Year of adoption	0.028**	0.000
	(0.012)	(0.009)
1 Year After	0.043*	-0.008
	(0.025)	(0.009)
2 Years After	0.012	-0.002
	(0.039)	(0.010)
3 Years After	-0.004	0.019*
	(0.017)	(0.010)
4 Years After	-0.004	0.012
	(0.017)	(0.013)
5 Years After	0.004	-0.010
	(0.025)	(0.008)
6 Years After	0.046	0.012
	(0.021)	(0.010)
Observations	199,543	1,024,481

Notes: Column (1) and (2) report coefficients from the model as shown by equation (7): the natural log hourly wage is regressed on family size, age, age square, gender, race, marital status, educational level, household status, Hispanic origin, union status, year fixed effects, state fixed effects, and a series of event leads and lags. Individual-level weight suggested by ASEC data is used in all regressions. Robust standard errors clustered at state level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4.7: Displacement effects of E-verify adoption, 2000-2014

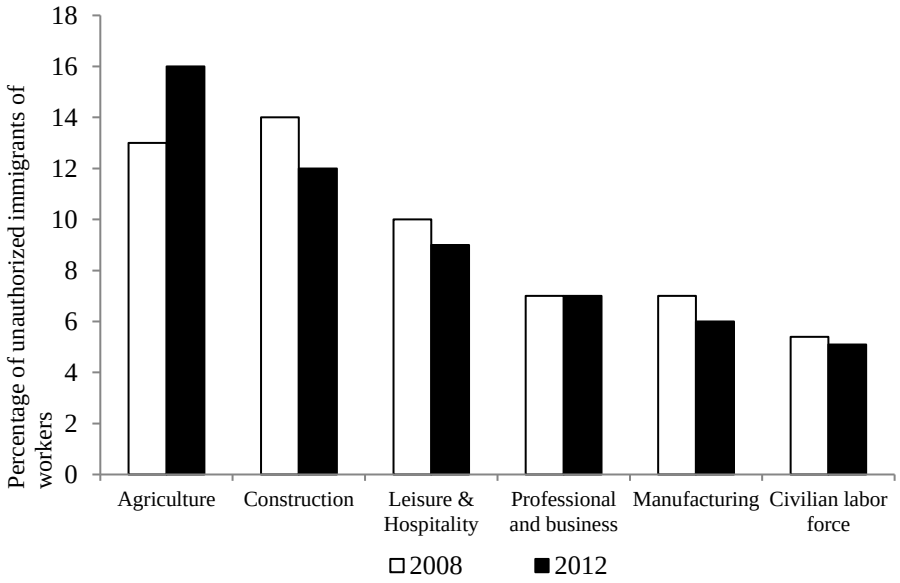
	Low-skill Natives/High-skill Natives Unweighted	Low-skill Natives/High-skill Natives Weighted
E-verify	0.0086**	0.0071**
	(0.0035)	(0.0031)
Year fixed effects	YES	YES
State fixed effects	YES	YES
State-specific year effects	YES	YES
Observations	1,024,481	1,024,481

Notes: Column (1) and (2) report coefficients from the model as shown by equation (5): Low-skilled workers are defined as high school dropouts and high-skilled workers are defined as those who complete at least high school. All demographic information is obtained from the ASEC for 2000-2014. Estimation of column (2) is weighted by the size of state labor force. Robust standard errors clustered at state level are reported in parentheses.
***p<0.01, ** p<0.05, * p<0.1.

Table 4.8: The effect of immigrant and citizen wages on the adoption of E-verify law

	(1)	(2)	(3)	(4)
Lagged immigrant wage	0.097		0.101	
	(0.141)		(0.142)	
Lagged citizen wage	0.348	0.359		
	(0.494)	(0.491)		
Lagged wage				0.238
				(0.268)
R^2	0.789	0.789	0.788	0.789
Observations	714	714	714	714
Year fixed effect	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes
State specific time trend	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes

Note: The dependent variable whether a state adopted comprehensive E-verify law that year is regressed on lagged immigrant, citizen, and general wage in addition to a set of other covariates including economic and demographic indicators (unemployment rate, per capita GDP, and share of immigrant population) and year fixed effects, state fixed effects, and state-specific time trends. The sum of the individual weight of population is used as weight in regression. Standard errors are made robust by clustering at state level.



Source: A Portrait of Unauthorized Immigrants in the United States, Pew Research Center, 2009

Figure 4.1: Percentage of unauthorized immigrants across industries

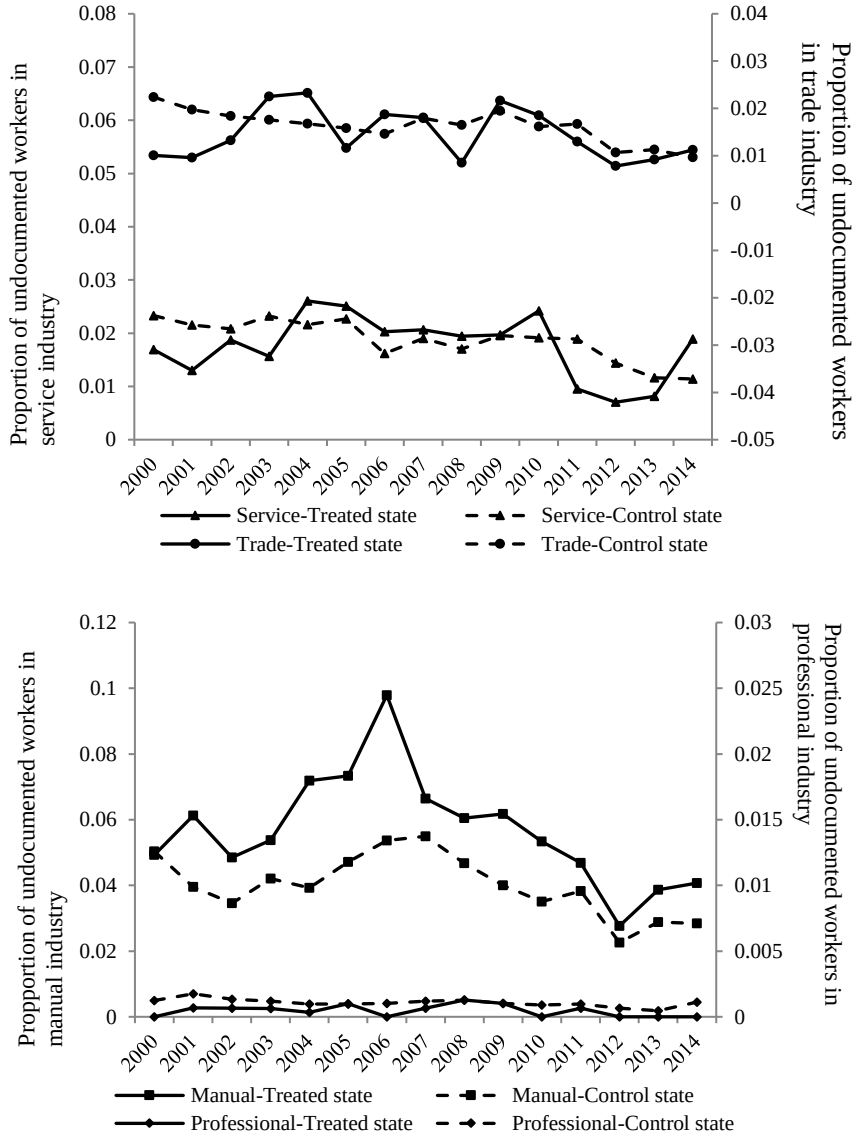
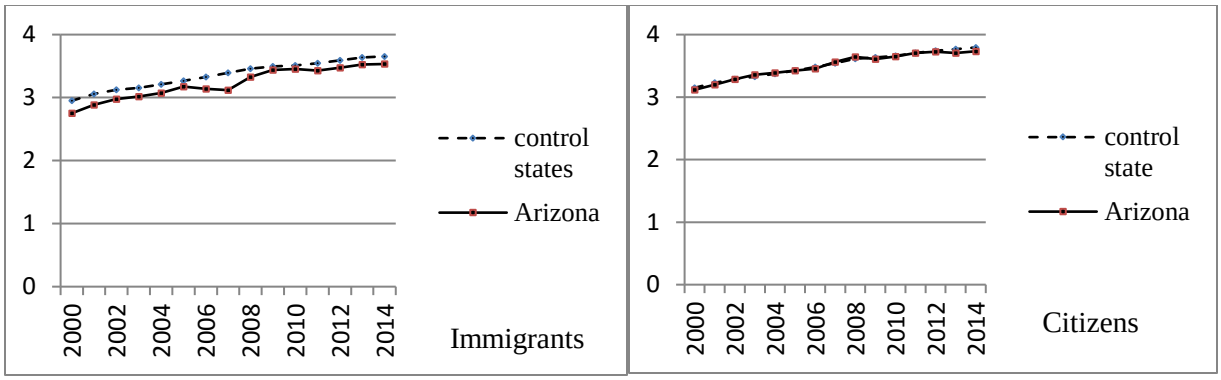


Figure 4.2: Trend of likely undocumented worker proportion in manual, service, trade and professional industry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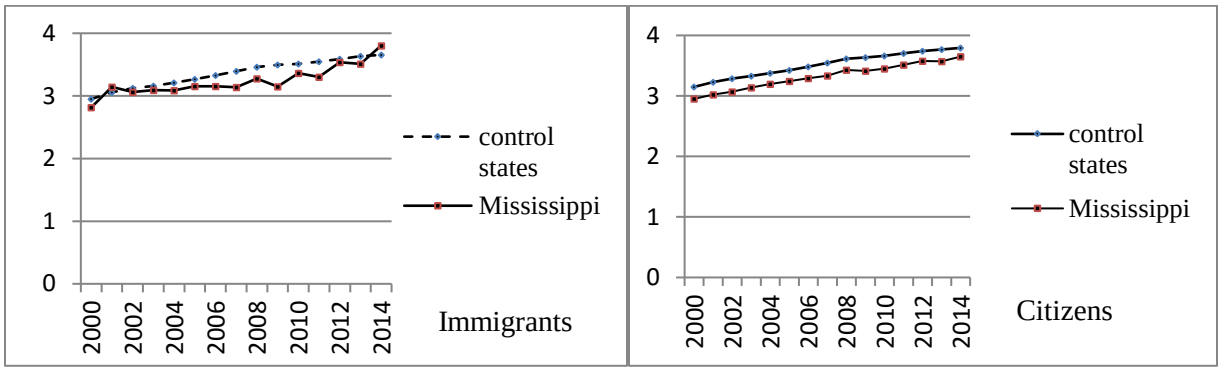
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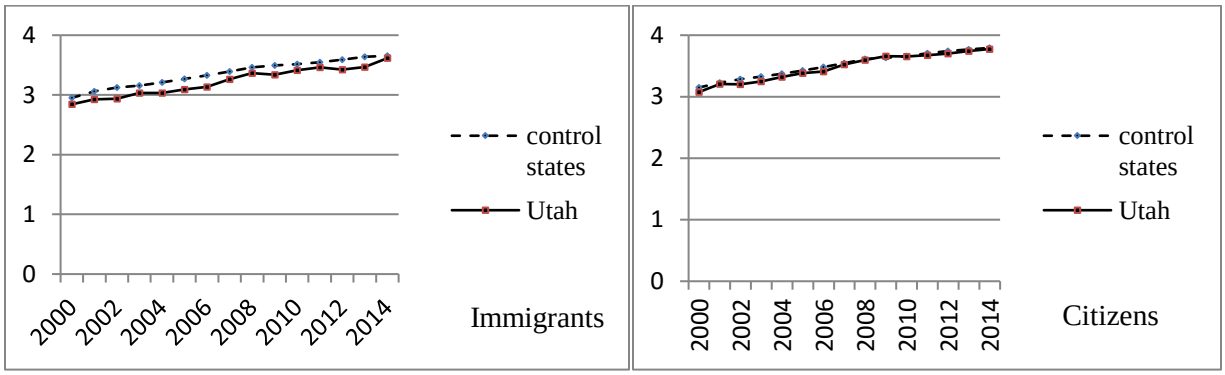
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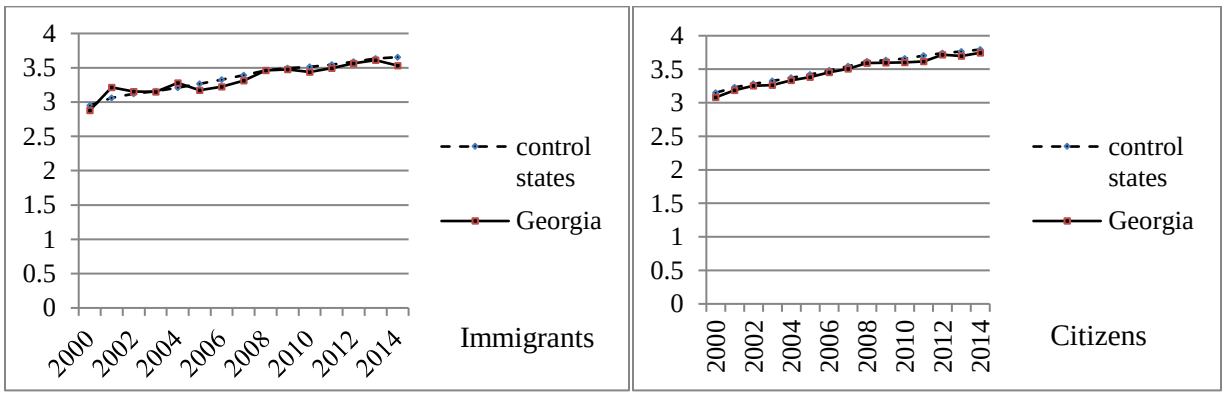
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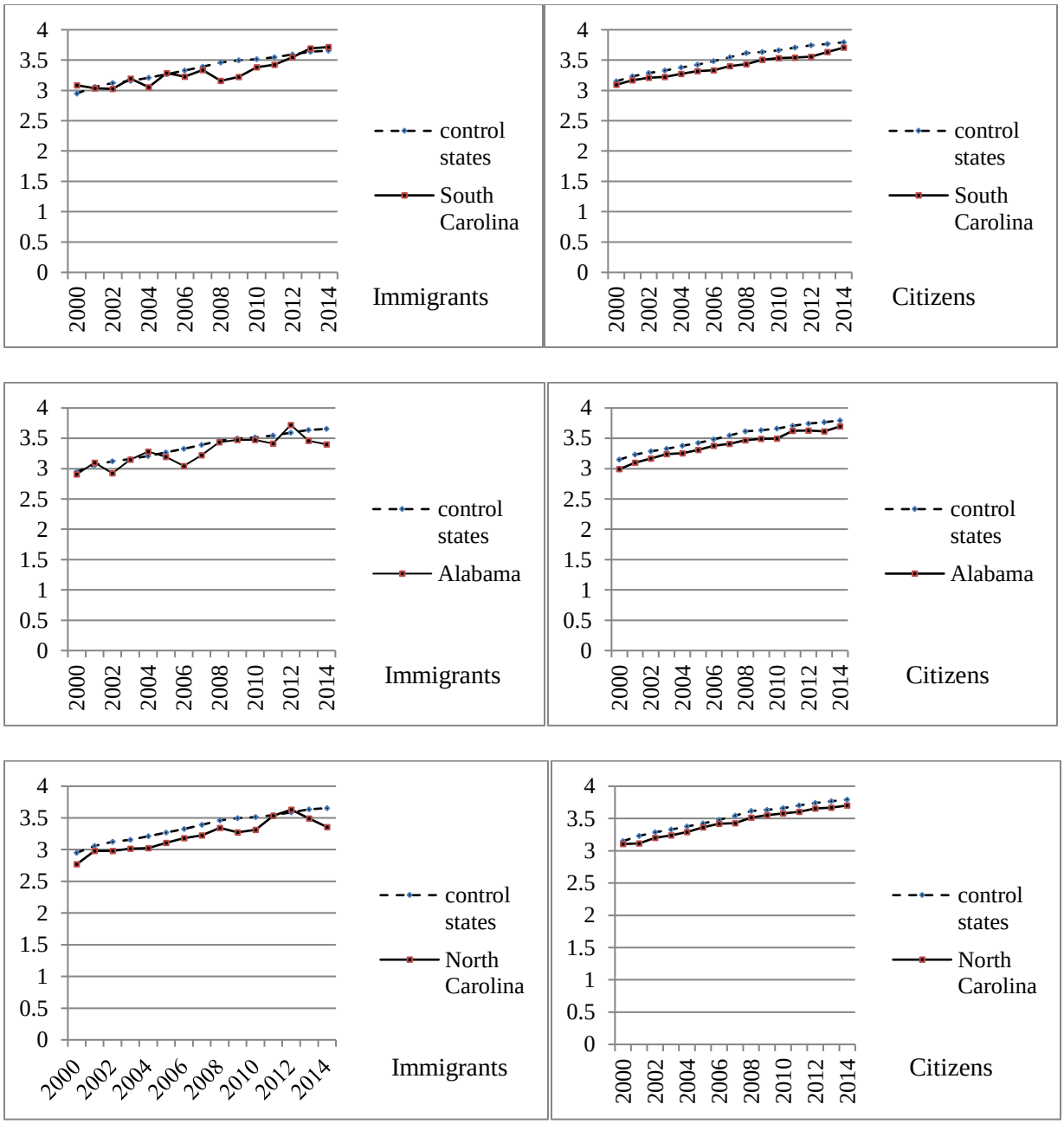


Figure 4.3: Difference in log hourly wage of U.S. immigrants and citizens

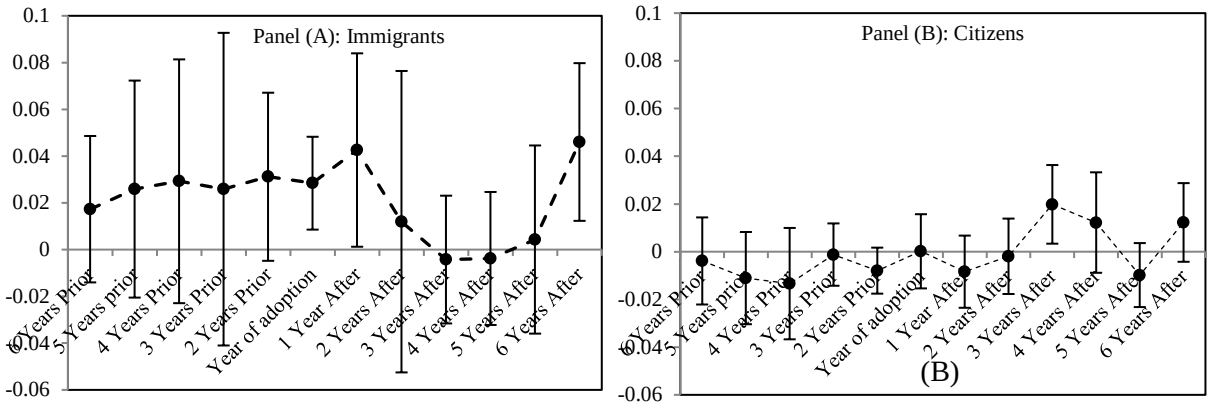
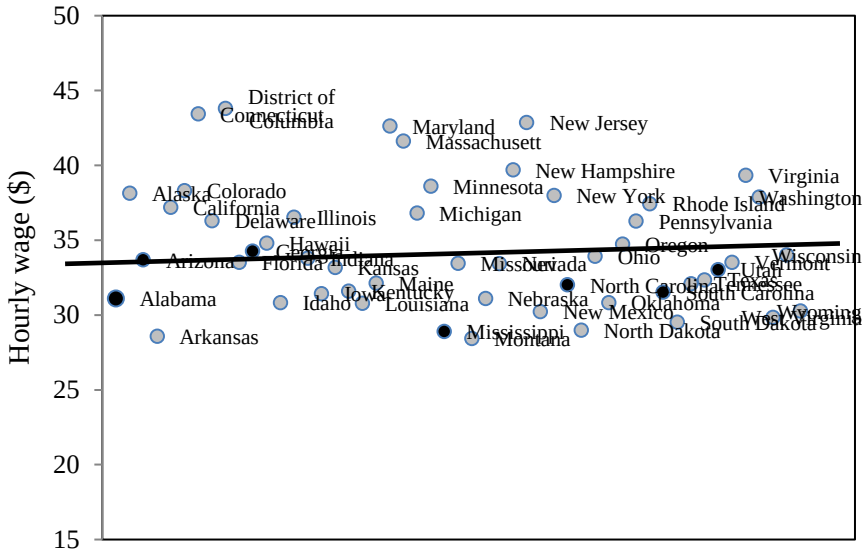


Figure 4.4: Differences of log hourly wages between treated and untreated states: Immigrants and Natives



Source: Graphics based on the ASEC sample from year 2000 to 2007

Figure 4.5: Average hourly wage in states with and without E-verify adoption: 2000-2007

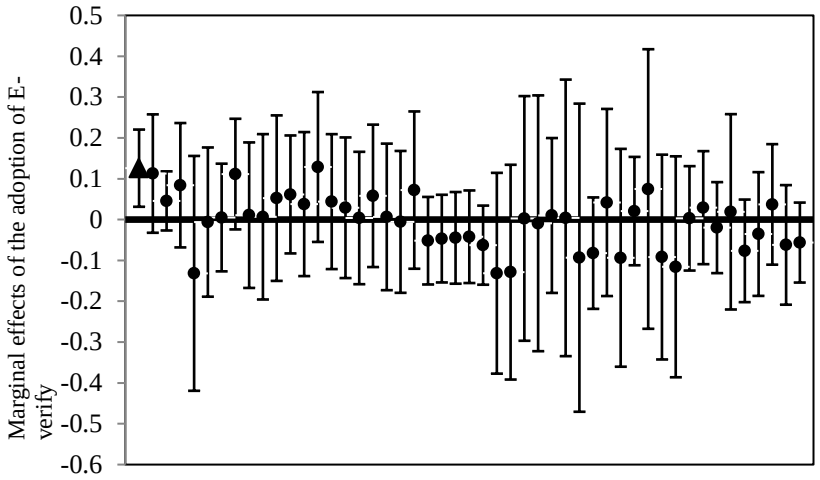


Figure 4.6: Marginal effects of placebo year of policy change: 2000-2007

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CHAPTER 5

SUMMARY AND CONCLUSIONS

This study examines three related topics in U.S. farm and immigrant labor markets by studying the health care use and employment time allocation of farm workers as well as the wages of immigrants. A variety of econometric methods, such as probit model, multinomial logit model, and Difference-in-Differences model, as applied in three chapters. Given the common background shared by three chapters, each one has unique primary objectives. The first chapter examines the health care use rate difference between documented and undocumented farmworkers and looks for the factors that affect the use gap between these two groups; the second chapter explored the time allocation decisions of farmworkers in the background of tightened immigration enforcement and economic recession; the third chapter looks at the wage change of native and immigrant workers in the U.S. due to the stringent immigration enforcement and try to evaluate the welfare loss of native and immigrant workers due to immigration policies.

This the first chapter investigates several facets of the health care utilization issue among farm workers of varied legal statuses. The empirical issues addressed include the determinants of the farm workers' overall utilization of health care services, their specific choices among several health care provider options, and their choices of the method(s) of payment for settling bills for their health care treatments. This chapter's results indicate that undocumented hired farmworkers have a statistically lower probability of using health care compared to documented workers. This is easily attributed to, among other things, their undocumented status, limited English speaking and reading proficiency, and low average income. Moreover, the Personal

Responsibility and Work Opportunity Reconciliation Act of 1996 policy and other similar restrictive policies adopted by federal and local governments would further limit the health care service utilization of immigrant hired farmworkers.

The first chapter thus draws attention to the need for a re-examination of existing restrictions on health care use of immigrants hired farmworkers as well as the effectiveness of promoting the public safety net services in the U.S. The farm sector continues to rely on immigrant workers to supply labor inputs for the more taxing farm tasks shunned away by domestic residents with a wider range of employment options. As this trend of immigrant labor dependence persists, it is, therefore, imperative to assist the farm sector in ensuring the demands of health care from hired farmworkers are met for the sake of maintaining a healthy, able, and reliable workforce that can supply the economy with its growing needs.

The second chapter has provided important empirical evidence on the determinants of employment decisions of farm workers under different legal immigration statuses. In general there seems to be a diminished interest in working in agriculture among workers with flexible employment options. Specifically, the predicted value of proportion of weeks devoted to farm work indicates that green card holders tend to spend the least proportion of workweeks to agricultural employment among all three farm worker categories. In contrast, undocumented workers have registered a higher workweek allocation rates in favor of farm work. This study's results indicate that the length of experience accumulated in farm work has influenced workers to remain employed in the farm and even increase their workweek allocation to farm jobs instead of switching to non-farm employment. Such retention effect, however, would diminish as the years of farm work experience accumulate. This result has been duplicated among groups of documented farm workers (citizens and green card holders).

This chapter's findings therefore clarify that the contention that the farm sector subsists primarily on foreign workers for its seasonal farm labor requirements should be made with caution and qualification. This chapter's findings suggest that such reliance only holds among farm workers whose undocumented status restricts their social visibility, mobility and job choices. In the absence of a more comprehensive dataset that traces the historical immigration path of foreigners granted permanent residence status (isolating those that previously held valid, unexpired visas from amnesty grantees and other illegal residents with undocumented status), this chapter's findings on the farm work allocation behavior noted among green card holders could lend some support to the legal status argument in farm workweek allocation behavior. These results can therefore imply that efforts to legalize the immigration status of undocumented aliens (such as the recent presidential amnesty grant in 2014) could only possibly lead to a diminishing supply of labor for the farm sector.

The widespread adoption of the federal E-verify system across several U.S. states has attracted a lot of attention. In addition to efficiently reducing the population of undocumented immigrants (Bohn, Lofstrom and Raphael 2014), E-verify is also expected to affect other cohorts, such as natives and legal immigrants, in terms of their employment opportunities and wages. Previous literature has studied the impacts of E-verify on the labor market outcomes of natives and immigrants at an aggregate level (Bohn, Lofstrom and Raphael 2015; Hotchkiss, Quispe-Agnoli and Rios-Avila 2015; Orrenius and Zavodny 2015). The third chapter contributes to the literature by estimating the impact of E-verify on wages of natives and immigrants by industrial groups and educational levels, providing evidence of the wage changes for the groups (low educational and skilled natives and immigrants) that directly compete with undocumented workers.

Findings of this chapter suggest that, on average, immigrants are more responsive to the adoption of E-verify than their native counterparts. Specifically, immigrants who are high school dropouts in manual industry experience a significant decrease of approximately 5.5% in their wage. On the contrary, the wages of immigrants who are high school graduates and work in service and retail trade industry increase after the adoption of universal E-verify mandates. However, the wage impact on immigrant population quickly fades away in two years after E-verify was adopted. Our findings provide evidence that the wage impacts of E-verify vary across industrial and educational groups, and have different responses according to the complementarity and substitutability between the population of undocumented immigrants and other cohorts, as well as the degree of dependence on undocumented immigrants of a particular industry. However, this article does not find significant wage impact of E-verify imposed on native workers in the U.S., even for natives who work in manual and service industry who are expected to be affected to a larger extent.