The Impact of E-verify Adoption on the Supply of Undocumented Labor in the U.S. Agricultural Sector

Tianyuan Luo
University of Georgia
Email: luoterry@uga.edu

Genti Kostandini
University of Georgia
Email: gentik@uga.edu

Jeffrey L. Jordan
University of Georgia
Email: jjordan@uga.edu

Abstract

We examine the effect of E-Verify mandates on agricultural labor supply and agricultural labor composition in each E-Verify adopting state in the U.S. Using the synthetic control method and individual level data for the 2004-2014 period our results suggest that comprehensive E-verify mandates only reduce the share of farm workers who are likely undocumented immigrants in Arizona and Alabama. Other states that adopted comprehensive E-verify experienced insignificant change in their likely undocumented population in farms. The results are supported by permutation tests and several robustness checks.

Key words: E-Verify, U.S. states, labor supply, agriculture.

Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1

Introduction

E-Verify, a federal system that determines the employment eligibility of new hires was established by the Illegal Immigration Reform and Immigrant Responsibility Act in 1996 as a voluntary program. E-Verify is a free internet-based system that compares employees data against U.S. government records to verify if an employee is lawful to work in the U.S. Since the mid-2000s, as a result of ineffective debates on immigration reform at the national level, some states have used E-verify to tackle the issue of illegal immigration by themselves.

The implementation level differs across states with most states only enforcing E-Verify on public agencies and contractors (Amuedo-Dorantes and Bansak 2012). Some states such as Arizona have enforced E-Verify in the private sector by requiring all employers to check the eligibility of all newly hired employees after January 1, 2008 and the level of compliance was high with about 700,000 newly hired workers from October 2008 and September 2009 (roughly half newly hired employees in the state) run through E-Verify (Berry 2010; Bohn, Loftstrom and Raphael, 2014). Other states (with the exception of Arizona in 2008, Mississippi in 2009, and South Carolina and Utah in 2010) that had E-Verify mandates by 2010 had only enforced them in the public sector and contractors (Amuedo-Dorantes and Bansak 2012). In addition, some states have exempted the E-verify usage in short-term (3-months) contract industries, such as agriculture, where employment is mostly of a temporary (seasonal) nature and have also exempted firms of smaller employees size (Amuedo-Dorantes and Bansak 2012). Therefore the impact of E-Verify in each state, especially for agriculture where more than half of workers are undocumented, is an empirical question that requires a state by state analysis.

There have been numerous studies on the impact of E-Verify adoption in general (e.g. Bohn, Loftstrom and Raphael, 2014; Amuedo-Dorantes, Puttitanun and Martinez-Donate, 2013;

Nowrasteh, 2012) or by industry (e.g. Amuedo-Dorantes and Bansak, 2012, Orrenius and Zavodny, 2007). Amuedo-Dorantes and Bansak (2012) that exploit the variation in the enactment and the degree of implementation of E-Verify mandates on employment, wages and industry. They find that statewide mandates reduce the likelihood of employment of unauthorized workers. In addition they find mixed effects on wages, and generally, a redistribution of likely unauthorized labor towards industries that are exempt from E-Verify, such as agriculture. In fact, using a differences-in-differences (DID) framework and data from 2000-2010, they find an average of 5.8 percent increase in the employment of likely unauthorized immigrants in agriculture. However, given the high demand for labor in the U.S. agricultural sector and the wide variety of crops, seasonality which can be quite different across states, a state by state examination is warranted.

Our objective in this paper is to examine the effect of E-Verify mandates on agricultural labor supply and agricultural labor composition in each E-Verify adopting state for the 2004-2014 period paying particular attention to the state-specific E-Verify restrictions. This analysis will provide insights on the effects of E-Verify in the supply of agricultural workers for each state and on the immigration debates that are expected to arise with the new administration.

Background

Employment Verification (E-verify) system is a free online program established by U.S. federal government that can be used by employers to verify the employment eligibility of newly hired employees and thus hinder the employment of workers who do not have proper working permit in the U.S. E-verify was first launched as a voluntary pilot program by the Illegal Immigration

Reform and Immigrant Responsibility Act of 1996 and its use was voluntary choices among firms in all 50 states.

However, due to the lax enforcement level of E-verify since its establishment, the effectiveness of ending unauthorized immigration intended by the federal government was severely undermined. As a result, it spurred an extraordinary wave of state-level immigration legislations during the recent decades and E-verify mandate became widely implemented legislations in an effort to curb the undocumented employment and promote the job opportunities for documented workers in the U.S.

The first and, arguably, the most restrictive E-verify mandate law at the state level was first adopted in Arizona, which is known as the Legal Arizona Workers Act (LAWA) in 2008 (Bohn, Lofstrom and Raphael 2015). LAWA requires all employers, including public and private, to verify the employment eligibility of newly hired workers through E-verify system. Following Arizona, more states adopted E-verify mandate but their enforcement level differed in terms of the inclusion of employer entities that are required to use E-verify. As mentioned, some states, such as Colorado and Florida, only apply E-verify law to state agencies and contractors. The states that adopted comprehensive E-verify mandates are Arizona, Georgia, North Carolina, Mississippi, South Carolina, Mississippi, and Utah.

Table 1 shows the states and the dates of comprehensive E-verify mandates adoption. Some states, such as Georgia, Mississippi and North Carolina, phased into the adoption of E-verify by setting different stages starting with requirements solely on public agencies or government contractors and then on private firms. There are concerns that the choice of cutoff year for the phase-in states may change the results. This article conducts a robustness check that assigns the cutoff year to other time and finds the results to be consistent.

Table 1. States with universal mandate of E-verify.

State	Universal E-verify Adoption Date
Arizona	Jan-08
Mississippi	Jul-11
Utah	Jul-10
Georgia	Jan-12
South Carolina	Jan-12
Alabama	Apr-12
North Carolina	Oct-12

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

Data and Empirical Strategy

The following section describes the data and the empirical method. We first discuss how we construct the state level variables for the empirical analysis. Then we present the synthetic control method that constructs counterfactual controls for treated units (i.e., states that adopted E-verify).

American Community Survey: 2004-2014

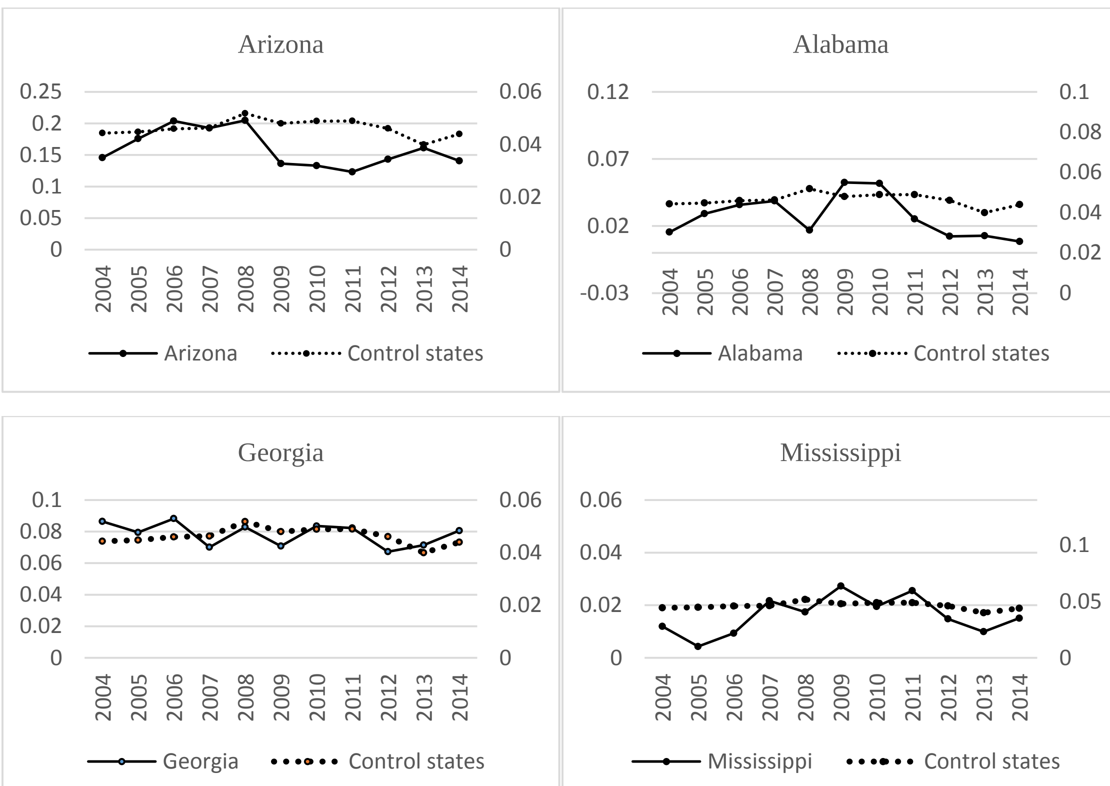
This study uses pooled data from the 2004-2014 American Community Survey (ACS) from the U.S. Census Bureau. ACS is a nationally representative large-scale survey that collect a wealth of information on demographics and labor outcomes of individual interviewees. This article uses a sample from ACS with a total individual observation of 507,204 and ACS does not provide specific identifier for the immigration status that distinguishes documented and undocumented immigrants. To examine the share of farm employees who are undocumented immigrants, as done by other studies, we use individual demographic information such as ethnicity, age, educational level, and citizenship status (citizen vs. non-citizen) to identify the likely undocumented immigrants. Meanwhile, variables that report on employment status and occupations and provide information for identifying the employees in farm sectors.

Based on the definitions of likely undocumented immigrants used by Orrenius and Zavodny (2015) and Amuedo-Dorantes and Bansak (2012), we define the likely undocumented immigrants as those who are non-citizen Hispanics and between 16-45 years old with an education level of less than high school. Meanwhile, we define those who report to have primary occupations in agricultural sector as farm workers. They can be farm operators, owners, unpaid family labor, or hired farm workers. Using this information, we calculate the share of farm workers who are likely undocumented immigrant for each state (state-level outcome of interest) by dividing the number of likely undocumented workers who have agricultural occupations by the whole population that work in agriculture.

In our empirical analysis we also include other state-level covariates. More specifically we use the share of female residents, population mean age, population mean education level, and the share of non-citizens. These data are also obtained from ACS and are generated in a similar way as the outcome of interest. Additionally, we use data from the Farm Income and Wealth Statistics provided by Economic Research Service of the U.S. Department of Agriculture and include in our analysis additional state-level variables. More specifically we include the gross receipts of farms income, the value of total agricultural production, the value of government payments, and the share of hired labor expenditure in total agricultural production cost for each state.

As explained in more detail in below, for each E-verify state we create a control group. Not all states in the U.S. are included in control group. For each E-verify adopting state, we take out all other states that adopted comprehensive E-verify during the period of 2004-2014. For instance, when examining the change in the share of undocumented immigrants on farms in Arizona, we exclude Alabama, Georgia, Mississippi, North Carolina, South Carolina, and Utah. Moreover, we also exclude the states that have a very small portion of their GDP (less than 0.5%) from agricultural sector. Using this criterion, we exclude New Hampshire, New York, Connecticut, New Jersey, Rhode Island, Massachusetts, Alaska, and Hawaii.

Before we start the empirical analysis, we provide graphs of trends on the share of farm workers who are undocumented for each E-verify adopting state and the controlled state. Figure 1 shows the comparison of trends in the share of farm workers who are likely undocumented immigrants over the period of 2004-2014.



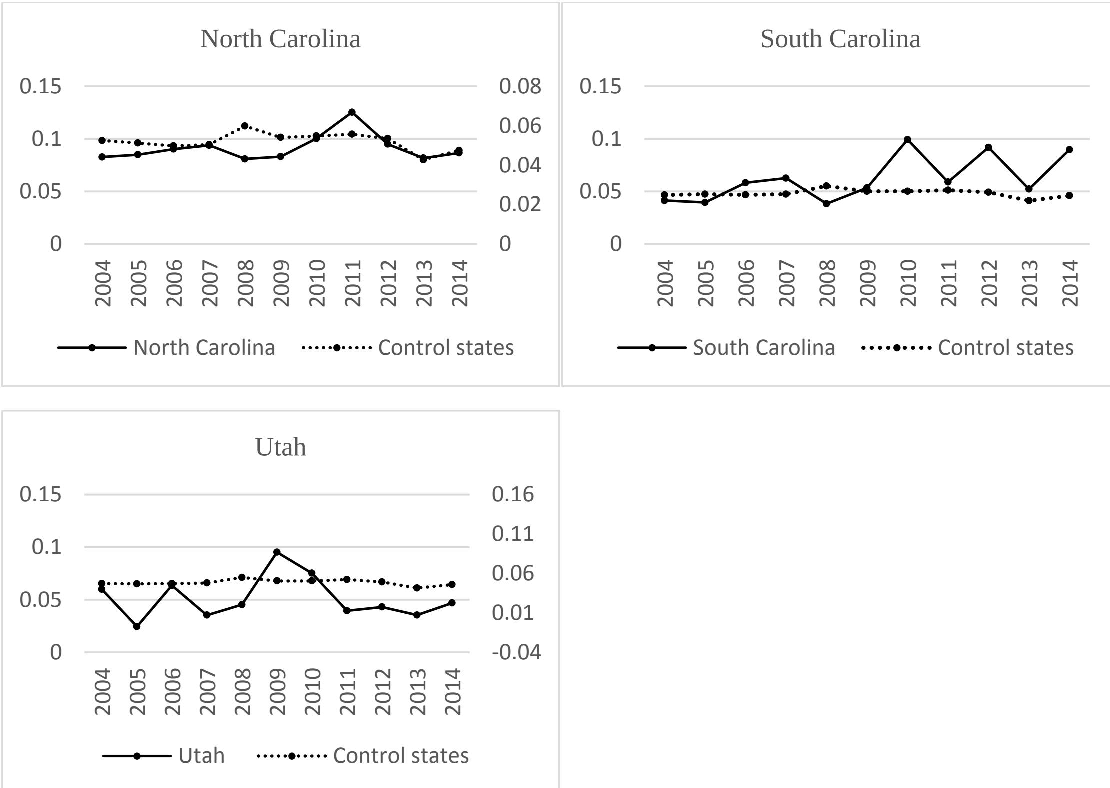


Figure 1. Trends of the share of farm workers who are likely undocumented immigrants in E-verify adopting states and non-adopting states.

From figure 1, based on the trends compared to their controlled groups, states can generally be described by 3 categories. The first category includes Arizona, Alabama, and Utah. These states experienced a decrease in the proportion of farm workers who are likely undocumented immigrant after the adoption of E-verify. The second category include Georgia, Mississippi, and North Carolina that show little divergence in the share from their controlled groups. South Carolina is in the third category experienced an increase in the share of farm employees who are likely undocumented immigrants. However, we would like to note that the oddly increasing trend found in South Carolina, which shows more fluctuations in trend than other states, may be due to data issues in the survey. To further explore and provide empirical evidence obtained from controlling for state-specific trends as well as other cofounding factors, we introduce the synthetic control method in the following section.

Empirical Strategy: Synthetic Control Method

We apply the synthetic control method (SCM) to examine the impact of E-verify adoption on the share of farm workers who are likely undocumented immigrants at the state level. One methodological advantage of SCM is that it does not impose assumption that the pre-treatment trends of both treated and control groups are parallel. Instead, it ensures the well-matched pre-trends between treated and control group by choosing a weighted combination of control states that would create a synthetic treated unit to approximate the relevant characteristics of the real treated unit. In the synthetic control method, the treated state is coded as $j = 0$ and the states included in the synthetic control group are coded as $j = (1,2, \ldots, J)$. Multiple diverse untreated units are included in the synthetic control group to increase the probability of more successfully approximating the characteristics of treated states before the adoption of E-verify during the pre-treatment period.

We construct a synthetic control group by choosing the states that are assigned positive weight through the data-driven process of SCM.[1] The rule of weight assignment is based on the minimization of the value of the distance shown as follows:

$$|| X_0 - X_1 W || = \sqrt{(X_0 - X_1 W)' V (X_0 - X_1 W)}$$

where X_0 is a $k \times 1$ vector that denotes the characteristics of treated state in the pre-treatment period, and X_1 is a $k \times j$ vector denotes that of the control units. Both X_0 and X_1 represent the outcome of interests as well as the covariates that may affect the share of farm workers who are likely undocumented immigrants in each state. All weights that are assigned to controlled states in the donor pool should be positive and sum up to one. The SCM generates a vector $W^* = (w_1, w_2, \ldots, w_J)$ that allocates the optimal weights to each state included in the donor pool. The states

[1] For more details on the SCM see Abadie, Diamond, and Hainmueller (2010).

with weights larger than zero would build a pre-intervention vector that best approximates the treated states. Meanwhile, not only each state in synthetic donor pool is assigned with a optimal weight, but also the covariates that used to control for the possible cofounding factors. A $k \times k$ vector V is also obtained which contains the weights calculated and assigned to the characteristics in vector X that indicates the importance of each covariate in the X vector in predicting change in the share of undocumented immigrants. The trends of the proportion of farm worker population with likely undocumented identity in treated and synthetic states are compared and the impact of E-verify adoption would be estimated from the gap between trends.

Table 2 presents the states in the donor pool for each treated state with positive weights. Based on these states, a synthetic treated state is created that optimally approximates the features of actual treated states. As can be seen from table 2, some treated state share the same states in control group but in general the selected control states by SCM for each treated state show evident geographical variations.

Table 2. Positive Weights for the States Selected for Synthetic Group.

Arizona		**Alabama**		**Georgia**		**Mississippi**	
California	0.256	California	0.035	Arkansas	0.083	Illinois	0.018
Nevada	0.402	Iowa	0.022	Delaware	0.106	Louisiana	0.289
Washington	0.341	Kentucky	0.767	Iowa	0.209	Michigan	0.126
		South Dakota	0.068	Maryland	0.025	Missouri	0.298
		Wyoming	0.108	New Mexico	0.178	South Dakota	0.269
				Texas	0.205		
				Washington	0.195		

North Carolina		**South Carolina**		**Utah**	
Idaho	0.264	Iowa	0.038	Kentucky	0.434
Louisiana	0.095	Kentucky	0.108	Maine	0.002
Nevada	0.058	Maryland	0.850	Nevada	0.274
Texas	0.583	Texas	0.004	Vermont	0.290

Table 3 presents the characteristics of each treated state and their corresponding synthetic controls. As pointed out by Abadie et al. (2010), the value of covariates in treated and control units should be similar to each other in order to reach an "inner optimization." The higher the level of match of these predictors, the better a synthetic control state is created and thus the more reliable the estimates.

Table 3. Means of covariates for treated states and synthetic states for the 2004-2014 period.

	Arizona		**Alabama**		**Georgia**		**Mississippi**	
	Treated	Synth.	Treated	Synth.	Treated	Synth.	Treated	Synth.
Log gross receipt of farms	15.14	15.16	15.44	15.42	15.91	15.93	15.51	15.51
Log total value of agricultural product	15.21	15.22	15.46	15.45	15.91	15.93	15.45	15.5
Log value of government payment	11.6	11.28	12.06	12.61	12.83	12.63	13.4	12.94
Share of hired labor cost	0.15	0.19	0.05	0.08	0.06	0.09	0.05	0.06
Share of non-citizen immigrants	0.13	0.12	0.03	0.03	0.07	0.07	0.02	0.02
Share of female	0.21	0.25	0.16	0.24	0.21	0.22	0.25	0.24
Mean age of agricultural population	40.59	37.91	38.86	43.27	39.14	42.64	42.48	42.77
Mean education of agricultural population	9.36	8.78	10.02	9.74	10.01	9.83	9.48	10.36
	North Carolina		**South Carolina**		**Utah**			
	Treated	Synth.	Treated	Synth.	Treated	Synth.		
Log gross receipt of farms	16.18	16.17	14.75	14.72	14.2	14.26		
Log total value of agricultural product	16.16	16.17	14.76	14.79	14.3	14.3		
Log value of government payment	13.17	13.09	11.91	11.27	10.69	11.02		
Share of hired labor cost	0.07	0.08	0.08	0.09	0.12	0.12		
Share of non-citizen immigrants	0.06	0.09	0.03	0.08	0.06	0.05		
Share of female	0.24	0.19	0.19	0.24	0.25	0.25		
Mean age of agricultural population	40.47	40.97	39.91	38.91	38.86	40.84		
Mean education of agricultural population	9.9	9.43	9.99	9.88	10.44	9.87		

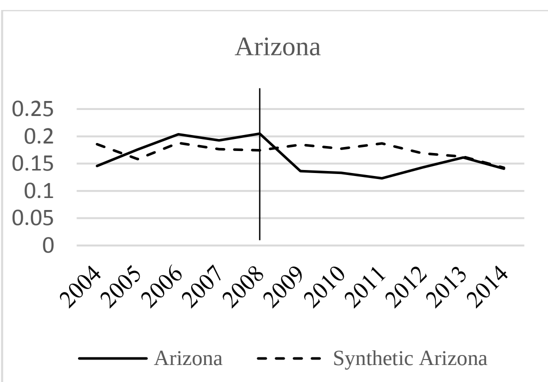
Results in table 3 indicate that synthetic control states that successfully approximate the seven E-verify states in terms of key characteristics that would predict the trend of the share of farm workers who are likely undocumented immigrants. The gaps that occur after the policy intervention could be regarded as the impact from the adoption of E-verify in treated states compared to the synthetic states that could have adopted E-verify but did not. In the next section, we present the main results that evaluate the impact of E-verify adoption.

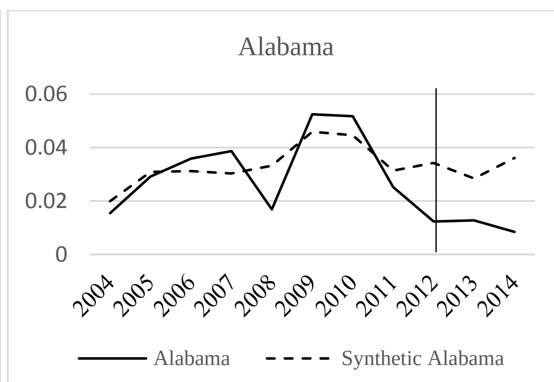
Empirical Results

This section first discusses the SCM results that show the change in the share of undocumented immigrants in farms after E-verify adoption. For each E-verify state compared to the synthetic control group, we present evidence that examine the significance level of our findings.

The plots of each treated state shown in Figure 2 indicate that the trends of synthetic controls resemble the actual states during the period prior to E-verify adoption. Based on the SCM results, we can divide the seven E-verify adopting states into two groups: the first group includes Arizona, Alabama, and Utah, which show declines on the share of likely undocumented after the adoption of E-verify. The second group includes Georgia, North Carolina, and South Carolina, which display little divergence between the trends of actual and synthetic treated states.

The trends of Arizona and synthetic Arizona exhibit well matched trends before the policy intervention and the average gap between the trends before the adoption of E-verify is only 0.002. This gap widened after 2008 and the average gap increased to 0.022, which means that the share of farm workers who are likely undocumented immigrants decreased by approximately 2% after the adoption of E-verify in Arizona. Moreover, we notice that the gap did not occur immediately in 2008, which is the year of E-verify adoption in Arizona. Strictly speaking, we cannot draw the conclusion that there was a decrease in the undocumented immigrant share because the large gap appears after the year 2008 may be due to that the rule of distance minimization between two trends is not imposed in the pre-treatment period. To further examine if the large gap occurred after 2008 in Arizona is caused by the adoption of E-verify, we reassign the cutoff years to 2010 and 2011 and find that the large gap still exist in 2009 and the magnitude of the gap remain the same. The adoption of E-verify decreased the population of likely undocumented immigrants but the impact seems to delay until one year later. There are two explanations for the delay: First, the high administrative cost and policy inefficiency may slow down the enforcement of E-verify law. Second, the local economies may need time to respond and readjust to the new immigration policy and the incompliance and identify fraud may further help to retain some undocumented population (Meissner and Rosenblum 2009; Nowrasteh 2012). This result for Arizona if similar to the one from Bohn and Lofstrom (2013), who find a decrease of 11% in the rate of employment for unauthorized workers in Arizona.





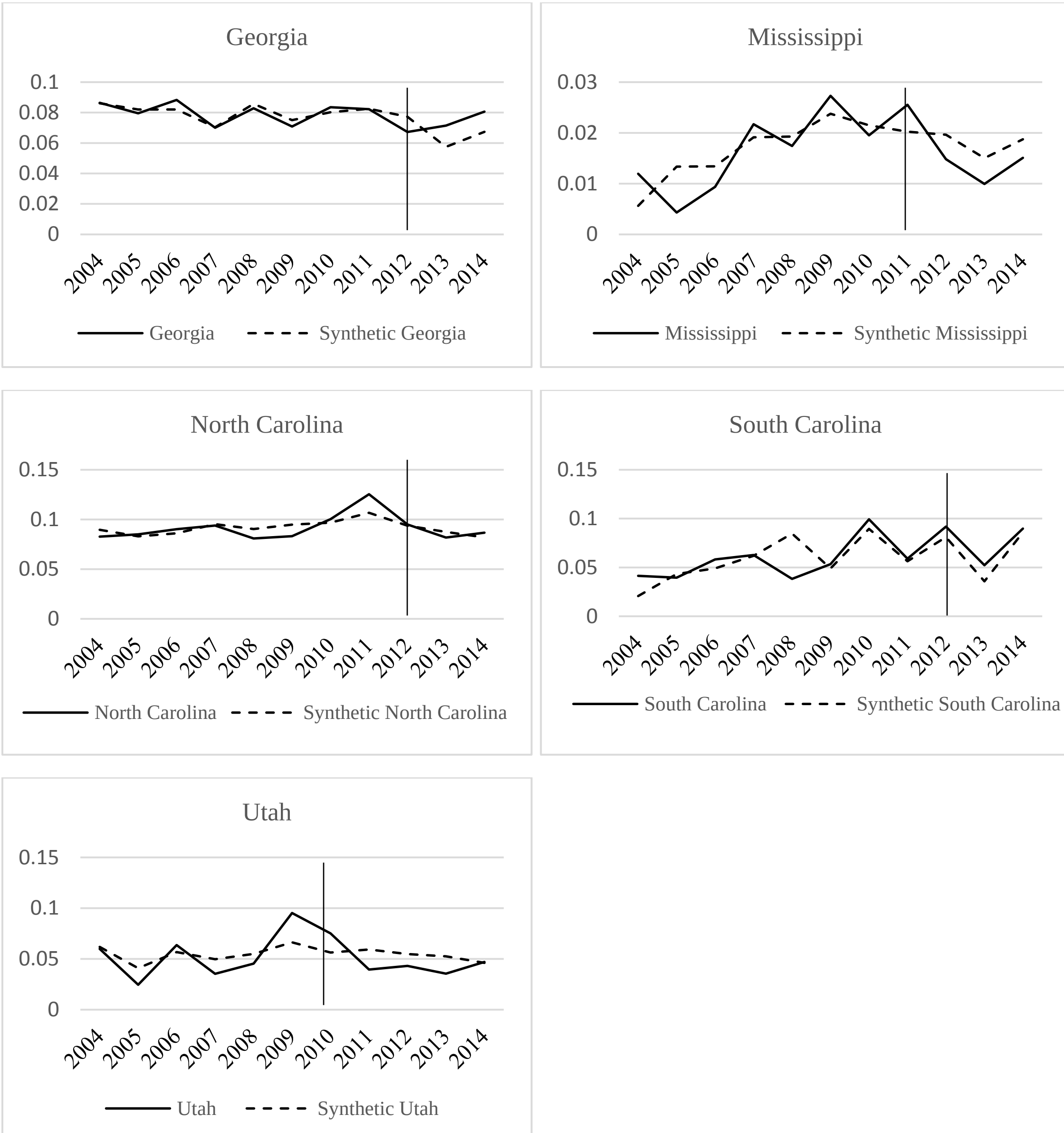
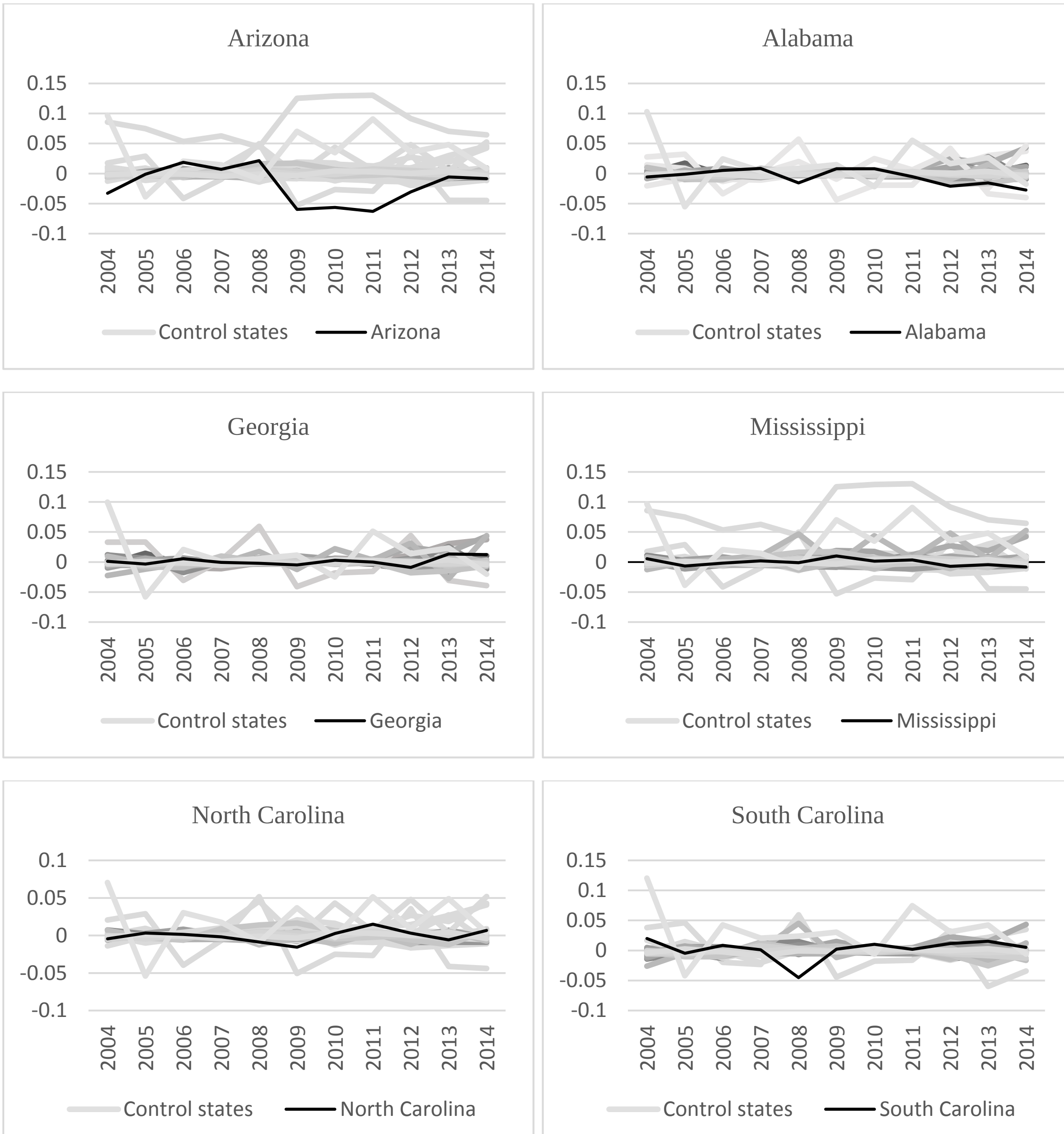


Figure 2. Share of farm workers who are likely undocumented workers in E-verify treated and synthetic states.

Alabama is the only other state that shows an instant and clear drop in the share of undocumented population after the adoption of E-verify. The average gap between the two trends before the adoption of E-verify is only about 0.00024. The average gap in the post period of E-verify adoption increased to 0.022, which is very close to the magnitude of the share gap increase in Arizona. Utah is the third state that shows a decrease in the share of farm workers who are likely undocumented immigrants after the adoption of E-verify compared to the synthetic control group. However, we would like to note that the pre-trends between Utah and synthetic Utah are not as well match as other E-verify adopting states and thus the result needs to be interpreted with caution. As can be seen from the plot of Utah, the average scale of divergence after E-verify adoption is very similar to that before the policy and it is difficult to conclude that the gap after 2011 in Utah is due to E-verify adoption.

The observed gap between treated and synthetic states could only provide information on the scale of impact but it is unable to show if the significance of the results. In the next part we present the results of permutation tests as suggested by Abadie, Diamond, and Hainmueller (2010) to examine the significance of synthetic control results. A permutation test assumes that a state in synthetic control group has adopted E-verify and generates the gaps between this placebo state and its synthetic control group. We repeat this procedure for all states included in the synthetic donor pool, collect all gaps of trend from placebo states, and compare them to that of the actual treated state. If the difference between the actual E-verify adopting state and its synthetic control group is larger than most of the placebo differences from other control states, then it could be concluded that the gap observed represent significant impact of E-verify. These results are presented in figure 3.

In figure 3, the difference between actual and synthetic units observed in Arizona and Alabama (black lines) stand out from the placebo differences (grey line). Thus the changes of likely undocumented immigrant in farms in Arizona and Alabama are significant. Utah also has an evident difference between two trends compared to the control states. However, the conclusion on the significance of the result should be treated cautiously due to the large differences in Utah that also exists before the policy adoption year. The rest of the E-verify adopting states show no significant results indicating that E-verify adoption did not affect the undocumented immigrant population in farms.



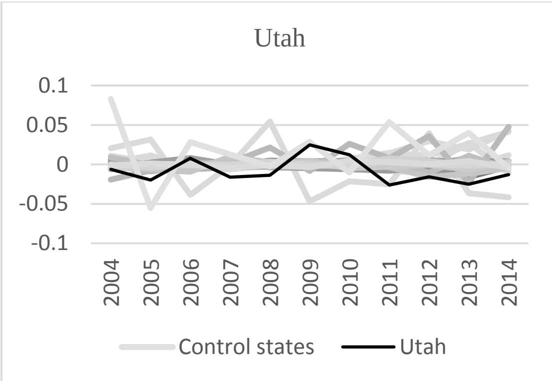


Figure 3. Permutation test results.

Based on the results of permutation test, we could draw a conclusion that the impact of E-verify adoption on the share of farm workers who are likely undocumented is twofold: on one hand, similar to previous studies (Bohn, Lofstrom, and Raphael 2014; Amuedo-Dorantes and Bansak 2012; Amuedo-Dorantes and Lozano 2015), the adoption of E-verify reduces the likely undocumented immigrants in agricultural sector (Arizona and Alabama); on the other hand, the adoption of E-verify imposes little impact on likely undocumented immigrants in farms (Georgia, Mississippi, North Carolina, and South Carolina).

Table 4. Differences in E-verify policies across states.

State	Exemptions	Phase-in period
Arizona	No	No
Alabama	No	No
Georgia	Yes (10 or fewer employees)	Yes (2012-2013)
Mississippi	No	Yes (2008-2011)
North Carolina	Yes (24 or fewer employees)	Yes (2011-2013)
South Carolina	No	No (but with amendment)
Utah	Yes (14 or fewer employees)	No

Source: http://cis.org/e-verify-at-the-state-level and www.lawlogix.com/e-verify.

As shown in table 4, there are two explanations for the differences in E-verify impact across the seven states. First, both Arizona and Alabama have no exemption for employers that have small amounts of employees. Other states made exemptions for some small businesses that they are not required to use E-verify. For instance, Georgia requires all private employers with more than 10 employees and Utah requires all private employees with more than 15 employees to use E-verify system. This could particularly benefit agricultural employers (Feere 2012) because many farms in the U.S. are small farms and they hire a lot of seasonal workers who may not be counted as formal employees. Second, as can be seen from table 4, both Arizona and Alabama did not have phase-in period for E-verify adoption, but most of other states usually have a 2-3 years phase-in period. The states without phase-in period may face with larger shock to farm sector because local economies of farms may not have time to find a way to retain undocumented workers. South Carolina did not have a phase-in period for E-verify policy but it exempted agricultural workers in the first place but amended the laws in later years. As a result, farm sector in South Carolina did have a quasi phase-in period to adjust its labor demand and supply, therefore reduced the shock brought by E-verify adoption.

Robustness Check

This section includes a series of robustness checks to examine the consistency of the synthetic control estimates of E-verify adoption impact on the undocumented immigrant share in the farm sector. First, we address the concerns that the spillover effects of E-verify adoption on neighboring states may bias the results. For instance, the undocumented immigrants who were in Arizona may migrate to states such as California, Texas, or New Mexico out of geographical (short distance) and ethnic (a large Hispanic population) concerns (Haq 2010). As a result, for each E-verify adopting state, we exclude the adjacent states that may become the potential destinations for those undocumented immigrants who may move to neighboring states under the pressure of E-verify. The exclusion of more states from the synthetic donor pool changes the weights assigned to other synthetic control states but the estimates obtained from the synthetic control method are similar to the main findings.

Second, we define the likely undocumented immigrants as those who are non-citizens and between 16-45 years old with education level of less than high school and Hispanic origins. To test if the change of the definition of likely undocumented immigrants would also alter the synthetic control estimates, we replace our definition with those used in the studies by Orrenius and Zavodny (2015) and Dorantes and Bansak (2012). Orrenius and Zavodny (2015) define likely undocumented workers as those immigrants who are not naturalized citizens and are from Mexico with at most high school education. Amuedo-Dorantes and Bansak (2012) define likely undocumented workers as immigrants who are 16-45 years old, Hispanic noncitizens with an educational level of high school or less. Our estimates using these alternative definition of likely undocumented immigrants vary a little but they are still in line with our main findings that Arizona, Alabama, and Utah experienced declines in the share of farm workers who are likely undocumented.

Third, as suggested by Abadie, Diamond, and Hainmueller (2015), the gap found by using synthetic control method may be due to a lack of predictive power of covariates instead of a result of E-verify adoption. As a result, we apply a test that assigns the placebo cutoff year to the years before the actual adoption of E-verify. If there are also large gaps following these placebo years, it means that the significant gap we find in the main results could just be an outcome of weak predictive power of covariates. For all seven states that adopted E-verify system, no state shows a large gap after the placebo policy intervention year, which suggest that the significant reduction in likely undocumented immigrants we found in some states are truly caused by the adoption of E-verify.

Fourth, we note that some states phased into the adoption of E-verify. For instance, North Carolina required all employers with 500 or more employees to use E-verify in October 2012 and then extend this requirement to all employers with 25 or more employees in July 2013. We have our concerns that the choice of cutoff year may affect the estimates shown in the synthetic control graph. To examine the possible changes brought by the alternative cutoff years in the states that have multiple phases of E-verify adoption, we reassign the cutoff year for the following states. We change the E-verify adoption year of Georgia and North Carolina from 2012 to 2013 and find that Georgia experienced an increase in the share of farm workers who are likely undocumented immigrants, however, the change is not significant and North Carolina experienced little change in the share. Both robustness results would draw very similar conclusions as the main findings. Mississippi has a long phase-in period from 2008 to 2011. We conduct robustness checks by forwarding the cutoff year to 2009, 2010, and 2011 and find no significant change that would alter our conclusions for Mississippi. The little impact of E-verify found in these states that phase into E-verify adoption is expected because it gives local economies a relatively longer period to adjust and cushion the labor supply shock caused by the stringent immigration policies.

Fifth, we further narrow the donor pool of the synthetic control group by excluding more states that have small share of GDP contribution (less than 0.1%) from the agricultural sector. Except for the changes found in the weights assigned to the controlled states (similar to the first robustness check that excluding neighboring states), this study finds that the conclusions from narrowing the state donor pool are still broadly in line with the main results.

Finally, in addition to the synthetic control method, this study examines the robustness of the main results by employing a Difference-in-Differences (DID) model specified as follows:

$$Share\_undoc_{st} = \alpha + \beta_1 E\_verify_{st} + X_{st}\varphi + \delta_t + \theta_s + \delta_t\theta_s + \tau_{st} + \varepsilon_{st}$$

where $Share\_undoc_{st}$ is a dependent variable indicating the share of farmworkers who are likely undocumented immigrants in state s and year t. E_verify_{st} is a dummy variable which equals one if a state adopted E-verify after the policy intervention year. X_{ist} includes state level characteristics. δ_t is year fixed effects, θ_s is state fixed effects, $\delta_t\theta_s$ are year by state effects, τ_{st} is the state-specific time trend, and ε_{st} is the error term. The results of DID model are reported in table 5.

Table 5. Difference-in-Difference estimates of E-verify adoption on the share of farm workers who are likely undocumented immigrants.

	Arizona (1)	Alabama (2)	Georgia (3)	Mississippi (4)	North Carolina (5)	South Carolina (6)	Utah (7)
E-verify	-0.045*** (0.011)	-0.022*** (0.008)	0.005 (0.006)	0.003 (0.004)	-0.019*** (0.003)	0.004 (0.004)	-0.038*** (0.006)
N	396	396	396	396	396	396	396

Note: All model specifications include year fixed effects, state fixed effect, state-specific time trend, and year by state fixed effect. Other covariates include gross receipt of farms income, value of total agricultural production, government payment, share of hired labor expenditure in total agricultural production cost, share of female residents, population mean age, population mean education level. Models are weighted by the population share of non-citizen immigrants. Huber-White robust standard errors are clustered at the state level. *p < 0.1, **p < 0.05, and ***p < 0.01.

The estimates provided by DID model are consistent with the results from the synthetic control method (except for North Carolina) that Arizona, Alabama, and Utah experienced significant decreases in the likely undocumented immigrant share by 4.5%, 2.2%, and 3.8%, respectively. The magnitude of the DID estimates are in general larger than that of synthetic control method but still within a close proximity and provide further support to the main conclusions.

Conclusion

From 2008-2012, seven states adopted comprehensive E-verify mandates that require employers to verify the employment eligibility of newly hired workers in order to curb the hiring of undocumented immigrants and to improve labor market outcome from U.S. native (Orrenius and Zavodny 2015). Using data from 2004-2014, we find that comprehensive E-verify mandates only reduce the share of farm workers who are likely undocumented immigrants in Arizona and Alabama. Other states that adopted comprehensive E-verify experienced insignificant change in their likely undocumented population in farms.

After examining the E-verify mandate policy in each adopting state, this article suggests that the disparities in E-verify impacts are mainly due to the differences in the enforcement level of E-verify laws. For states that experienced significant drops in likely undocumented population in farms, E-verify mandates were adopted in a very short period (no phase-in period) and no exemptions that based on the number of employees was made. Other states that have less restrictive E-verify laws may allow the local economies or farms to adjust to or find a way to retain undocumented population. As a result, it appears that there should be less of a labor concerns among farms if the state decides to gradually implement E-verify laws. But the farm sector in states that adopted more restrictive mandates may face with a labor shortage and the local government should be fully aware of these consequences when they decide to impose stringent immigration laws.

References

Abadie, A. Diamond, A. and Hainmueller, J. 2010. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. Journal of the American Statistical Association 105, 493-505.

Abadie, A., Diamond, A., and Hainmueller, J. 2015. Comparative politics and the synthetic control method. American Journal of Political Science, 59(2), 495-510.

Amuedo-Dorantes, C. and Bansak, C., 2012. The labor market impact of mandated employment verification systems. The American Economic Review, 102(3), pp.543-548.

Amuedo-Dorantes, C, Puttitanun, T., and Martinez-Donate, A. P. 2013. How do tougher immigration measures affect unauthorized immigrants? Demography 50(3), 1067-1091.

Berry, Jahna. 2010. ‘‘Arizona's Illegal Immigrants Can Easily Avoid E-Verify System,’’ Arizona Republic, August 17.

Bohn, Sarah and Magnus Lofstrom. 2013. Employment effects of state legislation. In Immigration, Poverty, and Socioeconomic Inequality, edited by David Card and Steven Raphael. New York: Russell Sage Foundation, pp. 282314.

Bohn, S., Lofstrom, M.,and Raphael, S. 2014. Did the 2007 Legal Arizona Workers Act Reduce the State's Unauthorized Immigrant Population? Review of Economics and Statistics, 96(2), 258-269.

Bohn, S., Lofstrom, M. and Raphael, S. 2015. Do E-verify mandates improve labor market outcomes of low-skilled native and legal immigrant workers?. Southern Economic Journal, 81:960-979.

Haq, Husna, 2010. Hispanics abandon Arizona, fleeing economy, immigration law,” The Christian Science Monitor, http://www.csmonitor.com/USA/Society/2010/0610/Hispanics-abandon-Arizona-fleeing-economy-immigration-law.

Meissner, Doris M., and Marc R. Rosenblum. 2009. The Next Generation of E-Verify: Getting Employment Verification Right. Migration Policy Institute.

Orrenius, P. M., and Zavodny, M. 2007. Does immigration affect wages? A look at occupation-level evidence. Labour Economics 14(5), 757-773.

Orrenius, Pia M., and Madeline Zavodny. 2015. The impact of E-Verify mandates on labor market outcomes. Southern Economic Journal 81, no. 4: 947-959.

Nowrasteh, A. 2012. The Economic Case Against Arizona's Immigration Laws. Cato Institute Policy Analysis 709.