THE EFFECTS OF E-VERIFY ON THE SHARE OF LABOR INTENSIVE AND CAPITAL INTENSIVE CROPS: EVIDENCE FROM FARM LEVEL DATA

by

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(Under the Direction of Genti Kostandini)

ABSTRACT

Immigration enforcement policies, such as E-Verify have a negative effect on the supply of farm labor. There is a growing literature that finds that agricultural producers are facing a shrinking labor supply and fewer studies examine how agricultural producers are adjusting to having less labor. This study examines how a shrinking labor force affects agricultural production decisions, specifically in terms of which crops to produce. We use state level E-Verify enforcement laws as a quasi natural negative labor shock. With less labor it is more challenging for agricultural producers to produce labor intensive crops which do not have available technology to substitute for labor. We find that in states that have enforced “strong” E-Verify laws, production of labor intensive crops decline and there is an increase of capital intensive crops. Based on our results, the opposite is true for “weak” E-Verify states.

INDEX WORDS: E-Verify, Immigration laws, Difference-in-Differences

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CHAPTER 1

INTRODUCTION

The United States agricultural sector relies heavily on the supply of immigrant workers for labor, especially undocumented workers. About 70 percent of farm workers are immigrants, and 50 percent of farm workers are undocumented immigrants according to the United States Department of Agricultural Economics Research Service (USDA ERS, 2018). However, recent research shows that this abundance of labor has declined, and the supply of labor is becoming more inelastic, forcing farmers to produce with fewer workers (Taylor et al., 2012; Kostandini et al., 2013; Ifft and Jodlowski, 2016; Watson, 2013; Hertz and Zahniser, 2013). The dependence of agriculture on immigrant labor has risen to a topic of debate when discussing immigration reform laws, promoting more research on the effects of immigration laws. Research indicates that local immigration enforcement laws have a negative impact on immigrant populations within the region of enforcement (Kostandini et al. 2013; Orrenius and Zavodny 2016; Bohn at al. 2014). The decline in the immigrant population from immigration enforcement laws has resulted in a decline of total farm workers (Luo et al. 2018; Kostandini et al. 2013; Ifft and Jodlowski 2016).

Although previous research does support a shrinking farm labor supply, it is still unclear how agricultural producers are adjusting. The alternative that is the most feasible for agricultural producers facing a labor shortage, at least in the short-term, is shifting to the production of capital intensive crops. This would be an option for producers of labor intensive crops, like fruits and vegetables. Other potential substitutes for migrant labor are; mechanization or native workers. However, studies have shown that both are at most partial substitutes for fruit and vegetable production (Ifft and Jodlowski, 2016; Luo et al., 2018). Mechanization has the potential to improve efficiency and reduce the costs of production, as it has been the solution for many agricultural producers when faced with a labor shortage. However, mechanization is not feasible for the production of most fruits and vegetables. This is in part due to high costs and also to available technology which is currently not able to handle crop harvesting properly to substitute for labor to a large degree. Fruits and vegetables can be challenging for machinery to handle because of inconsistent shapes and textures and sensitivity of crop to damage (Blanes et al., 2011). The harvesting process for fruits and vegetables is still far from becoming automated and still requires hand picking. As for native workers, previous studies show that native workers are mostly unwilling to be farm workers, even with a wage increase (Ifft and Jodlowski, 2016; Zahniser et al., 2012). Some native workers would enter the farm labor supply due to the decline of migrant workers, but not enough to compensate for the loss (Luo et al., 2018). A study conducted by the American Farm Bureau Federation assessed the impacts of eliminating entire access to immigrant workers for agricultural production and found that producers would have to increase wages between 16 and 47 percent to attract new workers. Increasing wages to attract new workers, however, would increase overall expenses to agricultural producers. This increase could decrease their competitiveness in the global markets or force them out of the industry (Levine, 2009; American Farm Bureau Federation, 2006).

Since there is currently no complete substitute for the loss of migrant workers, changing to a capital intensive commodity is the most feasible alternative for an agricultural producer, at least in the short run. For the average farm size in the United States, labor expenses account for 17 percent of total production expenses (Zahniser et al., 2012). However, if the farm produces fruits or vegetables, labor expenses are much higher. For farms producing fruits, labor expenses account for 48 percent of total production expenses and for farms producing vegetables, labor accounts for 35 percent of total production expenses (Zahniser et al., 2012). As a result, a decline in the supply of workers would negatively affect fruit and vegetable producers the most, giving them higher incentives to change their crop production choice. Switching to capital intensive crops would decrease labor expenses significantly. For agricultural production of capital intensive crops such as corn or soybeans, labor expenses account for only between 5 and 6 percent of their total expenses (Zahniser et al., 2012).

To our knowledge, there has not been a study that explicitly looks at crop share changes from immigration enforcement policies or any study that has looked at crop share effects from E-Verify laws at the state level. E-Verify is an online federal program that allows employers to verify their employee's legal authorization to work in the United States using U.S. Department of Homeland Security (DHS) and Social Security Administration (SSA) records. There is a lack of research about the impacts of E-Verify, especially within agriculture. This study examines the effects of a scarce labor supply on agricultural production decisions, using the enactment of state level E-Verify laws as a, well documented, natural negative labor shock. This study is the first to assess the crop share impacts from state-level E-Verify laws. The assumption to be tested is that with less labor available farmers will adjust by producing more capital intensive crops. Due to the importance of immigrant workers for agricultural production, policy makers could benefit from studies that focus on how farmers are adjusting due to E-Verify laws and how it could potentially affect the productivity and competitiveness of the US agricultural industry.

CHAPTER 2

BACKGROUND ON IMMIGRATION LAWS IN THE UNITED STATES

Immigration enforcement began to be a more important topic in the US policy in the 1990s when the undocumented immigration population was growing at a very fast rate, about 500,000 people per year (Passel, 2002). The public saw the population growth as a problem, with many believing immigrants arrived in the United States to seek welfare and public assistance benefits (Pantoja, 2006). In response, the federal government enacted the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA), strengthening United States immigration enforcement laws. The IIRIRA made deportation of undocumented immigrants easier and made legal immigration more challenging. IIRIRA also strengthened the ability of local law enforcement at the county, city and state level to pass and enforce immigration laws, enabling states, counties and localities to enter 287(g) agreements with U.S. Immigration and Customs Enforcements (ICE) and also enforce E-Verify. 287(g) agreements authorize trained law enforcement officers to enforce federal immigration laws such as, detaining undocumented immigrants, investigating individuals to determine their legal status, etc. E-Verify is a federal program that allows employers to electronically verify whether their employees are legally able to work in the United States using a federal database of worker eligibility. Under federal law E-Verify is volunteer-based only according to the United States DHS and United States Citizenship and Immigration Services (DHS and USCIS, n.d.).

Although IIRIRA was enacted in 1996, the first 287(g) agreement was not signed until 2002, with the Florida Department of Law Enforcement. By 2010, there were 70 agreements between ICE and either a state, city or county law enforcement (Gelatt et al. 2017). The intention of 287(g) agreements is to reduce the population of undocumented immigration, with deportation, while E-Verify is used to reduce undocumented immigrants in the workforce. Due to lack of action or enforcement of immigration policies like E-Verify by the federal government many states began to pass their own legislation to enforce immigration laws. In 2008, Arizona became the first state to enforce the use of E-Verify. It was required to be used by all employers, private or public without exceptions starting January 1, 2008. Arizona is considered to have one of the strictest state level E-Verify laws. The Arizona law was challenged in the Supreme Court but was upheld in 2011 (Feere, 2013). After this ruling, many more states began to embrace the use of E-Verify and enacted their own laws to enforce it. It became a common policy method used by states wanting to limit the undocumented immigration population in the workforce, in hopes of improving the labor market for legal residents. By 2012, 20 states had some policy to require the use of E-Verify for employment of at least some employees in the public or private sector or both. Most of these states only require the use of E-Verify for public sector employees (Feere, 2013).

Since agriculture is part of the private sector, only states that require the use of E-Verify in the private sector will be the focus of this study. There is a total of 7 states that require all or some private sector employers to use E-Verify. Only 3 of these states require it by all employers with no exceptions and no phase in period. These states are; Arizona, Alabama, and South Carolina. The 4 other states, Georgia, North Carolina, Mississippi and Utah require the use of E-Verify by most private employers with some exemptions, a phase in period, or both. (Feere, 2013). In Georgia, Utah, and North Carolina a private business under a certain number of employees is exempted from being required to use E-Verify, offering a “loophole”. More specifically, in Georgia private businesses with less than 10 employees are not required to use E-Verify and all private businesses that do not meet the exemption are required to use E-Verify on all of their employees. Utah requires employers with 15 or more employees to use E-Verify and North Carolina requires E-Verify for employers with 25 or more employees (Feere, 2013). These "loopholes" would cause less disruption to the agricultural industry especially to smaller farms. North Carolina also included an exemption for seasonal workers, with the explicit intention of minimizing disruption to the agricultural industry. As of 2013, North Carolina employers do not have to use E-Verify to verify the legal eligibility of workers that are employed for less than 9 months of the year. Prior to 2013, starting in 2011 North Carolina employers did not have to verify legal work eligibility of employees that work less than 90 days of the year (Feere, 2013). Although Mississippi currently does require the use of E-Verify by all private employees it is classified as a "weak" E-Verify states in the study because the state E-Verify law included a phase in period giving more time for agricultural producers to adjust. More specifically, the Mississippi law to enforce E-Verify was enacted in the beginning of 2008 and was first enforced on July 1, 2008. However only Mississippi employers with 250 or more employees were required to use E-Verify by July 1, 2008. By July 1, 2009 employers with 100 or more employees were required to use E-Verify for all employees. The phase in period ended in July 1, 2011 by which all employers regardless of the number of employees were required to use E-Verify. Information regarding current state-level E-Verify laws and the corresponding year enforcement began for each state can be found in Appendix 1.

CHATPER 3

LITERATURE REVIEW

There is some evidence from recent literature that labor intensive crop production declines in response to a decline in the undocumented immigrant population but not on E-Verify. A study by Ifft and Jodlowski (2016) found evidence of a decrease in vegetable production in United States counties that implemented 287(g) immigration enforcement policies. 287(g) policies at the county level have negative effects on the undocumented immigrant population (Kostandini et al., 2014; Ifft and Jodlowski, 2016). They used restricted United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS) farm level data and found an average of a 59 acre decline of vegetable production in the counties that enforced 287(g) policies. Not only was vegetable production on a decline but also total acres operated in a county with 287(g) policies declined by over 2,500 acres. The decline in acres operated was combined with a loss of 2,789 workers at the county level. Ifft and Jodlowski (2016) focused on the impacts of 287(g) policies at the county level which would have smaller cumulative impacts than E-Verify laws at the state level. Ifft and Jodlowski (2016) evaluated 50 counties that implemented 287(g) policies, while E-Verify impacts the entire state. The State of Alabama alone has 67 counties while Georgia has 159 counties.

A study conducted by the USDA Economic Research Service (USDA ERS) found similar results that support a decline in labor intensive crops in the presence of a decline in undocumented immigrant workers (Zahniser et al., 2012). The study used a General Equilibrium model to conduct a simulation of a scenario of a decline in the number of undocumented workers. The decline in undocumented workers was assumed to be caused by an unspecified policy change and was implemented in the simulation by changing the preferences of undocumented workers. The simulation was a 15 year projection that was compared to a 15 year base forecast, both beginning in 2005. The base forecast reflected the present immigration policies and laws in 2005. The study found that by year 15 of the simulation the population of undocumented workers (farm and nonfarm) had 5.8 million less workers compared to the base forecast, a decline of 40 percent in all sectors of the economy, including agriculture. The decline in undocumented workers resulted in a decline between 3.4 and 4.8 percent of farm workers. With less workers, there was a decline of agricultural output and exports, with labor intensive crops being negatively affected and to a greater extent than capital intensive crop production. Labor intensive crops such as fruits, tree nuts, vegetables, and nursery crops saw a long run decline between 2.0 and 5.4 percent in output and between 2.5 and 9.3 percent decline in exports depending on the sector. Capital intensive crops also experienced a decline, but a smaller one between 1.6 and 4.9 percent in output and between 0.2 and 7.4 decline in exports.

A similar study conducted by the Economic Analysis Team of the American Farm Bureau Federation (2006) assessed the impact to the agricultural sector from the loss of access to immigrant farm workers. The study found there would be significant economic losses to American agricultural producers from loss of access to immigrant farm workers. Their results found an estimated loss of farm income between $2.5 and $8 billion in the long-run to the US agricultural sector. The study states that the entire agriculture sector will face loss of income from higher costs and less production, with between $6.5 and $12.0 billion lost in production in the long-run and cost increases between $3.0 and $9.0 billion in the long-run. The largest impact would be faced by fruit, vegetable, nursery, and industrial livestock producers, all of which are labor intensive productions. They estimated that between 10 and 20 percent of the production of labor intensive commodities would shift to other countries. In this study they make the assumption that there would be no readily available substitute to migrant labor, such as native workers or mechanization. The study uses data from the United States Department of Agriculture (USDA) and Department of Labor (DOL). The previous two studies used simulation models to assess the impacts to the entire United States agriculture sector, rather than where immigration enforcement policies are present. Based on the previous studies there is a clear negative effect to agriculture when the supply of labor shrinks, especially to producers of labor intensive crops such as fruits and vegetables.

Since the enactment of E-Verify at the state level there has been research to evaluate the effectiveness of the policy. Previous research indicates that E-Verify is effective at reducing the undocumented immigrant population and reducing the employment rate of undocumented workers (Bohn et al., 2014; Bohn and Loftson, 2013; Orrenius and Zavodny, 2016; Luo et al., 2018). Some of these studies evaluated all E-Verify states, while it is also common for E-Verify research to focus on the impacts from E-Verify solely in the state of Arizona, the first state and one of the strictest to enforce it. When E-Verify was first enforced in Arizona it was part of an immigration enforcement legislation in Arizona called the 2007 Legal Arizona Workers Act (LAWA). LAWA was created to enforce the use of E-Verify to eliminate the hiring of knowingly undocumented workers. Due to the sensitivity of information regarding a person's legal status, most researchers have classified “likely undocumented workers” as: less-educated (high school education of less), prime working age (under 45), non-US citizen immigrant from Mexico and Central America. Studies by Bohn and Lofstrom (2013) and Bohn Lofstrom, and Raphael (2014) found the state level E-Verify law in Arizona to be very effective in reducing the number of undocumented workers. Both studies focused on Arizona and impacts from LAWA and used a synthetic control approach and difference-in-differences models. Bohn and Lofstrom (2013) found an 11 percent decline in the employment of undocumented workers in Arizona from the enforcement of LAWA in Arizona. Bohn, Lofstrom, and Raphael (2014) found a 17 percent decline in the undocumented population in Arizona that aligned with the timing of E-Verify enforcement and the decline was driven by those that are prime working age and are low-skilled workers. Both studies used monthly Current Population Survey data.

The main focus in the study by Orrenius and Zavodny (2016) was to examine the effects of E-Verify across states on the likely undocumented immigrant population. To conduct their study, they used 2005–2014 American Community Survey (ACS) data. Using the common classification of "likely undocumented workers", they find that E-Verify has a significant negative effect on the undocumented immigrant population within a state, with immigrants that arrived between 1 to 5 years ago being mostly negatively affected. Based on their results, they suggest that the population of immigrants that arrive 1 to 5 years ago falls by almost 40 percent in a state that had E-Verify law in effect for the entirety of the previous year, indicating a small lagged effect. When restricting the data to likely undocumented men who are not married the number rises to a decline of 50 percent of the population.

Although there is a significant amount of research that focuses on the effects of state-level E-Verify policies, there is a clear lack of research focusing on the effects to the agricultural sector. To our knowledge a study by Luo, Kostandini and Jordan (2018) is the first study that exclusively looks at the effects of E-Verify to the agricultural industry. Their study focuses on the impacts of LAWA in the state of Arizona, on the farm labor supply among farm households, using difference-in-differences models and the Community Population Survey data from 2000 to

2010. They find that 2007 LAWA significantly increased the likelihood of farm family laborers to choose an agricultural occupation by 3 to 5.5 percent and on non-Hispanic farms the impact is an increase of 11 percent. Much of this is attributed to the decline in the availability of farm workers, most of which are likely undocumented. Their study finds that the share of farm workers that are likely undocumented decreased by about 7 percent in Arizona after the implementation of 2007 LAWA. However, there still is a gap in the research about the effects of E-Verify to the agricultural industry across states and how that affects the share of labor and capital intensive crops.

CHAPTER 4

DATA

This study uses the restricted version of farm level USDA ARMS data for the years 2000-2016. To our knowledge, there is no previous research that has used the USDA ARMS data to evaluate the effects from E-Verify. The USDA ARMS is conducted annually and is a nationally representative sample of farms within the 48 contiguous United States. The data includes the number of harvested acres for over 15 crops, including fruits and vegetables as well as descriptive variables about the farm and farm operator, such as age, gender, total gross cash farm income, and the state the farm is located in. The fruits and vegetables variables are both listed as such in ARMS and there is not a more specific classification for fruit and vegetable crops. Weights are included in the data but similarly to Ifft and Jodlowski (2016) weights are not used in this study, since they were created for single-year analysis.

Among the crops that are included in the ARMS data, only crops that are grown in any of the 7 E-Verify states are included in this study. We categorized the crops into five different groups based on the labor intensity of the crop and similarity among the crops. Groups 1, 2, 3 contain capital-intensive crops. Group 1 consists of barley, corn, oat, rice, sorghum, and wheat. Group 2 consists of potatoes, canola, and peanuts, and group 3 consists of hay, tobacco, and cotton. Groups 4 and 5, consist of fruits and vegetables, respectively, which are both labor intensive crops. Categorizing a crop as labor intensive is based on the percentage of labor expenses that account for total production expenses. Labor expenses for fruits and vegetables (Group 4 and Group 5) producers range between 35 and 48 percent of total expenses (Zahniser et al., 2012). Group 1 consist of the crops with the least labor expenses, with the range being approximately 5 and 10 percent of total expenses. For group 2 the range is a bit higher with peanut production requiring about 12 percent of expenses spent on labor. These are all below the average for a United States farm, which spends about 17 percent of expenses on labor (Zahniser et al., 2012). The only crop other than fruits and vegetables that is above the national average is tobacco, with 26 percent of total production expenses spent on labor. However, unlike fruit and vegetable production, most of the tobacco production process has been mechanized giving tobacco producers the option to increase mechanization in the wake of a shrinking labor supply to maintain production levels (Ellington, 2018). The main variables of interest in this study are; crop shares in group 1, group 2, group 3, group 4, and group 5. The groups were created by adding all the harvested acres of each crop in each respected group at the farm level and dividing the total by total harvested acres at the farm level. The total harvest acres variable is the total number of acres harvested on a farm. This creates a proportion of how much each group is harvested on a farm and represent the crop share of that group on the total farm harvested area.

Information regarding state level E-Verify laws and the year they were implemented was gathered from each state's official website regarding E-Verify. The information for each state was added to the data set with the creation of a dummy variable, "poste", which represents the years after E-Verify was adopted. We also expanded the scope of our research by evaluating the differences in the strictness of state level E-Verify laws, by creating two more dummy variables, posteweak and postestrong. Posteweak represents states with exemptions for private businesses in their E-Verify laws (Georgia, Utah, Mississippi and North Carolina). The states with weaker E-Verify policies may have less disruption to the agricultural industry, especially for small farms. Postestrong represents states that require all private employers to verify each employee's legal eligibility to work in the United States, with no exemptions or phase in period (Arizona, Alabama, and South Carolina). Control variables included in the regression analysis are the gender of the principal farm operator, education level of the principal farm operator, the total gross cash farm income, age of the principal operator, and total acres operated on the farm. A list and description of the variables included throughout the regression analysis can be found below in Table 1.

Table 1. Description of Variables.

Variable	**Description**
op_gen	gender of principal farm operator
op_educ	education level of principal farm operator
igcfi	total gross cash farm income
op_age	age of farm principal operator
tacres	total acres operated
group1	crop share of barley, corn, oat, rice, sorghum, wheat and soybeans
group2	crop share of potatoes, canola, and peanuts
group3	crop share of hay, tobacco and cotton
group4	crop share of fruits
group5	crop share of vegetables
poste	equals 1 if state has E-Verify policy
postestrong	equals 1 if state has E-Verify policy with no exemptions
posteweak	equals 1 if state has E-Verify policy with exemptions

Table 2, which is presented below, provides the summary statistics of all the variables found in Table 1. Based on Table 2, we see that capital intensive crops make up the majority of the crop share in the United States, with group 1 and group 3 accounting for the largest portions. Group 1 accounts for 46 percent of crop share and group 3 accounts for about 36 percent of crop share. Group 1 having the largest portion of crop share is as expected, as it contains corn and soybeans two of the major agricultural commodities grown in the United States. Group 3, having the second largest share is also as expected as it contains hay and cotton, which are also two major agricultural commodities in the United States. Group 2 which contains potatoes, canola, and peanuts has the lowest crop share among all crops with only 0.8 percent of the crop share. Among labor intensive crops Group 4 accounts for 7.5 percent of crop share, and Group 5 accounts for 2.5 percent of crop share. The proportions of crop share do not add up to 1.00 or 100 percent because crops that are not grown in any of the E-Verify states were not included in this study. Nursery crops were also excluded from the study.

Table 2. Summary Statistics of Variables.

Variable	**Description**	**N**	**Mean**	**Std. Dev.**
op_gen	gender of primary operator	320203	0.942	0.233
op_educ	education class of primary operator	324345	2.704	0.944
igcfi	total gross cash farm income ($)	324345	679,014	3,176,332
op_age	age of primary operator	324345	56.64	12.50
tacres	total acres operated	324345	1,208.95	6,269.65
group1	crop share of barley, corn, oat, rice, sorghum, wheat and soybeans	259263	0.461	0.434
group2	crop share of potatoes, canola, and peanuts	259263	0.00829	0.0632
group3	crop share of hay, tobacco and cotton	259263	0.357	0.420
group4	crop share of fruits	259263	0.0755	0.258
group5	crop share of vegetables	259263	0.0250	0.130
poste	equals 1 if state has E-Verify policy	324345	0.0556	0.229
postestrong	equals 1 if state has "strong" E-Verify policy	324345	0.0112	0.105
posteweak	equals 1 if state has "weak" E-Verify policy	324345	0.0456	0.209

In order to provide a better understanding of the agricultural industry in the states which are the focus of in this study, we provide tables that give summary statistics of crop shares in selected states. More specifically, Table 3 presents the summary statistics of crop share groups 1-5 in only the 7 states that have E-Verify enforcement in the private sector. Table 4 presents the summary statistics of crop share groups 1-5 only including the 4 states (Georgia, North Carolina, Mississippi and Utah) with “weak” state level E-Verify laws, and table 5 presents the summary statistics of crop share groups 1-5 with only the remaining 3 states that have “strong” state level E-Verify laws enforced (Alabama, Arizona, and South Carolina).

Comparing Tables 3-5 to Table 2, crop shares for group 1 and 3 still remain the largest portions of total crop share. However, based on Table 3, crops in group 3 are much more important to the agricultural industry in the E-Verify states, compared to the entire United States. This holds to be true in Table 4 and Table 5, for both “weak” and “strong” E-Verify states. The proportion of group 3 crop shares increases by about 0.20 across all Tables 3-5, compared to Table 2. The importance of group 3 makes sense, as cotton and tobacco have high production levels in the southeast United States, where many of the state level E-Verify laws are concentrated (USDA NASS). There is also a higher level of production of group 2 crops, which is mostly likely due to the importance of peanut and sweet potato production in E-Verify states. However, the crop share for group 2 is only about 3-5 percent higher compared to the entire United States. Among labor intensive crops, E-Verify states produce lower levels of both group 4 (fruits) and group 5 (vegetables) and this holds for both “strong” E-Verify states and “weak” E-Verify states, which can be seen in Tables 4 and 5. Fruits and Vegetables only account for about 5-7 percent of the crop shares in E-Verify states compared to 10 percent of the crop share in Table 2. Tables 3, 4, and 5 are presented below.

Table 3. Summary Statistics of crop shares in All E-Verify States.

Variable	Description	N	Mean	Std. Dev.
group1	crop share of barley, corn, oat, rice, sorghum, wheat and soybeans	12506	0.309	0.398
group2	crop share of potatoes, canola, and peanuts	12506	0.0405	0.126
group3	crop share of hay, tobacco and cotton	12506	0.548	0.432
group4	crop share of fruits	12506	0.0389	0.186
group5	crop share of vegetables	12506	0.0212	0.126

Table 4. Summary Statistics of crop shares in Weak E-Verify States.

Variable	Description	N	Mean	Std. Dev.
group1	crop share of barley, corn, oat, rice, sorghum, wheat and soybeans	10495	0.320	0.405
group2	crop share of potatoes, canola, and peanuts	10495	0.0348	0.113
group3	crop share of hay, tobacco and cotton	10495	0.546	0.434
group4	crop share of fruits	10495	0.0392	0.187
group5	crop share of vegetables	10495	0.0189	0.119

Table 5. Summary Statistics of crop shares in Strong E-Verify States.

Variable	Description	N	Mean	Std. Dev.
group1	crop share of barley, corn, oat, rice, sorghum, wheat and soybeans	2258	0.229	0.341
group2	crop share of potatoes, canola, and peanuts	2258	0.0629	0.169
group3	crop share of hay, tobacco and cotton	2258	0.592	0.418
group4	crop share of fruits	2258	0.0346	0.173
group5	crop share of vegetables	2258	0.0304	0.151

CHAPTER 5

METHODOLOGY

In order to examine the effects of state level E-Verify laws on the share of capital intensive and labor intensive crops, a difference-in-differences (DID) model is used. More specifically, a DID model is used to determine if there is a change in crop shares of groups 1-5, before vs. after the enforcement of state level E-Verify laws, and if a change is present whether it is statistically significant. In order to assess the impact of state-level E-Verify, a dummy variable "poste" was created. A value of 1 or 0 is given to the variable poste. A 1 indicates that E-Verify is enforced in the state where a farm is located. This is assigned to all farms in a state the year E-Verify became enforced in the state and it is 1 as long as E-Verify is active. The year E-Verify began to be enforced in each E-Verify state along with a description of the law can be found in Appendix 1. A 0 for poste indicates E-Verify laws are not present at the time. States that never enforce E-Verify laws in the private sector act as control states. The use of poste captures the effect of a reduction of immigrant labor on the crop share for each group within an E-Verify state. The model below is estimated to determine these effects:

$$Group_{istf} = \alpha + \beta_1 PE_{st} + \beta_2 X_{stf} + \delta_t + \theta_s + \varepsilon_{istf} \qquad (1)$$

In model 1, PE_{st} is the dummy variable poste, $Group_{istf}$ represents the crop share group, and X_{stf} is a vector of control variables, which are listed in Table 1. For the variables in the model, *i* indicates which crop share group is tested, *s* represents the state, *t* represents the year, and *f* represents the individual farm. In the model, δ_t is the year fixed effect and θ_s is the state fixed effect. State and year fixed effects are important for unbiased results, more specifically for eliminating some of the effects of omitted variable bias. Since the data we are using is cross sectional data over time, we must control for unobserved effects that are attributed to changes over time and would impact all the states equally, such as an economic recession or inflation. State fixed effects control for any unobserved factors that differ across states. It controls for any effects across states and focuses on the effects within states (Pham and Van, 2010). Controlling for both year and state fixed effects is important to isolate the effects of E-Verify. Model 1 is estimated 5 times, once for each group 1-5. The coefficient of poste (β_1) is the main focus of the results. The coefficient of poste represents the change in crop share for the group of interest in the regression after the implementation of state level E-Verify laws.

As discussed previously, E-Verify laws are not the only laws being enacted by local governments to enforce immigration. 287(g) agreements have been used to control immigration and have a negative effect on immigrant population (Kostandini et al., 2013; Ifft and Jodlowski, 2016). In order to isolate the effects of state level E-Verify laws we included a dummy variable for county level and state level 287(g) agreements in the regression. Data regarding 287(g) agreements at the state and county level were downloaded from the ICE (United States Immigration and Customs Enforcement, 2017). We also included a dummy variable for immigration raids at the county level, as raids can also have a negative impact on the undocumented immigrant population from direct deportation and indirect signals deterring immigrants from residing in the area where the raid took place in. The main purpose of an ICE raid is to detain and deport undocumented immigrants. Raids can occur either at someone's home or at a worksite. Worksite raids became an increasing popular tactic used by ICE in the mid 2000s (Capps et al., 2007). The data on immigration raids was gathered from an extensive search of online news reports.

In order to differentiate between the strictness of state level E-Verify laws, as mentioned we also created dummy variables for the strictness of E-Verify laws (posteweak and postestrong). To determine the effects of "strong" vs. "weak" E-Verify laws from a shrinking labor force, on crop share production the following model is estimated:

$$Group_{istf} = \alpha + \beta_1 PW_{st} + \beta_2 PS_{st} + \beta_3 X_{stf} + \delta_t + \theta_s + \varepsilon_{istf} \qquad (2)$$

In model 2, the fixed effects and control variables are the same as those used in model 1. In model 2, PS_{st} is a dummy variable that equals 1 when a farm is located in a state that has enforced "strong" E-Verify in a specific year and equals 0 if "strong" E-Verify laws are not present. PW_{st} is also a dummy variable that equals 1 when a farm is located in a state that has enforced "weak" E-Verify in a specific year and equals 0 if "weak" E-Verify laws are not present. As mentioned, Arizona, Alabama, and South Carolina enacted "strong" E-Verify laws while Georgia, North Carolina, Mississippi, and Utah enacted weak E-Verify laws. Model 2 also was estimated 5 times, for each crop share group. The coefficient of postestrong (β_1) and posteweak (β_2) is the main focus of the results. The coefficient of PS_{st} represents the change in crop share for the group of interest in the regression after the implementation of "strong" state level E-Verify laws and the coefficient of PW_{st} represents the same after the implementation of "weak" state level E-Verify laws.

The most important assumption of a DID model is the parallel trends assumption and this assumption must hold for valid results. The parallel trends assumption states that in the absence of treatment, the difference between the control group and treatment group would be constant over time. More specifically, the trends of crop shares among the control states and E-Verify states must be the same prior to the passage of E-Verify. Once the intervention, or passage of a law in this case is imposed, changes in the trends of crops shares that differ between the control and treatment groups can be attributed to the impacts of E-Verify, controlling for state and year fixed effects and other control variables. A method to test whether the parallel trends assumption is satisfied is to check for pre trends. Prior to the use of E-Verify laws there should be no differences in the trends of crop share in the control states and treatment states. More specifically there should be no statistical significance changes in the share of crop groups between treatment and control states from one year to the next until the passage of the law. Once E-Verify is imposed on states, if an impact is present, there would be statistical significance changes in crop shares in E-Verify states compared to the control states. A pre trend analysis is included in this study. To test the trends of crop share leading up to the enforcement of E-Verify, we use leads and lags. We create a dummy variable to represent each year before and after the enforcement of the laws for each year 5 year before and 5 years after the enforcement of the law. Thus, 5 dummy variables were created for the 5 years before the law, and 5 dummy variables for the 5 years after the enforcement of E-Verify. The year E-Verify began to be enforced in a state is the base year. For example, this is how the dummy variables were created. If there was a 1 for the dummy variable "1 year before the law," this means the year that farm level observation was taken was the year before E-Verify began to be enforced. If there is no significant difference between trends of a crop share group in the control and treatment groups before the enforcement of the law, we can a assume the parallel trends assumption holds. Pre trend analysis was done for model 1 and model 2. For model 2, pre trend analysis was only completed for the "strong" E-Verify states and would only validate results for Post Strong E-Verify.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 Results

We present and discuss several sets of results of the DID model. First, we present the results of model 1 in Table 6 which shows the coefficient of the variable poste for each crop share group which includes all farms shares. Based on the results from the DID models. For each group E-Verify appears to have some effect on agricultural production decisions, due to a well documented reduction of labor supply. However, it does not fully align with our original hypothesis. Our original hypothesis was that there would be a decline in labor intensive crops (group 4 and 5) and an increase in capital intensive crops (group 1, 2, and 3). The results show that there is no statistically significant change to crop share groups 3 or 5. Surprisingly, there is a (weakly significant) increase of fruit production (group 4) a labor intensive crop group, an increase of 0.0038 or .38 percent. There is also an increase of .0095 or .95 percent for crop share group 2 a capital intensive crop group, which aligns with our hypothesis. However, for group 1, which is also a capital intensive crop group, E-Verify states experience a 0.0081 or .81 percent decline in group 1 crops which is significant at the 10 percent level. Since group 1 and group 2 have opposing results it is still unclear what are the effects of state level E-Verify laws on capital intensive crops. Overall, there does not seem to be a clear trend of the effects of E-Verify on capital intensive and labor intensive crops, based on Table 6. The results in Table 6 do not include state specific trends, only account for year and state fixed effects. This is also true for the remainder of the results, when “strong” and “weak” E-Verify states are compared and the Arizona case study as well. The Arizona case study examines the effects of E-Verify in the western US, more details and discussion are found further in the paper.

Following each set of regression results we present them results of the leads and lags specification of the regression. Pre trend analysis is conducted to determine if the parallel trends assumption holds and ultimately if the DID results are valid. The leads and lags results for model 1 in Table 6 are presented in Table 7. Based on Table 7, the results for group 1 in Table 6 should be interpreted with caution as there seems to be a pre trend. There is significant change in crop shares in group 1 most years prior to the enforcement of E-Verify. This implies group 1 did not have the same crop share trend and violates the parallel trend assumption that is necessary for a DID model to work properly. The results for group 2 and group 4 can be considered valid. For group 2 there is actually a trend reversal which provides some support of the results. For group 4 in the 3 years prior to the enforcement of E-Verify only one year shows a significant difference in the trends of crop share between E-Verify and control states, however it is weakly significant. This suggest the treatment and E-Verify states have a similar trend in the share of group 4 crops, the necessary parallel trends assumption holds. However, results in Table 6 for group 4 are weakly significant. Overall, it appears that generally E-Verify states increase the production of capital intensive crops.

Table 6. DID Regression Results of All E-Verify States Including All Farms with Production in Groups 1-5.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
Post E-Verify	-.0081*	0.0095***	-.0048	0.0038*	-.0010
	(0.0046)	(0.0013)	(0.0051)	(0.0023)	(0.0016)
Obs.	255252	255252	255252	255252	255252
R^2	0.3277	0.0843	0.2174	0.3489	0.0412

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

Table 7. Leads and Lags for all E-Verify States Including All Farms with Production in Groups 1-5.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
5 Years Before Law	0.0642***	0.0058**	-.0480***	-.0133***	-.0023
	(0.0081)	(0.0025)	(0.0091)	(0.0036)	(0.003)
4 Years Before Law	0.0501***	0.0043*	-.0473***	-.0123**	0.0039
	(0.0084)	(0.0024)	(0.0096)	(0.0049)	(0.0037)
3 Years Before Law	0.0759***	0.0032	-.0830***	0.0004	-.0049
	(0.009)	(0.0022)	(0.01)	(0.004)	(0.003)
2 Years Before Law	-.0204**	-.0074***	0.0362***	0.0079*	-.0050
	(0.0096)	(0.0023)	(0.011)	(0.0047)	(0.0034)
1 Year Before Law	0.0124	-.0049**	-.0024	-.0022	0.0048
	(0.0088)	(0.0023)	(0.0102)	(0.0041)	(0.0035)
1 Year After Law	0.0218**	0.0249***	-.0512***	-.0021	0.0072**
	(0.0089)	(0.0033)	(0.0102)	(0.0043)	(0.0036)
2 Years After Law	0.0727***	0.0045	-.0682***	-.0030	-.0003
	(0.0087)	(0.0029)	(0.0098)	(0.0045)	(0.0032)
3 Years After Law	0.0483***	0.014***	-.0561***	-.0021	-.0068**
	(0.0086)	(0.0028)	(0.0098)	(0.0047)	(0.0029)
4 Years After Law	-.0127	0.0059	0.0078	0.0019	0.004
	(0.0117)	(0.0042)	(0.0133)	(0.0062)	(0.004)
5 Years After Law	-.0165	0.0008	0.0315**	0.0087	-.0019
	(0.0129)	(0.0041)	(0.0144)	(0.0071)	(0.0035)
Obs.	255252	255252	255252	255252	255252
R^2	0.3283	0.0857	0.218	0.349	0.0413

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

However, as discussed state level E-Verify laws vary in strictness, and we estimate model 2 to differentiate between “strong” E-Verify laws with no exemptions, versus “weak” E-Verify laws that offer some exemptions for some private businesses with respect to the number of employees. Table 8 presents these results where the coefficient for postestrong and posteweak are reported for each crop share group. Based on the results from Table 8, our hypothesis generally holds for states that enforce E-Verify laws with no exemptions or phase in period, i.e. “strong” E-Verify states.

Results in Table 8 suggest that “strong” E-Verify states experience a .0105 or 1.05 percent decline in the share of fruit production (group 4), which is labor intensive, as our hypothesis expects. Vegetable production (group 5) which is also labor intensive, did not have a statistically significant change. Combined with a decline of fruit production, “strong” E-Verify states experience an increase in capital intensive crop share groups 1 and 2. The crop share for group 1 increased by 0.0215 or 2.15 percent, and the crop share for group 2 increased by 0.026, or 2.6 percent. Surprisingly, the share of group 3 declined by 0.0456 or 4.56 percent in strong E-Verify States. This is a surprise since group 3 consist of capital intensive crops (hay, tobacco and cotton). However, tobacco production has experienced significant decreases in the US and farmers are trying to move out of tobacco production. So, results in group 3 should be interpreted with caution.

Table 8. DID Regression Results of Strong and Weak E-Verify States.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
Post Strong E-Verify	0.0215**	0.026***	-.0456***	-.0105**	0.0016
	(0.0089)	(0.0042)	(0.011)	(0.0049)	(0.0041)
Post Weak E-Verify	-.0178***	0.0035**	0.0104*	0.0069***	-.0016
	(0.0049)	(0.0014)	(0.0055)	(0.0024)	(0.0017)
Obs.	255252	255252	255252	255252	255252
R^2	0.3278	0.0846	0.2174	0.349	0.0412

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

While the results from "strong" E-Verify laws align with our hypothesis, our hypothesis for states with "weak" E-Verify laws is not supported by the analysis. The effects of state level "weak" E-Verify laws are mostly the opposite compared to the effects of "strong" E-Verify laws for crop groups 1, 3, and 4. For the share of labor intensive crops in "weak" E-Verify states, fruit production (group 4) increases by 0.0069 or .69 percent and vegetable production does not have a statistically significant change. For capital intensive crops, "weak" E-Verify states experience an increase in the share of crops in group 2 of 0.0035 or .35 percent and an increase in group 3 crops of 0.0104 or 1.04 percent, however there is a decline of 0.0178 or 1.78 percent for the share of group 1 crops. The opposite effects of E-Verify in "strong" versus "weak" states may be attributed to a potential spillover effect, which is possible due to the geographic closeness of the E-Verify states. Each "weak" E-Verify state border at least one "strong" E-Verify state. This is discussed more in the following section. Increases in group 2 and no changes to group 5 were seen in both "weak" and "strong" E-Verify states. It is interesting to note that group 3 follows the same trend as group 4, suggesting group 3 may be more labor intensive than expected.

Leads and lags analysis was conducted for “strong” E-Verify states in order to check pre trends to test if the parallel assumption holds and presented in Table 9. This only tests the results for Post Strong E-Verify. More pre trend checks are needed for “weak” E-Verify states to validate the results of Post Weak E-Verify. Based on the results, there does not seem to be a statistically significant difference between the trend of crop share between the treatment and control group from year to year 3 years before the enforcement of E-Verify for group 1 and this supports the main findings for group 1. For group 2 there is a trend but the trend is reversed after the law and this provides support for the findings in group 2. Group 4 results are also supported with no significant difference 4 years before the law until the law with a weak difference 3 years before the law.

Table 9. Leads and Lags for Strong E-Verify States.

	Group1	Group2	Group3	Group4	Group5
5 Years Before Law	0.0851***	0.0055	-.0188	-.0572***	-.0082
	(0.0155)	(0.0058)	(0.0189)	(0.0079)	(0.0074)
4 Years Before Law	0.0909***	-.0097	-.0672***	-.0069	0.0131
	(0.0177)	(0.0059)	(0.0208)	(0.0088)	(0.0094)
3 Years Before Law	0.0221	-.0178***	-.0502*	0.0237*	0.0084
	(0.0224)	(0.0048)	(0.0269)	(0.0141)	(0.011)
2 Years Before Law	-.0004	-.0150**	-.0198	-.0049	0.005
	(0.0218)	(0.0068)	(0.0288)	(0.013)	(0.0097)
1 Year Before Law	-.0301*	-.0323***	0.0625***	0.00002	0.0002
	(0.0167)	(0.0043)	(0.0206)	(0.0096)	(0.0074)
1 Year After Law	0.0509***	0.1351***	-.1600***	-.0164*	-.0060
	(0.0172)	(0.0121)	(0.0216)	(0.009)	(0.0077)
2 Years After Law	0.0659***	-.0068	-.0740***	-.0165**	0.0098
	(0.0151)	(0.0065)	(0.0187)	(0.0072)	(0.0068)
3 Years After Law	0.1225***	0.0636***	-.1354***	-.0414***	-.0099
	(0.017)	(0.0093)	(0.0198)	(0.0091)	(0.008)
4 Years After Law	-.1060***	-.0659***	0.1157***	0.0327**	0.0141
	(0.0271)	(0.0115)	(0.0329)	(0.0146)	(0.0115)
5 Years After Law	-.1732***	-.0486***	0.0792	0.1186*	0.0091
	(0.0413)	(0.0069)	(0.0811)	(0.0703)	(0.0407)
Obs.	227880	227880	227880	227880	227880
R^2	0.337	0.0599	0.2178	0.3637	0.0457

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

Along with estimating models 1 and 2 with no restrictions, we also estimated the DID model 2 with restrictions, in order to expand our understanding of the effects of E-Verify laws. Our restrictions were only imposed on model 2, to continue our focus of differentiating the effects of "strong" versus "weak" state level E-Verify laws. We considered four restricted models. First, we estimated model 2 by including only observations with a crop share greater or equal to 0.01 for the crop group of interest in the regression. More specifically, when estimating model 2 for group 1, only farms that had a crop share of greater or equal to 0.01 for group 1 were included in the estimation. This was repeated for crop share groups 2-5. The rationale behind the use of this restriction was to eliminate farms that did not have much stake in the crop share group of interest.

Table 10. DID Regression Results of Strong and Weak E-Verify States with a 0.01 crop share restriction.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
Post Strong E-Verify	0.0049	0.031	-.0476***	-.0665	0.0043
	(0.0131)	(0.019)	(0.0093)	(0.044)	(0.0405)
Post Weak E-Verify	0.003	-.0026	0.0093*	0.037*	-.0027
	(0.0055)	(0.0126)	(0.005)	(0.0221)	(0.0215)
Obs.	151599	6945	147452	23301	15433
R^2	0.2427	0.2089	0.2353	0.14	0.1581

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

The results of this regression, in Table 10, do not provide any additional insights into the effects of E-Verify laws. However, the effects to crop share groups 3 and 4 for both “strong” and “weak” E-Verify states remains consistent. “Strong” E-Verify states again surprisingly have a decrease in group 3 crops with a decline of .0476 or 4.76 percent. “Weak” E-Verify states experience an increase in group 3 crops of .0093 or .93 percent and an increase in group 4 crops of 0.037 or 3.7 percent, but the results are weakly significant. The leads and lags results for this model are found in Table 11. The results suggest the results of crop group 3 in “strong” E-Verify states are biased. There is a statistically significant difference between the trend in the share of group 3 crops between the treatment and control group violating the parallel trends assumption. The results for Post Weak E-Verify cannot be validated based on Table 11.

Table 11. Leads and Lags for Strong E-Verify States with a 0.01 crop share Restriction.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
5 Years Before Law	-.0210	0.0494	-.0956***	-.0137	-.0747
	(0.0183)	(0.0304)	(0.0165)	(0.0799)	(0.069)
4 Years Before Law	0.064***	0.1127**	-.1053***	-.1293	0.1262
	(0.0201)	(0.0447)	(0.0193)	(0.0966)	(0.0844)
3 Years Before Law	0.0747**	-.0466	-.0082	0.0104	0.0954
	(0.0298)	(0.0437)	(0.0233)	(0.0753)	(0.0889)
2 Years Before Law	0.068*	0.0773	0.0171	-.0011	-.0448
	(0.0372)	(0.0707)	(0.0227)	(0.0997)	(0.0856)
1 Year Before Law	0.0193	-.0331	0.0556***	-.0715	0.0006
	(0.0324)	(0.037)	(0.0155)	(0.0824)	(0.0899)
1 Year After Law	-.1122***	0.0596**	-.2149***	-.0056	0.0486
	(0.022)	(0.0295)	(0.0197)	(0.0915)	(0.1135)
2 Years After Law	0.105***	0.0318	-.0533***	-.1774**	0.0013
	(0.026)	(0.0405)	(0.0145)	(0.0783)	(0.0668)
3 Years After Law	0.0022	0.0844**	-.1845***	-.1869**	-.0414
	(0.0205)	(0.0368)	(0.0183)	(0.0879)	(0.0662)
4 Years After Law	0.0946***	0.0355	0.2107***	0.0105	0.0277
	(0.0347)	(0.078)	(0.0288)	(0.1143)	(0.0984)
5 Years After Law	-.0245		0.2093***	0.2666***	0.1267
	(0.1049)		(0.0408)	(0.08)	(0.1697)
Obs.	139126	3564	127125	21880	13854
R^2	0.2423	0.2179	0.2408	0.1432	0.1731

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

The second restricted model follows a similar restriction as the first, but instead of a 0.01 restriction a 0.25 restriction was used. More specifically, we estimated model 2 but only included observations that had a crop share greater or equal to 0.25 for the group of interest in the regression. For example, when estimating model 2 for group 1, only farms that had a crop share of greater or equal to 0.25 for group 1 were included in the estimation. This was again repeated for crop share groups 1-5. The rationale behind this was similar to that of the first restriction, but in this restriction, farmers would have a larger stake in the crop group, potentially resulting in larger changes. For example, an agricultural producer that grows a labor intensive crop that is less than 25 percent of their total crop production might have an easier time to maintain production levels with a shrinking labor force compared to an agricultural producer that producers labor intensive crops at a higher level. The results of this restricted model are presented in Table 12. Comparing Table 12 to the previous results, only group 3 and group 4 contain consistent results. Among “weak” E-Verify states an increase in group 4 crops remains consistent. Specifically, in these results there is an increase in group 4 crops of .0308 or 3.08 percent. “Weak” E-Verify states again experience a decline of group 3 crops, a decline of.0359 or 3.59 percent in this version.

Table 12. DID Regression Results of Strong and Weak E-Verify States with a 0.25 crop share restriction.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
Post Strong E-Verify	-.0036	0.033	-.0343***	-.0113	-.0292
	(0.0125)	(0.0272)	(0.0076)	(0.0338)	(0.0383)
Post Weak E-Verify	-.0017	-.0190	-.0038	0.0308**	-.0040
	(0.0049)	(0.0181)	(0.0041)	(0.015)	(0.0225)
Obs.	141166	3526	109156	20645	8521
R^2	0.222	0.146	0.1723	0.0732	0.1736

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

Based on the leads and lags results in Table 13, the decline in the share of group 3 crops experienced by “strong” E-Verify states does not hold to be valid. In table 13 there is differences in the trend of the share of group 3 crops in the years prior to the enforcement of E-Verify, violating the parallel assumption and making the results biased. More pre trend analysis is needed to validate effects to “weak” E-Verify states.

Table 13. Leads and Lags for Strong E-Verify States with a 0.25 crop share Restriction.

	Group1	Group2	Group3	Group4	Group5
5 Years Before Law	-.0645***	0.0326	-.0877***	-.0395	0.037
	(0.0172)	(0.046)	(0.0148)	(0.0728)	(0.0728)
4 Years Before Law	0.0315*	0.1544**	-.0363**	0.0225	0.0108
	(0.0178)	(0.0619)	(0.0159)	(0.0657)	(0.0723)
3 Years Before Law	0.0534**	-.0630	0.0186	-.0308	0.0216
	(0.0257)	(0.0529)	(0.0167)	(0.067)	(0.0774)
2 Years Before Law	0.0457	0.1808*	0.0537***	0.0081	-.1258
	(0.032)	(0.0941)	(0.0155)	(0.071)	(0.1269)
1 Year Before Law	0.0271	-.0432	0.0259**	-.0632	0.0102
	(0.0305)	(0.0602)	(0.0122)	(0.0692)	(0.09)
1 Year After Law	-.1281***	0.0556	-.1812***	-.0113	0.0324
	(0.0223)	(0.0413)	(0.0175)	(0.0748)	(0.0898)
2 Years After Law	0.0741***	0.0364	-.0188	-.0506	-.0338
	(0.0232)	(0.0501)	(0.0115)	(0.0637)	(0.0604)
3 Years After Law	-.0046	0.1275***	-.1420***	-.0330	0.0142
	(0.0191)	(0.048)	(0.0163)	(0.0594)	(0.0577)
4 Years After Law	0.054*	0.0019	0.1926***	-.0873	-.1799*
	(0.0319)	(0.1015)	(0.0225)	(0.0891)	(0.0965)
5 Years After Law	0.0519		0.1801***	0.0884*	0.0688
	(0.1382)		(0.0405)	(0.0528)	(0.1441)
Obs.	130512	1924	91652	19584	7722
R^2	0.2293	0.1562	0.1878	0.0728	0.1835

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

The third restriction that was imposed on model 2 is to only include farms with greater than 200 total acres operated. This restriction allows us to focus more on “larger” farms which should have a greater level of disruption to production from a shrinking in farm labor. The results for model 2 that only includes farms with greater than 200 acres are found in Table 14. Based on Table 14 there are many consistencies when comparing this model only to the non restricted version of model 2 (Table 8). First, both “strong” and “weak” E-Verify states experience an increase in group 2, which aligns with our hypothesis. In this restricted model “strong” states have an increase of .0348 or 3.48 percent and “weak” states have an increase of

.0049 or .49 percent. Second similarity is the effect on group 3 crops, where “strong” states experience a decline. In this restricted model “strong” states experience a decline of .0410 or 4.10 percent in the share of group 3 crops. It is surprising again that the results are negative for “strong” E-Verify states, since group 3 consists of capital intensive crops. There is also an increase in the share of fruits in “weak” E-Verify states of .0101 or 1.01 percent. An increase in fruit production in “weak” E-Verify states has been seen in other results.

Table 14. DID Regression Results of Strong and Weak E-Verify States Including Farms with greater than 200 acres.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
Post Strong E-Verify	0.0094	0.0348***	-.0410***	-.0017	0.0001
	(0.0112)	(0.0057)	(0.0127)	(0.0045)	(0.0044)
Post Weak E-Verify	-.0101	0.0049***	-.0049	0.0101***	-.0016
	(0.0061)	(0.0019)	(0.0064)	(0.0024)	(0.0015)
Obs.	170104	170104	170104	170104	170104
R^2	0.3374	0.1341	0.2453	0.2368	0.0756

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

Based on the leads and lags results for this model, in Table 15 the results experienced by “strong” E-Verify states for crop share group 3 are not supported by the parallel trend assumption. Group 2 however experiences a trend reversal similar to the one found in the previous specifications.

Table 15. Leads and Lags of Strong States Including Farms greater than 200 acres.

	Group1	Group2	Group3	Group4	Group5
5 Years Before Law	0.0678***	0.0065	-.0103	-.0439***	-.0059
	(0.0184)	(0.0077)	(0.0202)	(0.0079)	(0.0082)
4 Years Before Law	0.0914***	-.0150**	-.0523**	-.0249***	0.0037
	(0.0211)	(0.0076)	(0.0233)	(0.0064)	(0.0086)
3 Years Before Law	0.0304	-.0230***	-.0458	0.0153	-.0027
	(0.0305)	(0.0075)	(0.0344)	(0.0154)	(0.0101)
2 Years Before Law	-.0197	-.0181*	0.0207	-.0184**	0.0174
	(0.0301)	(0.0108)	(0.0356)	(0.0085)	(0.0132)
1 Year Before Law	-.0502**	-.0399***	0.0893***	-.0089	0.0039
	(0.0229)	(0.0068)	(0.0262)	(0.0094)	(0.0091)
1 Year After Law	0.0043	0.1483***	-.1410***	-.0131**	0.0083
	(0.0198)	(0.0137)	(0.0222)	(0.0066)	(0.0088)
2 Years After Law	0.0565***	-.0121	-.0412*	-.0115*	0.0159*
	(0.0201)	(0.0097)	(0.0227)	(0.0067)	(0.0081)
3 Years After Law	0.0883***	0.0655***	-.1158***	-.0233***	-.0130*
	(0.019)	(0.011)	(0.0203)	(0.0076)	(0.0073)
4 Years After Law	-.0253	-.0726***	0.0796**	0.0104	0.002
	(0.0344)	(0.0145)	(0.0375)	(0.0096)	(0.0089)
5 Years After Law	-.1999***	-.0507***	0.1484	0.1267	0.0155
	(0.0558)	(0.0078)	(0.0907)	(0.0796)	(0.0467)
Obs.	153749	153749	153749	153749	153749
R^2	0.3382	0.0943	0.2451	0.2501	0.0798

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

In Arizona, 60 percent of farms that have sales of melons and vegetables operate on a farm that is 10 acres or less (Kerna et al., 2016). Based on this information, the third restriction estimated (only including farms with 200 acres or more) eliminated many observations of vegetable and fruit producers. In hopes of revealing information regarding effects to the share of vegetables we created our fourth restriction. For our fourth restriction we estimate model 2 including only farms with less than 15 acres operated.

Table 16. DID Regression Results of Strong and Weak E-Verify States Including Farms up to 15 acres.

	Group1	Group2	Group3	Group4	Group5
Post Strong E-Verify	-.0092	-.0020*	-.0100	-.1027*	0.0692
	(0.0258)	(0.0011)	(0.0652)	(0.0581)	(0.0465)
Post Weak E-Verify	-.0191	0.0041	0.037	0.0479	0.0024
	(0.017)	(0.0044)	(0.0306)	(0.0294)	(0.0236)
Obs.	10353	10353	10353	10353	10353
R^2	0.126	0.0093	0.2923	0.3065	0.0416

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

Results in Table 16 suggest that among “strong” E-Verify states, there is a decline in the share of group 2 and group 4 crops. “Strong” states experience a decline in the share of group 2 crops of .0020 or .2 percent and a decline of .1027 or 10.27 percent in the share of fruits. The magnitude for the decline in fruit production among “strong” E-Verify states is large indicating E-Verify has a large disruption to agriculture but it is weakly significant. Based on the leads and lags results in Table 17 for the Table 16 results, the effect to fruit production experience in “strong” E-Verify states is not supported. The results in 17 indicate the parallel trend assumption does not hold for group 4. Over all, there are no consistent results among all the restricted versions of model 2.

Table 17. Leads and Lags for Strong E-Verify States Including Farms up to 15 acres.

	Group1	**Group2**	**Group3**	**Group4**	**Group 5**
5 Years Before Law	-.0167	0.0005	0.0878	-.0772	0.0316
	(0.0154)	(0.0006)	(0.1109)	(0.0544)	(0.0782)
4 Years Before Law	-.0133	-.00004	-.1762**	0.1875	0.0072
	(0.0166)	(0.0008)	(0.0802)	(0.1309)	(0.0965)
3 Years Before Law	-.0296*	0.0016**	-.0761	0.0799	0.0082
	(0.0162)	(0.0008)	(0.1271)	(0.0922)	(0.0767)
2 Years Before Law	-.0141	-.0005	-.2416***	0.1376	-.0965***
	(0.0142)	(0.0012)	(0.0642)	(0.1707)	(0.0328)
1 Year Before Law	-.0344	0.0007	-.3138***	0.3774***	-.0991***
	(0.0211)	(0.0009)	(0.0934)	(0.136)	(0.0332)
1 Year After Law	0.1655	-.0014	0.1209	0.0037	-.1090***
	(0.1764)	(0.0012)	(0.1936)	(0.1426)	(0.0321)
2 Years After Law	-.0564***	-.0035**	0.065	-.1563**	0.0368
	(0.0172)	(0.0018)	(0.1203)	(0.0726)	(0.0731)
3 Years After Law	-.0398***	-.0018	-.1193	-.0974	0.023
	(0.015)	(0.0014)	(0.1003)	(0.1025)	(0.097)
4 Years After Law	0.0044	0.001	-.0329	0.0484	0.1
	(0.0129)	(0.0008)	(0.1364)	(0.1601)	(0.1507)
5 Years After Law	0.0073	-.0004	-.1079	0.1002	0.1669
	(0.0162)	(0.0013)	(0.0825)	(0.2968)	(0.2786)
Obs.	9590	9590	9590	9590	9590
R^2	0.1329	0.01	0.2978	0.3102	0.045

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

6.2 Discussion

Based on the results in Table 8, where we estimate model 2 with all observations the effect of E-Verify in "strong" E-Verify states, aligns with our hypothesis. A likely explanation for the increase in group 1 crops, which are capital intensive, among "strong" E-Verify states is that it is the result of a shrinking labor force. With less labor available agricultural producers have shifted to producing more capital intensive crops. Unlike "strong" E-Verify states, "weak" E-Verify states experienced a decline in group 1 crops (capital intensive) and consistently an increase in group 4 crops (labor intensive), which is the opposite of our hypothesis. A plausible explanation for this is that immigrant workers are moving to “weak” E-Verify states from “strong” E-Verify states. This could be possible due to the geographic closeness of “weak” E-Verify states and “strong” E-Verify states. All three of the “weak” E-Verify states (Georgia, North Carolina, Mississippi, and Utah) border at least one “strong” E-Verify state (Alabama, Arizona, and South Carolina). More specifically, Georgia (weak) borders Alabama (strong) and South Carolina (strong), North Carolina (weak) borders South Carolina (strong), Mississippi (weak) borders Alabama (strong) and Utah (weak) borders Arizona (strong). With a possible increase in labor supply in “weak” E-Verify states, agricultural producers are able to produce more labor intensive crops such as fruits. It seems that agricultural producers in “weak” E-Verify states are opting to produce labor intensive crops over capital intensive crops, resulting in a decline in the share of group 1 crops, which are found in all the results of all versions of model 2. There is however a need for further research to examine the effects of a potential labor movement between “weak” and “strong” E-Verify states to further support this claim.

The overall trend of the impact of E-Verify among “strong” E-Verify states aligns with our hypothesis, mostly when focusing on the results of Table 8, except for group 3. Group 3 is consistently negative for “strong” E-Verify states across the versions for model 2. This may suggest that the crops in group 3 do not have a feasible substitute for labor or may be more labor intensive than originally anticipated. Group 3 consist of cotton, tobacco, and hay. Cotton and tobacco production are very important to 2 of the 3 “strong” E-Verify states, and the decline in production of group 3 is most likely driven by these crops. However, tobacco is more likely to be susceptible to negative impacts from loss of labor because it is more labor intensive than cotton and hay, based on its percentage of expenses allocated to labor. In addition, many tobacco farmers are reducing production due to less demand. Future research that classifies tobacco as a labor intensive crop or removes the crop from the study might give more insight.

For the results where the parallel assumption does not hold there are other methods to estimate and validate the results, such as using a synthetic control method (SCM). Future research should also consider using propensity score matching to have a treatment and control group that have less variance, by choosing farms in control and treatment states that have similar trends and levels of crop share and other characteristics prior to the enforcement of the law.

A consistency among most all the results, is that there is no change in the share of group 5 crops, vegetables. One possible explanation for this is that there were not enough observations of farms that produce vegetables in the E-Verify states. Since the USDA ARMS data used in this study is a national representative sample of farms in the 48 contiguous states the number of vegetables farms in a state within the data set reflects the importance of vegetable production within a state. Many of the states in the southeast, where many of the E-Verify policies are concentrated, do not produce high levels of vegetables. Crops that are more important to southeastern states include, cotton, tobacco, corn, soybeans, potatoes, and peanuts, all of with are capital intensive crops (USDA NASS, 2018). Future research that uses data that is more specific to each state and includes data for a majority of farms within a state, may give more insight into the changes to vegetable production from the adoption of state level E-Verify.

6.3 Arizona Case Study

To attempt to gain more insights on the effects of E-Verify on vegetable production, we conducted a case study on Arizona. In Arizona vegetable production is an important part of the agricultural sector. In 2015, Arizona produced the second largest quantity of production (cwt) for lettuce (head, leaf, romaine) in the country according to the Arizona Department of Agriculture (AZDA, n.d.). In order to determine the effects of E-Verify on crop share in Arizona, we estimated model 1 only including states in the western region of the US. States used in the case study were, California, Washington, Oregon, Arizona, New Mexico and Nevada. The results for the Arizona case study using model 1, are found in Table 18.

Table 18. Arizona Case Study DID Regression Results.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
Post E-Verify	0.0297	-.0101**	-.0428	-.0652***	0.001
	(0.0198)	(0.0042)	(0.0308)	(0.0248)	(0.0161)
Obs.	33907	33907	33907	33907	33907
R^2	0.0767	0.0126	0.1392	0.1777	0.0259

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

Based on these results there is still no conclusion on the effects of E-Verify on vegetables production. However, there is a highly significant decline in fruit production of .0652 or 6.52 percent. Fruit production is also very important to Arizona's agricultural industry, so it seems that E-Verify has some effects on agricultural production. Surprisingly, the result suggest Arizona experienced a decline of group 2 crops (canola, peanuts, and potatoes), capital intensive crops, of .0101 or 1.01 percent. Arizona does not produce canola or peanuts, however they do produce potatoes. Although potatoes are not a major crop to Arizona, when considering production of melon, lettuce, sweet potatoes, and potatoes, Arizona produces the 5th most based on quantity in the entire county in 2018, according the United States Department of Agriculture National Agricultural Statistical Services (USDA NASS, 2018), so there would be some level of disruption in Arizona from a decline in group 2 crops.

Based on Table 19, which presents the leads and lags pre trend analysis the results in group 2 and group 4 hold to be valid. There is no statistical change in crop share between the treatment states and the control states prior to the enforcement of the law, indicating their trends were the same. The parallel trends assumption holds.

Table 19. Arizona Case Study Leads and Lags.

	Group1	**Group2**	**Group3**	**Group4**	**Group5**
5 Years Before Law	0.0372	0.0005	0.2285***	-.1468***	-.0284
	(0.0288)	(0.0102)	(0.0472)	(0.0396)	(0.0269)
4 Years Before Law	-.0193	-.0039	0.1906**	-.0118	-.0241
	(0.0438)	(0.0061)	(0.0776)	(0.0668)	(0.039)
3 Years Before Law	0.0335	-.0019	-.0459	0.0501	0.0109
	(0.0525)	(0.006)	(0.0801)	(0.0681)	(0.0434)
2 Years Before Law	-.0525	-.0052	-.0221	0.0021	-.0088
	(0.049)	(0.0062)	(0.0872)	(0.0685)	(0.0438)
1 Year Before Law	0.1058**	-.0071	-.0651	-.0683	-.0169
	(0.0531)	(0.0062)	(0.0762)	(0.0654)	(0.0413)
1 Year After Law	-.0329	-.0112**	-.0422	-.0434	-.0020
	(0.0463)	(0.005)	(0.0708)	(0.0596)	(0.043)
2 Years After Law	0.0456	-.0120**	-.0632	-.0449	0.0556
	(0.0424)	(0.005)	(0.0643)	(0.0516)	(0.0413)
3 Years After Law	0.076***	-.0090*	0.0636	-.1474***	-.0252
	(0.0277)	(0.0049)	(0.0431)	(0.0354)	(0.0248)
4 Years After Law	-.0672*	-.0014	-.0189	-.0026	0.0007
	(0.0383)	(0.0019)	(0.0662)	(0.042)	(0.0286)
5 Years After Law	-.1706***	0.0004	-.0063	0.1469**	0.0288
	(0.0426)	(0.0016)	(0.083)	(0.0723)	(0.0414)
Obs.	33907	33907	33907	33907	33907
R^2	0.0771	0.0126	0.1406	0.1781	0.0262

Note: Robust Standard errors in parenthesis, * p < 0.1, ** p<0.05, *** p<0.01. Control variables included are gender of principal farm operator, education level of principal farm operator, age of farm principal operator, total gross cash farm income, total acres operated, year fixed effects and state fixed effects.

CHAPTER 7

CONCLUSIONS

This study used difference-in-differences models to determine the effects of a shrinking labor force on agricultural production decisions. More specifically, we examined the effects of E-Verify on the share of capital intensive and labor intensive crops using farm level data. State level E-Verify enforcement laws act as a quasi-natural negative labor shock, based on previous research. Results that grouped all E-Verify states together did not give a clear conclusion on the impacts of state level E-Verify laws. Then we expanded the scope of our research by comparing the effects depending on the strictness of the state's E-Verify laws. These results suggest that a state that enforces E-Verify for all employers with no exceptions or phase in period, i.e. has "strong" E-Verify laws, faces a decline in labor intensive crops, and an increase in capital intensive crops. With fewer workers available, agricultural producers cannot produce the same level of labor intensive crops such as fruits. Producers of fruits do not seem to increase wages or use mechanization to sustain production levels, but instead switch to an alternative crop that is more feasible. There is no clear explanation for the decline in crop production of capital intensive crop group 3 in "strong" E-Verify states. Further research is needed to gain more understanding on the effects immigration laws have on the production of cotton, hay and tobacco. There is also no clear conclusion on the effects to the share of vegetable production, due to lack of statistical significance. Further research may want to consider using data with more observations of vegetable producers within the E-Verify states. The results also suggest that immigrant workers may be moving from "strong" E-Verify states to "weak" E-Verify states.

With more workers in “weak” E-Verify states, these states have experienced an increase in fruit production, which is consistent among all results. Further research using leads and lags and using SCM is needed to further test these results.

The wave of immigration laws since the early 2000 has resulted in a well documented loss of farm labor in states and jurisdictions that have enacted them. Based on the results of our study farmers are changing crop share from more labor intensive to less labor intensive crops suggesting that states with “strong” E-Verify laws need to account for the loss of agricultural labor and the resulting decline in the production of labor intensive crops. Given that crop productivity is dependent on agro climatic conditions, changing to more capital intensive crops may results in less profits and loss of competitiveness. Without any government intervention, farmers in states and jurisdictions in “strong” E-Verify states that produce labor intensive crops may no longer be competitive and may ultimately leave the agricultural industry. In order for states and the US to remain competitive in the agricultural economy, policymakers must work to maintain production of labor intensive crops if immigration enforcement laws are enacted. Among others, there are two main policy avenues to limit some of the negative effects of E-Verify on the production of crops. The first is to increase the level of foreign agricultural workers, through granting more exemptions to the agricultural sector. The second is to invest in mechanization.

In order for states to maintain the supply of migrant agricultural labor, policymakers could improve the efficiency of the H2-A visa program. The H2-A visa program allows selected foreign workers to enter the US to fill seasonal agricultural jobs. Improvements could be made such as making the application process easier and less expensive for agricultural producers and foreign workers and increasing the total number of H2-A visas accepted. This would be an effective method to maintain levels of migrant agricultural workers. Policy makers could also main levels of migrant workers, by offering more “loopholes” in their E-Verify laws. States should consider “weak” E-Verify laws rather than “strong” E-Verify laws. Another policy option is, to create policies that invest in the research and development of mechanization for the harvesting of fruits and vegetables, in order to ensure that vegetable and fruit producers remain competitive and productive in the US and global market in the long run.

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APPENDICIES

Appendix 1 Description of State-Level E-Verify Policies

State	Year	Current Description of Law
Alabama	2012	E-Verify required for all public and private employers
Arizona	2008	E-Verify required for all public and private employers
Georgia	2011	E-Verify is required by all private employers with more than 10 employees. Had phase in period
Mississippi	2008	E-Verify required for all public and private employers. Had phase in period
North Carolina	2011	E-Verify is required by all private employers with more than 25 employees. Seasonal workers (9 months or less) are exempted from being verified. Had phase in period
South Carolina	2012	E-Verify required for all public and private employers
Utah	2011	E-Verify is required by all private employers with more than 15 employees

Source: http://www.ncsl.org/research/immigration/state-e-verify-action.aspx