The Impact of Immigration Enforcement on the Farming Sector

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Abstract

This paper examines the effects of state and local immigration enforcement efforts on the U.S. Farming sector. We use variation in enforcement efforts generated by the timing of adoption of 287(g) programs by state and county law enforcement agencies (allowing local officers to be trained to perform several immigration officer duties). Nearly 70 jurisdictions adopted such measures between 2002 and 2011. Difference in Differences (DD) models are estimated using individual level data from the 2004-2010 waves of the American Community Survey (ACS) and county level data from the 1997, 2002 and 2007 waves of the U.S. Census of Agriculture. We find robust evidence that immigration enforcement efforts by county authorities have reduced immigrant presence. We also find evidence that wages of farm workers, general patterns of labor use in farms and farm profitability may have been affected in a manner consistent with labor shortages. There is no clear evidence that state efforts have lead to notable effects.

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1 Introduction

The passage of the Illegal Immigration Reform and Immigrant Responsibility Act (IRRA) of 1996 added Section 287(g) to the Immigration National Act (INA), allowing federal authorities to enter into agreements with state and local law enforcement agencies for purposes of immigration enforcement. Given that immigrants are an important source of labor for agriculture, such reforms have raised concerns about a shortage of labor in the US agriculture. Section 287(g) allows the US Immigration and Customs Enforcement (ICE) deputy director to enter into agreements with state and local law enforcement agencies, permitting designated officers to perform immigration law enforcement functions, provided that the local law enforcement officers receive appropriate training and function under the supervision of ICE officers (Capps et al., 2011).

Even though the act was signed in 1996, the first actual contract between ICE and a state authority (Florida Department of Public Safety) was signed in 2002. From 2002 until 2011 there have been 69 jurisdictions in the US that have adopted the 287(g) program including states (e.g. Alabama, Florida, Arizona, Georgia) and counties from different states (e.g. Cobb county, Georgia; Gaston County, North Carolina; Davidson County, Tennessee, etc.).

These programs were specifically targeted to remove illegal immigrants with criminal charges. However, about half of the program activity (defined by the number of immigration detainers issued) has involved people who have not committed felonies but rather immigrants who were detained for misdemeanors and traffic offenses (Capps et al., 2011). By 2011, 186,000 illegal immigrants have been identified for removal under this program and 126,000 of them departed voluntarily (Parrado, 2011). However, some academics and advocacy groups claim that most of the people arrested and deported were not the criminals that the program was supposed to apprehend, but they were apprehended for minor offenses and during routine traffic stops (Lacayo, 2010).

There is some evidence that immigrants left jurisdictions that signed 287(g) agreements (e.g. Capps et al. (2011); Rivas (2008); Barry (2009); Juby and Kaplan (2011)). For instance, Frederick County (MD) which signed the agreement in 2008, placed almost 80 percent of the detainers under petty crimes or traffic offenders and experienced a 61 percent drop in the Hispanic population while neighboring counties experienced an increase (Capps et al., 2011). To date, however, there has been no systematic examination of the effect that local enforcement of 287(g) programs has on immigrant populations.

In addition to 287(g) programs, the ICE has also intensified the number of visible, large-scale immigration raids to apprehend undocumented immigrants. The number of undocumented immigrants arrested at workplaces increased more than sevenfold from 500 to 3,600 between 2002 and 2006 (Capps et al., 2007). But more importantly, work-site raids targeted and removed hundreds of immigrants on the same locality, and brought high-profile criminal (fraud) charges on those apprehended working without proper documentation.

Agriculture is highly depended on migrant workers and thus, it is important to know whether these immigration efforts affected agricultural labor in the jurisdictions that adopted the 287(g) and that were affected by raids. The issue of immigration laws and labor shortages in agriculture has been a prominent one for the past decade. To our knowledge, there is no study that has examined the effects of the 287(g) programs and immigration raids on agricultural labor. We use local variation on the timing of adoption of 287(g) programs to assess the implications of these immigration laws on agriculture. Specifically, using individual level data from the American Community Survey (ACS) we first provide evidence on whether 287(g) adoptions result in reductions of immigrant populations. We then use data on farm workers in the ACS to examine the impact that these laws have had on the wages of those employed in agriculture. Using data from the Census of Agriculture we then assess the impact of 287(g) programs on agricultural labor use and crop choices.

The paper proceeds as follows. Section two reviews the literature on immigration and labor shortages and provides a description of 287(g) programs along with counties and states that signed them. Section three lays out the methodology and data used in this study. Results are presented in section four and conclusions are drawn in section five.

2 Immigration laws and labor shortages

Concerns about the effect of immigration laws and labor shortages in the agricultural sector started in 1986 with the passage of the Immigration Reform and Control Act (ICRA) that approved a series of steps to provide around 1.1 million illegal workers with legal status. In addition it established an H-2A agricultural guest worker program and put sanctions on employers who knowingly hired illegal workers. The fears on labor shortage on agriculture rose as experts on the industry predicted that newly legalized workers would leave agriculture and move to other sectors (Tran and Perloff, 2002). However, Tran and Perloff (2002) using nationally representative data from the National Agricultural Worker Survey estimated transitional probabilities showing that they are the same across job categories and legal status.

With the passage of IRRA in 1996 there has been (mostly anecdotal) evidence that there are labor shortages in the agricultural sector. For example, Hotakainen (2011) reports that Washington state apple growers experienced labor shortages in 2011. McKissick and Kane (2011) conducted a survey among fruit and vegetable farmers in Georgia and their findings suggest that most of the respondents experienced labor shortages reporting a 40 percent reduction in labor availability compared to the normal peak harvest employment. Others have also argued for real wage increases and labor scarcity on farms (e.g. UCDavis (2006); Preston (2006)).

There have been attempts in the literature to argue against a labor shortage. For example, Martin (2007) looks at the labor price data arguing that if there was a shortage, then there would be a sharp increase in the price of labor for agriculture. Further, Martin (2007) states that there were labor shortages during 2006-2007 season but shortage complaints dropped during 2008-2009. Levine (2009) examines farm employment and unemployment data and concludes that there is no evidence of a nationwide labor shortage but does not preclude the existence of shortages in particular areas at specific points in time. Holt (2008) argues for a shortage of labor supply in the agricultural sector. A study by Ruark and Moinuddin (2011) on the effects of replacing unauthorized with authorized workers found insignificant effects on profitability in agriculture.

To our knowledge, current empirical work on the effect of immigration laws on labor shortages in agriculture is based on studies that are mainly descriptive in nature. Other studies such as Devadoss and Luckstead (2011) that are more empirical rely on theoretical models and simulation analysis to look at the effect of more immigration laws on agricultural wages (rise) and employment (shortage). Zahniser et al. (2012) employ a computable general equilibrium model and suggest that an expansion of the H-2A Visa program results in 1-2 percent increase in agricultural output for labor intensive sectors associated with a decrease of 6 percent in U.S. born agricultural workers and a decrease (3 percent) in earnings of those who continue to work in the sector. In addition, tighter immigration laws may result in a 2-4 percent relative decrease in the output of agricultural labor-intensive sectors, 1 percent relative decrease in the economic welfare of authorized immigrants and the U.S.-born at the aggregate level.

Nonetheless, the effects of immigration laws on the U.S. economy have attracted attention among labor economists and lawyers (e.g. Pham and Van (2010); Hanson (2009)). To our knowledge, Pham and Van (2010) is the only empirical study to look at immigration laws (including the 287(g) program) and their impact on the local communities using county level economic and legal data for the U.S. starting in 2005 when a large volume of immigration laws were enforced. They use differences-in-differences (DD) estimation and find that immigration law enactments have a small negative effect (1-2 percent on unemployment) in jurisdictions that enact them.

2.1 Background on 287(g) immigration laws

Enacted in 1996, 287(g) laws allow the federal government to sign agreements with states and local enforcement agencies to deputize officials to enforce immigration laws. The program remained inactive until September 11, 2001 and then it started gaining interest among several states and jurisdictions (Lacayo, 2010). While the primary intention of the program has been to apprehend criminals, in many of the cases immigrants were detained for minor offenses. In fact, 287(g) laws have created an insecure environment for the Hispanic population. For example a survey from the Pew Hispanic Center Survey found that one in ten Hispanics adults report that they have been asked about their paperwork by police or other authorities (Lacayo, 2010). There are three models under which the 287(g) program operates. The first model, known as the Jail Enforcement Officers (JEO) model or "jail model", exclusively trains police officers who work in jail and detention facilities to screen those arrested and place civil warrants on noncitizens who enter their facilities. The second model, known as the Task Force Officers (TFO) model or "field model", trains patrol officers who are mobile within the jurisdiction "to check the immigration status of individuals they encounter in the course of their routine law enforcement duties." Of the active Memorandum of Understanding (MOAs), 31 are JEO, 24 are TFO, and 16 are a combination of the two models (Lacayo, 2010). Table 15 (Appendix A) illustrates states and jurisdictions that have enacted such laws and Table 16 indicates counties that have experienced raids.

3 Methodology and Data

3.1 Overview

Enforcement efforts through the use of 287(g) agreements are expected to make localities less attractive for undocumented alien workers. Immigration laws in counties and states may thus have two effects. First, because of fear of being deported undocumented immigrants may leave these jurisdictions and move to jurisdictions that are not subject to these laws. Second, laws may deter new immigrants from coming to reside or work in jurisdictions with 287(g) programs as they face a higher risk of being subject to the law enforcement authorities. We first test this proposition using individual level data from the American Community Survey (ACS). Legal status is not observed, however, we examine if the incidence of those who report noncitizen status and foreign-born individuals who have been in the country for 20 years or fewer declines disproportionately in adopting counties.

Given that more than 50 percent of agricultural workers in the U.S. are illegal (United States Department of Labor, 2005) such movements may significantly affect the supply of agricultural labor. Reductions in the supply of agricultural labor would put upward pressure on farm wages; we would thus expect disproportionate increases in the wages of those working in agriculture in adopting jurisdictions relative to other communities that did not change their immigration enforcement efforts. This proposition is tested with individual level data on over 50,000 workers who declare farm labor as their primary occupation in the ACS.

When faced with higher prices, farm owners could adopt less labor-intensive practices and substitute for capital and machinery. We examine possible changes in agricultural input use and crop choices with data from the census of agriculture. Unfortunately, the public use data do not report hours of labor used, or the hourly cost of labor, rather only number of workers and total expenses on labor are reported. This makes a direct examination of labor use and wage impossible. However we examine changes in the expenditure shares for labor, fuel and machinery. If labor shortages have put upward pressure on wages, we would expect the cost share of labor to have declined and that of fuel and machinery to have increased. We also provide a more direct test of whether farmers have changed production methods in response to 287(g) programs by examining the impact on the share of cropland used for vegetable production (a relatively labor intensive activity). Finally we examine whether adopting jurisdictions have experienced disproportionate changes in farm income. Under fairly general assumptions on production technology the profit function is non-increasing in input prices, so farm incomes are expected to have declined disproportionally in 287(g) counties.

3.2 Data

Individual level data for this study come from the Census Bureau's American Community Survey (ACS). The ACS collects data on 250,000 households each month (with no household surveyed more than once). The survey elicits demographic information such as gender, race, ethnicity etc. Immigration information is also elicited; respondents report their place of birth, and if the place of birth is outside of the U.S. they report the number of years that they have lived in the U.S. and whether they are U.S. citizens (including permanent residents). Information on education, work activities (labor force and employment status, annual earnings, weeks worked and average number of hours worked per week) is also reported. Most importantly, the occupation of the respondents' primary job (defined as the one that takes up the majority of one's weekly time) is elicited. This makes it possible to focus attention on the wages of farm workers. Finally, the ACS provides geographic information at levels of aggregation below the state level, but the county where respondents reside is not always reported. Starting with the 2005 wave, the ACS reported counties if they exceed a population of 65,000, and has created geographic areas called Public Use Micro Data Area (PUMA) that are available for all respondents. PUMAs are areas with a minimum population of 100,000 people and they do not cross state lines. Larger counties contain several PUMAs, while multiple smaller counties may be contained within PUMAs. With very few exceptions (mostly in some cities in Virginia and some Native American Areas) it is always the case that a county is either fully contained in a PUMA or fully contains several PUMAs. 287(g) programs are implemented either at the state or the county level; State is available at the ACS, so it is always possible to determine if an individual is subject to a state-level 287(g) program each year. Regarding county level efforts, for individuals in PUMAs that contain multiple counties and at least one program county it is not possible to determine with certainty whether they are subject to the program or not, so it is not clear if they are treated or control individuals. We exclude PUMAs with multiple counties and at least one program county from the analysis. All PUMAs that are fully contained in a county or those that do not contain a program county are used. This excludes 10 of the 49 program counties from the analysis that uses ACS data. The remaining areas include identifiable counties or multi county areas known not to have a program. Table 1 presents the number of jurisdictions that adopted each year as well as the number of farm workers in these jurisdictions. Summary statistics of the variables used from the ACS by type of jurisdiction are presented in Table 2.

In addition to the individual level data, this study also utilizes county level data for all U.S. counties. Most of the county level data come from county-level tabulations from the Census of Agriculture (1997, 2002 and 2007) conducted every five years from the USDA National Agricultural Statistical Survey (NASS) (USDA, 2012). USDA's NASS provides county level information on labor expenses, number of hired workers and fuel expense, among other things. County level demographic information is available from the U.S. Census Bureau.

Information on the implementation of 287(g) programs by state and county was collected from the U.S. Immigration and Customs Enforcement (ICE, 2011). Immigration raid information was found through an extensive search on news articles and other printed media.

Descriptive statistics of the county level data for all the variables used in this study are shown in Table 3. For each county in the U.S. we have information for all the adjacent counties so we know all the counties neighboring those where immigration laws were enforced (United States Census Bureau, 2012). Similarly we create dummy variables for the counties adjacent to counties in states that adopted and adjacent to individual counties that are not in states that signed 287(g) agreements.[1]

Information on raids was collected from publications in the media in order to record counties where the raids were located and the same procedure was followed to identify counties adjacent to raid counties. The last set of policy variables are pre law dummies for all jurisdictions under 287(g) agreements and subject to raids. They are especially helpful to identify pre-trends.

[1]If a county signed a 287(g) agreement and it is also part of a state that also signed an agreement, it is coded as a separate county.

3.3 Empirical Model

We examine the impact of three treatments: (1) state-wide task forces, (2) county-level contracts between ICE and local law enforcement agencies and (3) high profile, documented raids aiming to detain and remove illegal immigrants. We first examine if these policies have exerted a disproportionate effect on: (a) the incidence of self-reported noncitizens, (b) immigrants in general, (c) immigrants who have spent 20 years or fewer in the U.S. Then we examine the impact of earnings of workers who report farming as their primary occupation. A difference-in-differences (DD) approach is used to explain variation in individual outcomes within-county over time. Specifically, in year-t, individual-i resides in county c in state s; we estimate the following equation:

$$y_{it} = \beta P_{ct} + \alpha X_{it} + \gamma_c + \tau_t + \epsilon_{it}. \tag{1}$$

Depending on the specification, y_{it} measures wages or immigrant status for individual i in year t. Measures of the couty's program status in year t, (P_{ct}) and measures of individual level demographic characteristics of respondents (X_{it}) capture observable influences on the outcomes.

Unobservable influences are partitioned into three additive components: a county fixed effect captures time-stable county-specific influences (γ_c), a year fixed effect (τ_t) captures differences in outcomes across years, and idiosyncratic influences remain in (ϵ_{it}). Throughout the paper we cluster standard errors at the county-level. To allow β to capture the effect of program participation for state and county-level programs, we first define P_{ct} as a post-adoption indicator by jurisdiction level: $1(\text{Law}_{ct})$ for counties and $1(\text{Law}_{st})$ for programs adopted at the state level in post adoption years.

Because 287(g) participation is not randomly assigned, there may be systematic unobserved differences between counties that influence both program adoption and outcomes, which would bias estimates of program effects. The inclusion of county fixed effects allows us to identify the effects of the program by studying changes in outcomes over time, within county. Year fixed effects identify aggregate year-specific effects (τ_t), across all individuals. This is a generalization of the DD model that allows us to capture time effects and program effects separately because of variation in the timing of adoption across jurisdictions. The model is identified by assuming that program participation(P_{ct}) is uncorrelated with unobserved influences (ϵ_{it}) conditional on other observables and fixed effects:

$$Cov[P_{ct}, \epsilon_{it}|X_{sit}, 1_i, 1_t] \equiv 0 \tag{2}$$

Thus program effect estimates are unbiased even if program adoption is based on stable differences in outcome levels. If, for instance, counties with higher shares of immigrants are more likely to adopt or to adopt earlier than counties with lower levels, this does not bias estimates. However, if areas with growing immigrant shares were more likely to adopt, this could cause bias. The crucial assumption is that within-county, time-varying, unobserved influences on outcomes are not systematically related to adoption. (Bertrand et al., 2004) stress the importance of choosing the right control group. The assumption of "no time varying unobservable differences" between the treatment and control groups implies that these two groups would follow similar trends in the absence of treatment. This assumption is testable for trends preceding adoptions since we have data for multiple years. We test for the presence of differential trends in outcomes among non-adopters and future adopters *prior to adoption*. We do this by relaxing the assumption of a constant program effect over years relative to adoption, and measure program participation status (P_{ct}) via a full set of leads and lags. We set to zero all county-years in non-program (control) counties as well as the year immediately prior to adoption for adopting jurisdictions. Each remaining year in adopting counties is then specified in terms of it's temporal distance from the adoption year (e.g. 1(2 years pre adoption), 1(3 years pre adoption), and so on). These leads and lags nonparametrically describes the differences in trends (measured as a deviations in each year relative to the last year before adoption) prior and after the 287(g) start date, between adopters and non adopters. This makes it possible to determine if adopters and non adopters were experiencing differential trends on each year leading up to adoption and if they do so after the program starts. Statistically identical pre-trends provide evidence that the crucial "parallel trends" assumption is satisfied. As an additional check, we identify counties that are adjacent to program counties but are not themselves subject to a law, and use them as a control category. The idea is that any time-varying unobservables that affect outcomes and program status are likely to be more similar among geographic neighbors.

The remainder of the analysis examines enforcement effects on agricultural labor use and payments, fuel expenses, crop choices and farm income with county level data from 1997, 2002 and 2007. We are still able to estimate DD models to isolate the impact of each enforcement type on counties subject to enforcement, but with only three observations for each county we cannot separate time from program effects. As above, pre-to-post law differences in outcomes among program counties are compared against two control groups, all non adopters and those adjacent to adopters. Specifically, we estimate:

$$Y_{ct} = \gamma_c + \theta_T + \beta_j X_{jct} + \alpha_k Law_k * T_{07} + \alpha_k Law_k * T_{97} + \delta_{ka} Law_{ka} * T_{07} + \delta_{ka} Law_{ka} * T_{97} + \epsilon_{ct} \quad (3)$$

where Y_{ct} is the outcome variable in county c and year t (e.g. labor use, number of workers hired, labor expense, etc). γ_c and θ_t are county fixed effects and year fixed effects, respectively. X_{ct} is a vector of county-observable time-varying attributes. As noted, all adoptions examined here coincided between 2002 and 2007, so $Law_k * T_{07}$ is equal to one for counties that become subject to the K_{th} policy (county 287(g), state task force or immigration raid) between 2002 and 2007. In turn $Law_k * T_{97}$ capture pre-program trends for counties about to become subject to enforcement. The same interactions are also included for adjacent counties, $Law_{ka} * T_{07}$ indicates that an adjacent county has become subject to the law between

02 and 07, and Law_{ka}*T_{97} is one if an adjacent county will become subject to enforcement [2]. Similarly here, omitted time-varying county attributes that are correlated with policy adoption and the outcome Y can still, bias estimates, but differences in pre-adoption levels are not of concern. We note that controlling for a number of time-varying county attributes can help, but these need to be treated with caution because some may, in fact, legitimately mediate the impact of the policy on farmers.

We focus our attention on these outcome variables of interest: hired labor expense per unit of land, share of hired labor expense on total production expense, expense per hired worker, number of workers hired per unit of land, share of fuel expense on total production expense, machinery value per unit of land, share of vegetable acres per unit of land and farm income per unit of land. All these variables are available at the county level for years 1997, 2002 and 2007. It has to be noted that hired labor (comprising on average more than 80 percent of the total farm labor) is just one component of the total farm labor hired by U.S. farms. The other part is comprised of contract labor which is more seasonal and is brought by contractors and other agricultural intermediaries (Martin, 2007). With the exception of the expense per worker hired and farm income, all other outcome variables are divided by the land in farms for the initial survey period, 1997.

4 Results

In order gain some insights on the impact of immigration enforcement on immigrant movements (noncitizens) we first examine how the share of immigrants in the adopting states and counties changes during the pre and post law periods. Counties and states that adopted 287(g) programs and efforts to raid establishments performed arrests and deported noncitizens. Thus in the post law period one would expect the share of non citizens to drop either because people left or new immigrants may prefer to reside in non program counties where

[2] All but one 287(g) laws were signed after 2002. Florida is the only exception that signed the agreement on July, 2002. However, Florida did not report any arrest until later years and for the purpose of this study Florida is considered to have a post law period in 2007 only.

they do not face the risk of getting checked by immigration authorities. Table 4 presents results of DD estimates for three different outcome variables; the incidence of noncitizens (Specification 1), incidence of all foreign born (Specification 2) and incidence of foreign born individuals who have been in the country for fewer than 20 years (Specification 3). 287(g) contracts executed by county-level authorities have a negative impact on the shares of immigrants in adopting counties, suggesting that immigration enforcement force immigrants to either move to other non-adopting counties or discourage new immigrants from moving to a program county. Specifically, the point estimate associated with the incidence of a noncitizens in post program county-years is -0.0044 ($p<0.01$). The average share of noncitizens in the overall sample is 7.8 percent, while in adopting counties it is 16.1 percent, so a 0.4 percentage point decline marks nearly a 5 percent drop relative to the sample average or nearly a 3 percent drop relative to the average in adopting counties due to the policy. As noted, there may still be time-varying unobservables that can bias results, but these may be more likely to exist in geographically adjacent control counties than in the whole sample. The models included indicators of adjacent counties in years where at least one neighbor has adopted a program. The DD estimates for adjacent counties are nearly zero. This increases confidence that these findings are not confounded by unobserved trends. Immigration status is, however, self reported. So there is a possibility that illegal immigrants in enforcement areas are less likely to self report illegal status than otherwise similar peers. Immigrant status (regardless of legal residence) may be less likely to be miss-reported since language differences are likely to be apparent for foreign born individuals. We thus estimate an additional specification (2) with incidence of any foreign born individual as a dependent variable. The estimate is negative, but smaller (-0.0025) and not statistically significant at conventional levels. However, a majority of foreign born individuals are legal and not affected by the policy. To narrow the analysis down to foreign born individuals who are more likely to not have legal status we estimate the impact of enforcement on the incidence of a foreign born individual who reports having been in the U.S. for fewer than 20 years (Specification

3). The overwhelming majority of immigrants with more than 20 years in the U.S. are very likely to have obtained legal status. Estimates indicate a drop of 0.048 ($p<0.01$), a very similar result to that in specification (1). For the other two enforcement methods, state level 287(g) contracts and raids, we do not find a negative effect on the incidence of migrants; the estimate is actually positive for state level enforcement. This may reflect existing pre-trends. The "parallel trends" assumption is perhaps the most important in a DD framework. We examine the presence of pre-trends by estimating full dynamic models (with full leads and lags relative to the pre-adoption year) for county-level 287(g) programs to examine if the negative effect may be in part due to a pre-existing differential trend in adopting counties. While unlikely, it could be the case that in the pre law period, the share of noncitizens was actually declining in the last years prior to adoption. In that case the result may simply be the continuation of a trend. Table 5 presents parameter estimates associated with each year pre-adoption and each year post-adoption with the single year prior to adoption and all non adopting county-years set to zero. Figure 1 plots the DD estimates and 95 percent confidence intervals. For each pre-law period the deviation relative to the pre-adoption year is virtually equal to those in the control counties, indicating no pre-trends. In each post adoption year the estimates increase in magnitude, likely reflecting a true program effect.

A decrease in the share of noncitizens in the post law counties suggests that there may be labor shortages, especially in the agricultural sector that relies heavily on immigrant labor. Fortunately, ACS has information on the wages of agricultural workers which we explore next. Table 6 provides estimates of the DD model on wages of farm workers with a set of controls for individual characteristics. The dependent variable is the log of wages earned from employment in entities not owned by themselves or family members. In the first column (Specification 1) the control group includes farm workers in all counties in the U.S. that are not subject to 287(g) immigration laws. These estimates suggest that farm workers in the post law counties may have experienced an increase in wages, however, the coefficient is not significant at conventional levels. Farm worker wages in adjacent counties in post program years, however, have declined disproportionally, and while this difference is not statistically different from wage changes in the control group, it is statistically different from the estimate for post-program county-years. For purposes of illustration, we estimate a DD model where only adjacent county farm worker are used as a control group (Specification 2). Estimates indicate an 11.2 percent increase in wages in post law county-years, relative to same-year changes in non program adjacent counties. Adjacent counties could be a better control group because of geographic proximity and more similar trends compared to all other non program counties that are not in such vicinity. It is important to note that we do not know the exact number of hours that each individual worked, but included controls for the average number of hours worked weekly and the number of weeks worked. The full leads and lags specification (Table 7) indicates no significant pre-trends and an increase in the post law period for the counties that adopted 287(g) programs. This can be more clearly seen in Figure 2 where the coefficients and 95 percent confidence intervals are plotted; coefficients fluctuate around zero with no visible trend in the pre law period and then there is an increase in the first post low period that continues in the years following adoption.

Given that the ACS does not provide additional information on the U.S. agricultural sector, we turn our attention to the county level information from the Census of Agriculture to further explore any effects of immigration laws on various agricultural outcomes at the county level.

These models use county level data from the 1997, 2002 and 2007 waves of the Census of Agriculture. For each state and county subject to 287(g) laws or raids we include a pre (1997-2002) and a post (2002-2007) adoption dummy (equal to one in post and pre years if subject to the policy and zero otherwise) to be able to see the changes in trends before and after the enforcement effort went into effect; we also do the same for all non program counties that are adjacent to a program county. Four specifications are used to explore each outcome variable. The first specification (1) includes every county in the sample. The second specification (2) leaves out counties that have less than $1.5 million of agricultural crop sales (the minimum in adopting counties). We do this since counties with very little agriculture may have a substantially different production function and may not be good controls. The third specification (3) only includes in the control group those counties that will be subject to an enforcement contract after 2007, the last year in our data; again the idea here is that future adopters that have not yet adopted may provide a better control group than all counties. The last specification (4) includes the log of total land in farms as a control, the log of total land in farms and crop land each year as additional controls. Given that farmers may change their crop production area as a response to potential changes in labor availability, this additional specification may offer additional insights on the results of the DD analysis. Specifically, this last model provides insight on the extent to which observed effects on the outcome variable operate through an increased propensity to retire land in general or crop land in particular as labor costs increase.

First we examine the impact of the programs on labor expenses as a share of total expenditures. Figure 3 plots labor expense shares for each group of counties before and after enforcement efforts. The labor share in 287(g) was increasing before adoption while in control (Never Adopters) and adjacent counties it was either flat or slightly declining. Between 2002 and 2007 labor expense shares experienced a steeper decline than in either control or adjacent counties. Table 8 presents formal regression evidence of these patterns. Both the pre-program increase and post-program decline are statistically different ($p<0.01$) from the omitted category (Never Adopters) and adjacent counties. These results indicate that while labor expense shares were actually increasing disproportionally in 287(g) counties before the program, program adoptions may have led to a trend reversal and a decline in labor expense shares that is not matched by trends in never adopters or adjacent non program counties. Results are stable across all four specifications. No evidence that counties experiencing immigration raids were different from the control before or after the raid was found. Program states also experienced similar trends to program counties before adoption, but the decline after the program was much smaller, and not statistically different from the controls or adjacent counties after the program.

Expenses per worker is examined in Table 9 and illustrated in Figure 4 . This outcome should be interpreted with caution as information on how many weeks or hours per week each worker has worked during the year is not available. So this is not a wage rate; a higher expense per worker could reflect lower turnover (individuals being employed longer) or the same workers being employed for more hours each week, in addition to higher wage rates. However, a higher expense per individual worker is consistent with a tighter labor market. The results in Table 9 show that expenses per worker were increasing at the same rate statistically as in never adopters and adjacent non adopters, as there are no statistically significant pre-trends. After adoption growth in expenses per worker in program counties exceeded that of never adopters and that of adjacent counties ($p<0.01$). These estimates are also stable across all four specifications suggesting a program effect on expense per worker consistent with a tighter labor market. Estimates of the impact of county-level 287(g) programs on the number of workers hired per unit land in farms in 1997 is also consistent with a tighter labor market. Table 10 indicates a disproportionate decrease in workers hired in program counties, while, as shown also in Frigure 5 trends before adoption were identical to control and adjacent counties. The third specification (1A) presents the results with the full sample winsorized at 95 percent as the number of hired workers had some outliers. However, the main results do not change.

So far the analysis provides some evidence that labor may have become more expensive, outlay per worker has increased and the number of workers hired has dropped in post law counties, even when we control for cropland area. However, neither of these results is indicative of a substitution effect from labor to other inputs. The only evidence of a substitution effect thus far has come from the documented decline in the labor expense share of total production expenses. Next, we look for corroborating evidence of a substitution effect. The first outcome examined is the share of fuel expense on total production expense (Table 11 and Figure 6) and the second is the logarithm of machine value per unit of land (Table 12 and Figure 7). The share of fuel expense is not different compared to the control group for the post counties but it has increased more than in adjacent non program counties. We also find no significant changes in machine values per unit land relative to never adopters or adjacent counties.

We also look for evidence of a substitution effect by examining program effects on the share of vegetable acres per unit of land used (Table 13). Figure 8 plots the share of vegetables acres per unit of land available. If labor becomes scarce one would expect the share of vegetables plants to drop in post law jurisdictions as vegetables are more labor intensive. Farmers may switch to other crops that are less labor intensive. Estimates show a decline in the vegetable share in post 287(g) county-years but estimates are imprecise.

Finally we examine the impact of 287(g) programs on farm incomes. Farm income at the county level is the net cash farm income measured for all operations in the county for each year. These results are presented in Table 14 where the dependent variable is the log of farm income per acre available in each year. Results indicate that farm income in adopting counties has decreased relative to the control group after the adoption of the law. In the pre law period, farm incomes in adopting counties were increasing and after the adoption of the law the trend was reversed. This is clearly illustrated in Figure 9 which plots the log of farm income per unit of land avaiable each year.

5 Conclusions

We examine the impact of the 287(g) programs on the farming sector using individual data from the ACS as well as county level data from the Census of Agriculture for those counties and states that have signed 287(g) agreements with the federal government as well as counties that were subject to ICE raids. DD regressions highlight several possible effects of immigration laws on adopting jurisdictions. First and foremost, using individual level data, we find a decrease in the share of noncitizens in the adopting counties in the post law period and an increase in the wages of farm workers in these counties. Second, we find that adopting counties have experienced a decrease in the number of workers hired compared to both non-adopters and adjacent counties. In addition, post law counties seem to pay more per hired worker in the post law period but this may be due to higher wages or more annual time worked for each individual. All this evidence is consistent with labor shortages being created by county level 287(g) agreements. Some evidence from the literature also points out that the 2006-2007 period has been subject to a series of labor shortage complaints which were relatively higher than previous years (e.g Martin (2011); WSJ (2007); Preston (2007)). Martin (2011) suggests that a booming economy in 2006-2007 displaced agricultural workers toward higher paying jobs (e.g. construction) but the displacement slowed down in 2008 as the economy began to slow down. We add direct evidence of disproportionate moves of illegal immigrants from program counties and some evidence of higher wages and altered labor use patterns. We also tested if labor movements and higher prices translated into a substitution effect from labor to capital, but the evidence is more mixed. We document a drop in the expenditure share of labor (relative to total production costs) but do not find clear evidence of an increase in the use of fuels or machinery, nor do we find statistically significant evidence that farmers switched away from labor expensive products (vegetables). We do find evidence that farm incomes may have declined disproportionally in the post law counties. Finally we find no program effects on immigrant shares or farm wages in states adopting 287(g) programs at the state level or counties that had been subject to ICE raids. However, as mentioned previously county level adoption differs significantly from the state level adoption as at the state level there may be counties (especially more rural counties) where enforcements never take place. For example, Florida signed 287(g) agreements in 2002 at the state level but there are very few 287(g) related arrests reported in Florida.

This study provides some evidence that 287(g) programs have affected immigrant presence, agricultural labor and farm profitability. Given the importance of labor in the agricultural sector, further research using individual farm level data may provide additional insights on the effects of immigration laws on the farming sector. As a stronger wave of immigration law enactments by several states (e.g. Arizona, Georgia) has taken place during the last two years, further empirical research is very important for the agricultural sector in the U.S.

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6 Tables

Table 1: Counts of Counties and Workers by 287(g) status

	Control	Adopted County	Adjacent	Adopted State	Total
			County Counts by Year		
2005	470	1	2	43	516
2006	462	5	6	43	516
2007	416	13	19	68	516
2008	353	31	37	95	516
2009	332	33	49	102	516
2010	324	39	51	102	516
County-Years	2357	122	164	453	3096
			Farm Worker Counts by Year		
5	7836	65	304	477	8682
6	8090	182	399	592	9263
7	7423	232	623	955	9233
8	6443	343	695	1495	8976
9	6684	377	728	1538	9327
10	6755	559	837	1479	9630
Worker-years	43231	1758	3586	6536	55111

Table 2: Summary statistics by 287(g) status (ACS)

Group	Control		Adopted County		Adjacent		Adopted State	
Variable	Mean	S.E	Mean	S.E	Mean	S.E	Mean	S.E
Log wage	9.141	1.251	9.293	1.100	9.211	1.119	9.178	1.212
Not Citizen	0.418	0.493	0.580	0.494	0.610	0.488	0.395	0.489
Demographics								
Age	32.846	12.493	35.077	11.900	34.656	11.884	33.707	12.416
Female	0.230	0.421	0.283	0.451	0.285	0.451	0.232	0.422
Black	0.031	0.172	0.033	0.178	0.034	0.182	0.070	0.256
Hispanic	0.473	0.499	0.649	0.477	0.645	0.479	0.393	0.488
High School	0.320	0.467	0.282	0.450	0.272	0.445	0.345	0.476
Asc	0.113	0.317	0.085	0.279	0.083	0.276	0.106	0.308
Bs	0.004	0.066	0.009	0.097	0.004	0.067	0.005	0.073
Weeks worked								
14-26	0.114	0.318	0.121	0.326	0.124	0.330	0.112	0.316
27-39	0.119	0.324	0.109	0.312	0.137	0.344	0.095	0.293
40-47	0.077	0.266	0.081	0.273	0.090	0.287	0.065	0.247
48-49	0.030	0.171	0.019	0.137	0.032	0.176	0.029	0.169
50-52	0.493	0.500	0.544	0.498	0.475	0.499	0.556	0.497
Hours per week	41.052	15.331	39.698	12.239	41.003	12.639	40.126	14.497

Table 3: Summary statistics by 287(g) status

Group	Control			Adopted County			Adjacent County			Adopted State		
Variable	Mean	S.E.	Obs.	Mean	S.E.	Obs.	Mean	S.E.	Obs.	Mean	S.E.	Obs.
Log Lbr. Exp. /Acre	2.40	1.33	7296	2.598	1.417	1150	4.05	1.27	54	3.48	1.08	21
Lbr Exp. Share	0.09	0.07	7295	0.112	0.082	1151	0.18	0.12	54	0.11	0.08	21
Exp. per Worker	0.47	0.28	7268	0.54	0.31	1144	0.73	0.30	54	0.59	0.21	21
Hired Workers (100s)	0.77	5.46	7361	0.778	5.014	1171	1.78	2.90	56	0.84	0.69	21
Log Mach. Val. /Acre	5.15	0.86	7412	4.835	1.073	1198	5.64	0.60	57	5.62	0.49	21
Fuel Exp. Share	0.06	0.02	7394	0.055	0.028	1192	0.04	0.02	56	0.05	0.02	21
Share Vegies	0.01	0.02	5213	0.011	0.035	839	0.01	0.02	56	0.02	0.02	19
Log Farm Inc. /Acre	3.61	1.36	6535	3.634	1.760	1010	4.68	1.46	51	4.48	1.03	19
Total Ag Land (100000s)	3.01	3.35	7425	3.122	5.994	1200	1.96	2.24	57	3.81	6.57	21
Cropland (100000s)	1.53	1.52	7434	0.636	1.106	1206	0.67	0.67	57	1.96	3.11	21
Group	Adjacent State			Raid			Adjacent Raid			All Sample		
Log Lbr. Exp. /Acre	1.79	1.25	223	2.833	1.249	165	3.66	1.41	78	2.44	1.35	8987
Lbr Exp. Share	0.08	0.06	223	0.101	0.082	165	0.12	0.11	78	0.10	0.08	8987
Exp. per Worker	0.57	0.38	221	0.35	0.28	165	6.00	2.48	78	4.82	2.92	8951
Hired Workers (100s)	0.26	0.33	228	0.732	1.106	168	1.45	2.03	87	0.77	5.24	9092
Log Mach. Val. /Acre	4.49	1.30	231	5.372	0.612	169	5.76	0.61	87	5.11	0.91	9175
Fuel Exp. Share	0.06	0.03	231	0.049	0.022	168	0.05	0.02	86	0.06	0.03	9148
Share Vegies	0.00	0.00	133	0.007	0.024	145	0.02	0.03	69	0.01	0.03	6474
Log Farm Inc. /Acre	2.76	1.76	204	3.840	1.577	136	4.70	1.06	83	3.61	1.44	8038
Total Ag Land (100000s)	4.74	5.68	231	2.344	3.698	171	1.56	1.44	87	3.04	3.88	9192
Cropland (100000s)	1.47	1.70	231	0.948	1.387	171	1.04	1.06	87	1.39	1.50	9207

Table 4: Impact of the 287(g) Program on the Share of Immigrants in Area

	(1)	(2)	(3)
Post County	-.0044***	-.0025	-.0048***
	(0.0017)	(0.0019)	(0.0018)
Post County Adj	-.0004	-.0031	-.0028
	(0.0022)	(0.003)	(0.0022)
Post State	0.0018*	0.0011	0.0032***
	(0.0009)	(0.0011)	(0.001)
Post Raid	0.001	0.0281*	-.0078
	(0.0043)	(0.0168)	(0.006)
N	10567024	10567024	10567024
R^2	0.0723	0.1333	0.0795
Areas	517	517	517

Notes: Standard errors are in paranthesis and *, ** and *** denote statistical significance at 10 %, 5 % and 1 %, respectively. Standard errors are clustered at the PUMA level.

Table 5: Impact of the 287(g) Program on the Share of Immigrants in Area

	(1)	(2)	(3)
5 Years Pre County	0.0006	0.0002	0.007
	(0.0045)	(0.0054)	(0.006)
4 Years Pre County	0.0013	-.0025	0.0048
	(0.0043)	(0.0048)	(0.0043)
3 Years Pre County	0.0043	0.0044	0.0069**
	(0.0027)	(0.003)	(0.0029)
2 Years Pre County	0.0041*	0.0022	0.0044**
	(0.0022)	(0.0025)	(0.0022)
1 Year Post County	0.0002	0.0011	0.0013
	(0.0022)	(0.0024)	(0.0022)
2 Years Post County	-.0051**	-.0036	-.0042*
	(0.0022)	(0.0025)	(0.0023)
3 Years Post County	-.0043*	-.0037	-.0063**
	(0.0024)	(0.0026)	(0.0026)
4 Years Post County	-.0117***	-.0090***	-.0162***
	(0.003)	(0.0033)	(0.0031)
5 Years Post County	-.0188***	-.0140***	-.0275***
	(0.0031)	(0.0035)	(0.0035)
6 Years Post County	-.0274***	-.0321***	-.0475***
	(0.0044)	(0.0045)	(0.0047)
5 Years Pre Adj County	0.0046	0.0033	0.0028
	(0.0051)	(0.0051)	(0.0053)
4 Years Pre Adj County	0.0062	0.0054	0.008*
	(0.0038)	(0.0051)	(0.0046)
3 Years Pre Adj County	-.0017	0.0001	0.0011
	(0.003)	(0.0039)	(0.0031)
2 Years Pre Adj County	-.0006	0.0006	0.0009
	(0.0027)	(0.0038)	(0.0028)
1 Year Post Adj County	-.0021	-.0028	-.0026
	(0.0029)	(0.0039)	(0.003)
2 Years Post Adj County	-.0004	-.0028	-.0034
	(0.0029)	(0.0041)	(0.003)
3 Years Post Adj County	-.0031	-.0057	-.0054
	(0.0033)	(0.0045)	(0.0034)
4 Years Post Adj County	-.0058	-.0063	-.0070*
	(0.0041)	(0.0055)	(0.0042)
5 Years Post Adj County	-.0084*	-.0091	-.0134***
	(0.0049)	(0.0064)	(0.0046)
6 Years Post Adj County	-.0051	-.0037	-.0181**
	(0.0062)	(0.0093)	(0.0085)
N	10567024	10567024	10567024
R^2	0.0724	0.1333	0.0796
Areas	517	517	517

Table 6: Impact of the 287(g) Program on Log Wages

	(1)	(2)
Post County	0.0683	0.1123**
	(0.0471)	(0.0501)
Post Adj County	-.0470	
	(0.0323)	
Post State	0.0751**	0.1201**
	(0.0294)	(0.0504)
Post Raid	0.0364	
	(0.1129)	
Age	0.067***	0.0562***
	(0.0026)	(0.0064)
Age Squared	-.0007***	-.0006***
	(0.00003)	(0.00008)
Female	-.1728***	-.1428***
	(0.0107)	(0.0235)
Black	-.1096***	-.1026*
	(0.0245)	(0.0592)
Highest degree high school	0.1043***	0.1298***
	(0.0092)	(0.0209)
Some College no BS	0.1649***	0.1239***
	(0.014)	(0.036)
BS Degree or Higher	0.1961***	0.14
	(0.0652)	(0.1782)
Worked 14-26 Weeks	1.0986***	1.1370***
	(0.0211)	(0.0592)
Worked 27-39 Weeks	1.5319***	1.5073***
	(0.0189)	(0.0492)
Worked 40-47 Weeks	1.8147***	1.7831***
	(0.0208)	(0.0511)
Worked 48-49 Weeks	1.9508***	1.9347***
	(0.0253)	(0.057)
Worked 50-52 Weeks	2.0747***	2.0628***
	(0.0176)	(0.0447)
Avg. Hours Worked	0.0223***	0.0228***
	(0.0004)	(0.0011)
N	55111	8148
R^2	0.6897	0.6705
Areas	514	119

Table 7: Impact of the 287(g) Program on Log Wages

	(1)	(2)
5 Years Pre County	-.0157	-.0730
	(0.1402)	(0.1374)
4 Years Pre County	0.0137	-.0183
	(0.1062)	(0.1118)
3 Years Pre County	0.2086**	0.1922**
	(0.0915)	(0.0933)
2 Years Pre County	0.0299	0.0383
	(0.0841)	(0.0874)
1 Year Post County	0.0945	0.1071*
	(0.0634)	(0.0645)
2 Years Post County	0.1515**	0.1908**
	(0.0755)	(0.0775)
3 Years Post County	0.1045	0.1489**
	(0.0649)	(0.0693)
4 Years Post County	0.1216	0.1811**
	(0.0784)	(0.081)
5 Years Post County	0.0408	0.0704
	(0.0586)	(0.0643)
6 Years Post County	0.122	0.1392
	(0.0888)	(0.0943)
5 Years Pre Adj County	-.0590	
	(0.1714)	
4 Years Pre Adj County	0.1344	
	(0.1048)	
3 Years Pre Adj County	0.0803*	
	(0.0483)	
2 Years Pre Adj County	-.0131	
	(0.0544)	
1 Year Post Adj County	-.0315	
	(0.0382)	
2 Years Post Adj County	-.0301	
	(0.0449)	
3 Years Post Adj County	-.0505	
	(0.0507)	
4 Years Post Adj County	-.0764*	
	(0.0401)	
5 Years Post Adj County	-.0385	
	(0.0497)	
6 Years Post Adj County	0.0014	
	(0.0407)	
N	55111	8148
R^2	0.6898	0.6706
Areas	514	119

Table 8: Impact of the 287(g) Program on the Share of Hired Labor on Total Expense

	(1)	(2)	(3)	(4)
Post Law County	-.019**	-.018**	-.016*	-.022***
	(0.008)	(0.008)	(0.009)	(0.008)
Pre Law County	-.022**	-.023***	-.020**	-.019**
	(0.009)	(0.008)	(0.009)	(0.008)
Post Law Adj County	-.003	-.004	-.001	-.002
	(0.008)	(0.004)	(0.006)	(0.004)
Pre Law Adj County	0.005	0.004	0.007	0.004
	(0.007)	(0.004)	(0.005)	(0.004)
Post Law State	-.003	-.004**	-.001	-.003**
	(0.004)	(0.002)	(0.003)	(0.002)
Pre Law State	-.013***	-.010***	-.010***	-.012***
	(0.004)	(0.002)	(0.003)	(0.002)
Post Law Adj St	-.009	-.010***	-.007*	-.009***
	(0.007)	(0.003)	(0.004)	(0.003)
Pre Law Adj State	-.003	-.005*	-.0009	-.004
	(0.008)	(0.003)	(0.004)	(0.003)
Post Raid	-.006**	-.006	-.004	-.011
	(0.002)	(0.009)	(0.012)	(0.01)
Pre Raid	-.013***	-.014	-.011	-.013
	(0.003)	(0.009)	(0.012)	(0.01)
Post Adj Raid	-.002	-.003	0.0004	-.002
	(0.004)	(0.007)	(0.009)	(0.007)
Pre Adj Raid	-.002	-.003	-.0001	-.002
	(0.004)	(0.007)	(0.009)	(0.007)
Land in 100k Acres				-.005***
				(0.0007)
Land Squared				0.0001***
				(0.00002)
Cropland in 100k acres				-.004***
				(0.001)
Cropland Squared				0.0006***
				(0.0002)
N	8981	7766	2555	8981
R^2	0.887	0.899	0.855	0.888
Areas	3046	2742	875	3046

Table 9: Impact of the 287(g) Program on Expense per Worker

	(1)	(2)	(3)	(4)
Post Law County	520.565**	515.934*	532.073*	520.565**
	(265.319)	(282.465)	(303.757)	(265.319)
Pre Law County	-390.359	-388.810	-411.246	-390.359
	(245.137)	(260.391)	(271.313)	(245.137)
Post Law Adj County	-504.251***	-531.612***	-684.659***	-504.251***
	(165.174)	(178.355)	(218.292)	(165.174)
Pre Law Adj County	-333.838**	-347.721**	-250.033	-333.838**
	(160.517)	(173.608)	(204.321)	(160.517)
Post Law State	-544.121***	-570.898***	-518.638***	-544.121***
	(114.303)	(125.988)	(170.748)	(114.303)
Pre Law State	-118.368	-146.558	-63.462	-118.368
	(109.191)	(120.117)	(159.325)	(109.191)
Post Law Adj St	-365.816	-337.984	-456.865	-365.816
	(331.055)	(359.958)	(355.670)	(331.055)
Pre Law Adj State	-664.631**	-698.486**	-483.912	-664.631**
	(309.188)	(338.029)	(331.988)	(309.188)
Post Raid	-1316.009**	-1337.387**	-937.937*	-1316.009**
	(513.821)	(545.672)	(557.383)	(513.821)
Pre Raid	-1164.192**	-1162.887**	-1137.306**	-1164.192**
	(506.399)	(537.781)	(520.164)	(506.399)
Post Adj Raid	38.309	-7.569	18.151	38.309
	(371.035)	(399.402)	(391.964)	(371.035)
Pre Adj Raid	97.672	74.514	65.117	97.672
	(346.125)	(371.637)	(364.687)	(346.125)
Land in 100k Acres			-270.697***	
			(104.824)	
Land Squared			3.175	
			(2.707)	
Cropland in 100k acres			1225.294***	
			(206.386)	
Cropland Squared			-80.372***	
			(27.042)	
N	8664	7594	2415	8664
R^2	0.808	0.804	0.824	0.808
Areas	2887	2640	804	2887

Table 10: Impact of the 287(g) Program on the Number of Hired Workers per Unit of Land in 1997

	(1)	(2)	(1A)	(3)	(4)
Post Law County	-.288***	-.285***	-.196***	-.265***	-.291***
	(0.056)	(0.06)	(0.05)	(0.062)	(0.056)
Pre Law County	-.012	-.013	0.023	-.018	-.011
	(0.056)	(0.06)	(0.05)	(0.062)	(0.056)
Post Law Adj County	0.023	0.026	-.028	0.045	0.038
	(0.031)	(0.035)	(0.027)	(0.036)	(0.031)
Pre Law Adj County	0.053*	0.061*	0.072***	0.046	0.035
	(0.031)	(0.035)	(0.027)	(0.036)	(0.031)
Post Law State	0.017	0.01	0.015	0.04**	0.013
	(0.011)	(0.014)	(0.01)	(0.018)	(0.011)
Pre Law State	-.025**	-.022	-.023**	-.031*	-.028**
	(0.011)	(0.014)	(0.01)	(0.018)	(0.011)
Post Law Adj St	0.038**	0.04*	0.037**	0.061**	0.038*
	(0.019)	(0.022)	(0.017)	(0.025)	(0.019)
Pre Law Adj State	-.017	-.019	-.018	-.024	-.022
	(0.019)	(0.022)	(0.017)	(0.025)	(0.019)
Post Raid	0.027	0.03	0.026	0.05	-.091
	(0.071)	(0.075)	(0.062)	(0.077)	(0.071)
Pre Raid	-.021	-.023	-.022	-.028	-.024
	(0.071)	(0.075)	(0.062)	(0.077)	(0.07)
Post Adj Raid	-.029	-.035	-.030	-.006	-.029
	(0.053)	(0.059)	(0.047)	(0.059)	(0.053)
Pre Adj Raid	0.079	0.081	0.079*	0.073	0.082
	(0.053)	(0.059)	(0.047)	(0.059)	(0.053)
Land in 100k Acres					0.004
					(0.005)
Land Squared					-.0001
					(0.0001)
Cropland in 100k acres					-.050***
					(0.009)
Cropland Squared					0.011***
					(0.001)
N	8976	7805	8976	2565	8976
R^2	0.955	0.955	0.954	0.939	0.956
Areas	2991	2727	2991	854	2991

Table 11: Impact of the 287(g) Program on the Share of Fuel Expense on Total Production Expense

	(1)	(2)	(3)	(4)
Post Law County	-.004	-.003	-.002	-.005
	(0.007)	(0.004)	(0.006)	(0.005)
Pre Law County	-.009**	-.008**	-.005	-.008*
	(0.004)	(0.004)	(0.006)	(0.005)
Post Law Adj County	-.011***	-.009***	-.009**	-.010***
	(0.001)	(0.002)	(0.004)	(0.003)
Pre Law Adj County	-.008***	-.007***	-.004	-.008***
	(0.001)	(0.002)	(0.004)	(0.003)
Post Law State	0.015***	0.006***	0.016***	0.014***
	(0.004)	(0.001)	(0.002)	(0.0009)
Pre Law State	-.0008	-.0007	0.003	-.0008
	(0.003)	(0.001)	(0.002)	(0.0009)
Post Law Adj St	0.007	0.004***	0.009***	0.007***
	(0.006)	(0.002)	(0.003)	(0.002)
Pre Law Adj State	-.002	-.006***	0.001	-.002
	(0.004)	(0.002)	(0.003)	(0.002)
Post Raid	-.015***	-.014***	-.013*	-.018***
	(0.001)	(0.005)	(0.008)	(0.006)
Pre Raid	-.009***	-.008	-.005	-.008
	(0.001)	(0.005)	(0.008)	(0.006)
Post Adj Raid	-.009***	-.007*	-.007	-.009*
	(0.002)	(0.004)	(0.006)	(0.004)
Pre Adj Raid	-.004**	-.003	-.0007	-.004
	(0.002)	(0.004)	(0.006)	(0.004)
Land in 100k Acres				-.0003
				(0.0005)
Land Squared				-2.40e-06
				(9.90e-06)
Cropland in 100k acres				-.002**
				(0.0008)
Cropland Squared				0.0004***
				(0.0001)
N	9141	7870	2633	9141
R^2	0.761	0.809	0.704	0.761
Areas	3060	2769	882	3060

Table 12: Impact of the 287(g) Program on the Logarithm of Machinery Value per Unit of Land in 1997

	(1)	(2)	(3)	(4)
Post Law County	-.054	-.031	-.032	-.013
	(0.068)	(0.06)	(0.089)	(0.065)
Pre Law County	-.110	-.104*	-.090	-.150**
	(0.068)	(0.059)	(0.089)	(0.065)
Post Law Adj County	0.017	0.029	0.039	0.033
	(0.038)	(0.035)	(0.052)	(0.036)
Pre Law Adj County	-.019	-.013	0.001	-.026
	(0.038)	(0.035)	(0.052)	(0.036)
Post Law State	0.173***	0.019	0.195***	0.139***
	(0.013)	(0.014)	(0.027)	(0.013)
Pre Law State	0.056***	-.029**	0.076***	0.069***
	(0.013)	(0.014)	(0.027)	(0.014)
Post Law Adj St	0.017	0.044**	0.038	0.008
	(0.023)	(0.022)	(0.036)	(0.023)
Pre Law Adj State	-.033	-.022	-.013	-.043*
	(0.023)	(0.022)	(0.036)	(0.024)
Post Raid	-.053	-.032	-.032	-.086
	(0.086)	(0.075)	(0.111)	(0.082)
Pre Raid	-.048	-.042	-.028	-.057
	(0.086)	(0.075)	(0.111)	(0.082)
Post Adj Raid	-.147**	-.150**	-.125	-.135**
	(0.065)	(0.058)	(0.085)	(0.062)
Pre Adj Raid	-.091	-.090	-.071	-.097
	(0.065)	(0.059)	(0.085)	(0.062)
Ln Land in Farms				0.306***
				(0.027)
Ln Crop Land				-.007
				(0.013)
N	9156	7888	2646	9073
R^2	0.98	0.982	0.976	0.98
Areas	3051	2765	881	3049

Table 13: Impact of the 287(g) Program on the Share of Vegetable Acres Used per Unit of Land Available in 1997

	(1)	(2)	(3)	(4)
Post Law County	-.004	-.004	-.002	-.003
	(0.003)	(0.002)	(0.002)	(0.002)
Pre Law County	-.0004	-.0004	-.0001	-.001
	(0.003)	(0.003)	(0.002)	(0.002)
Post Law Adj County	-.0009	-.0009	0.0003	-.0005
	(0.001)	(0.001)	(0.001)	(0.001)
Pre Law Adj County	0.004**	0.004***	0.004***	0.003**
	(0.001)	(0.002)	(0.001)	(0.001)
Post Law State	-.0008	-.0009	0.0004	-.0008
	(0.0005)	(0.0007)	(0.0008)	(0.0006)
Pre Law State	-.00005	-.00005	0.0002	0.0001
	(0.0005)	(0.0007)	(0.0008)	(0.0006)
Post Law Adj St	-.002***	-.002	-.0003	-.002
	(0.0005)	(0.002)	(0.001)	(0.001)
Pre Law Adj State	-.00003	-.00004	0.0002	-.0003
	(0.0005)	(0.002)	(0.001)	(0.001)
Post Raid	-.001**	-.001	0.0002	-.002
	(0.0004)	(0.003)	(0.003)	(0.003)
Pre Raid	0.001**	0.001	0.001	0.0008
	(0.0005)	(0.003)	(0.003)	(0.003)
Post Adj Raid	0.002	0.002	0.003	0.002
	(0.002)	(0.003)	(0.002)	(0.002)
Pre Adj Raid	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Land in 100k Acres				0.0009***
				(0.0003)
Land Squared				-1.00e-05*
				(6.02e-06)
Cropland in 100k acres				0.002***
				(0.0005)
Cropland Squared				-.0001*
				(0.00007)
N	6474	5756	1941	6474
R^2	0.902	0.9	0.932	0.903
Areas	2516	2282	737	2516

Table 14: Impact of the 287(g) Program on the Log of Farm income per Acre available each Year

	(1)	(2)	(3)	(4)
Post Law County	-.543***	-.568**	-.407	-.528**
	(0.152)	(0.235)	(0.257)	(0.232)
Pre Law County	-.539***	-.553***	-.493**	-.540**
	(0.141)	(0.213)	(0.234)	(0.211)
Post Law Adj County	-.179	-.178	-.042	-.191
	(0.222)	(0.144)	(0.153)	(0.132)
Pre Law Adj County	-.155	-.086	-.110	-.142
	(0.2)	(0.14)	(0.149)	(0.128)
Post Law State	-.335***	-.304***	-.199**	-.333***
	(0.109)	(0.053)	(0.078)	(0.051)
Pre Law State	0.092	0.128**	0.138*	0.104**
	(0.092)	(0.053)	(0.077)	(0.05)
Post Law Adj St	0.266	0.248***	0.402***	0.262***
	(0.199)	(0.088)	(0.104)	(0.081)
Pre Law Adj State	0.449**	0.453***	0.494***	0.473***
	(0.177)	(0.088)	(0.105)	(0.083)
Post Raid	0.093	0.071	0.23	0.163
	(0.193)	(0.268)	(0.292)	(0.269)
Pre Raid	0.927***	0.913***	0.972***	0.926***
	(0.299)	(0.268)	(0.292)	(0.266)
Post Adj Raid	-.037	0.008	0.099	-.035
	(0.091)	(0.21)	(0.223)	(0.2)
Pre Adj Raid	-.027	0.016	0.019	-.030
	(0.097)	(0.21)	(0.224)	(0.201)
Cropland in 100k acres				0.083**
				(0.035)
Cropland Squared				-.009**
				(0.004)
N	7887	7146	2227	7887
R^2	0.851	0.847	0.849	0.851
Areas	2901	2644	842	2901

7 Figures

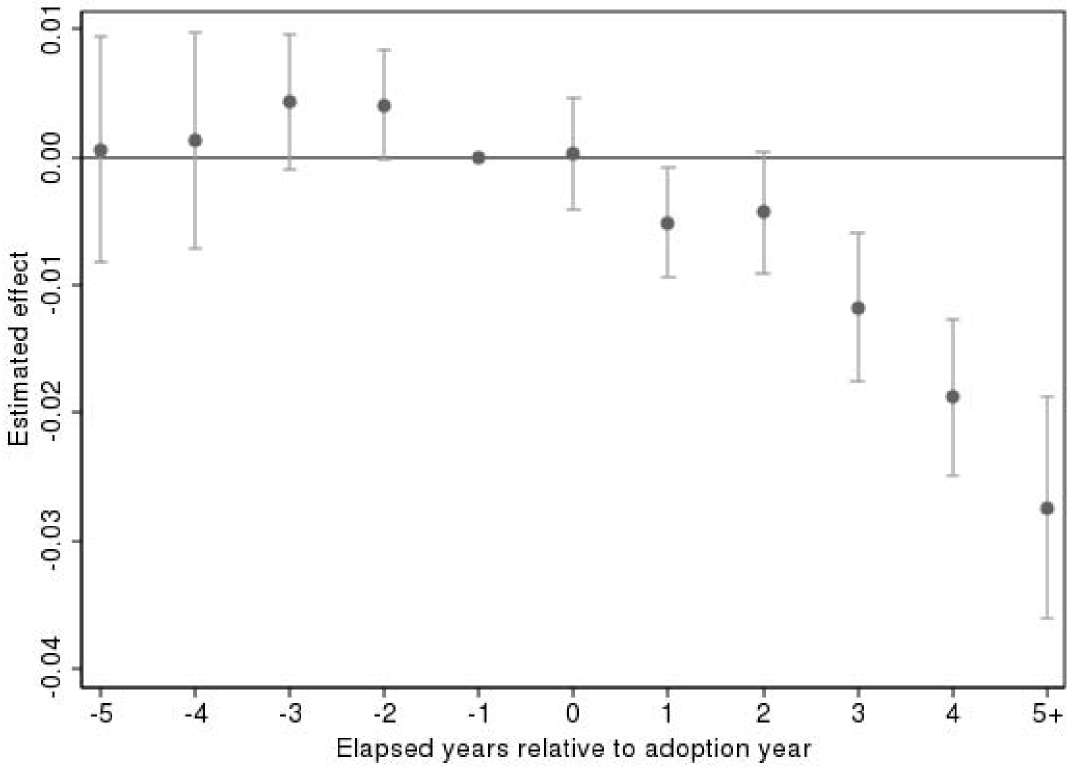

Figure 1: Estimated impact of 287(g) programs on the share of non citizens for years before, during and after adoption

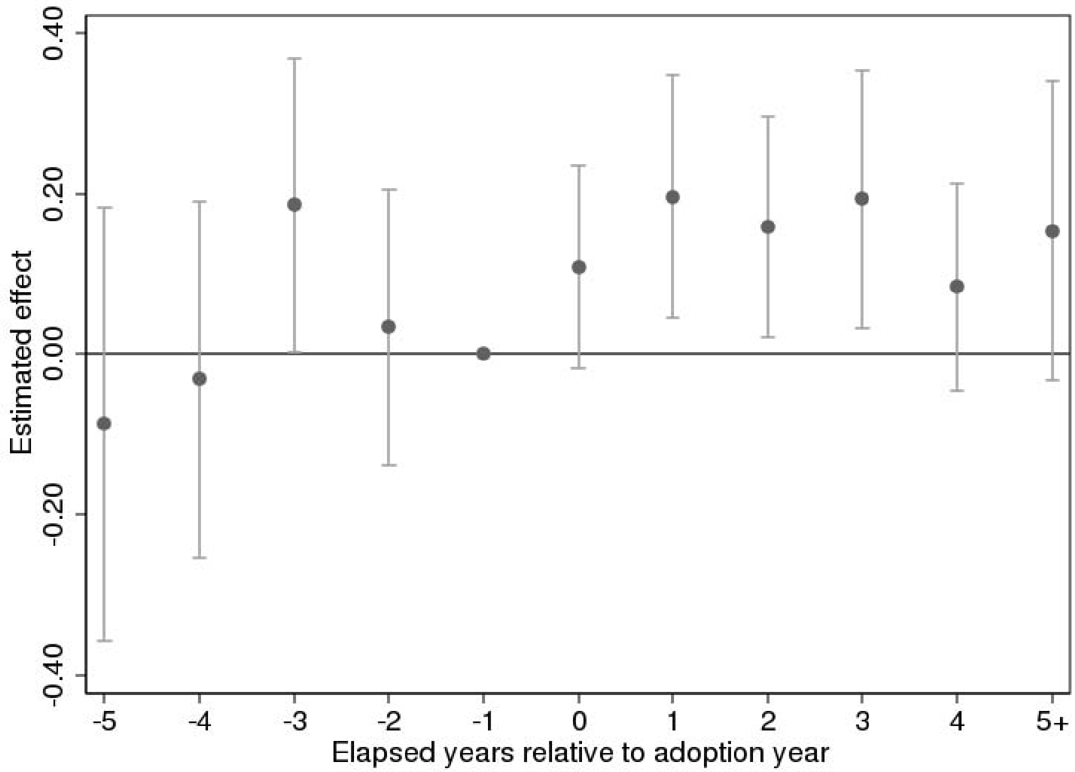

Figure 2: Estimated impact of 287(g) programs on log wages of farm workers for years before, during and after adoption

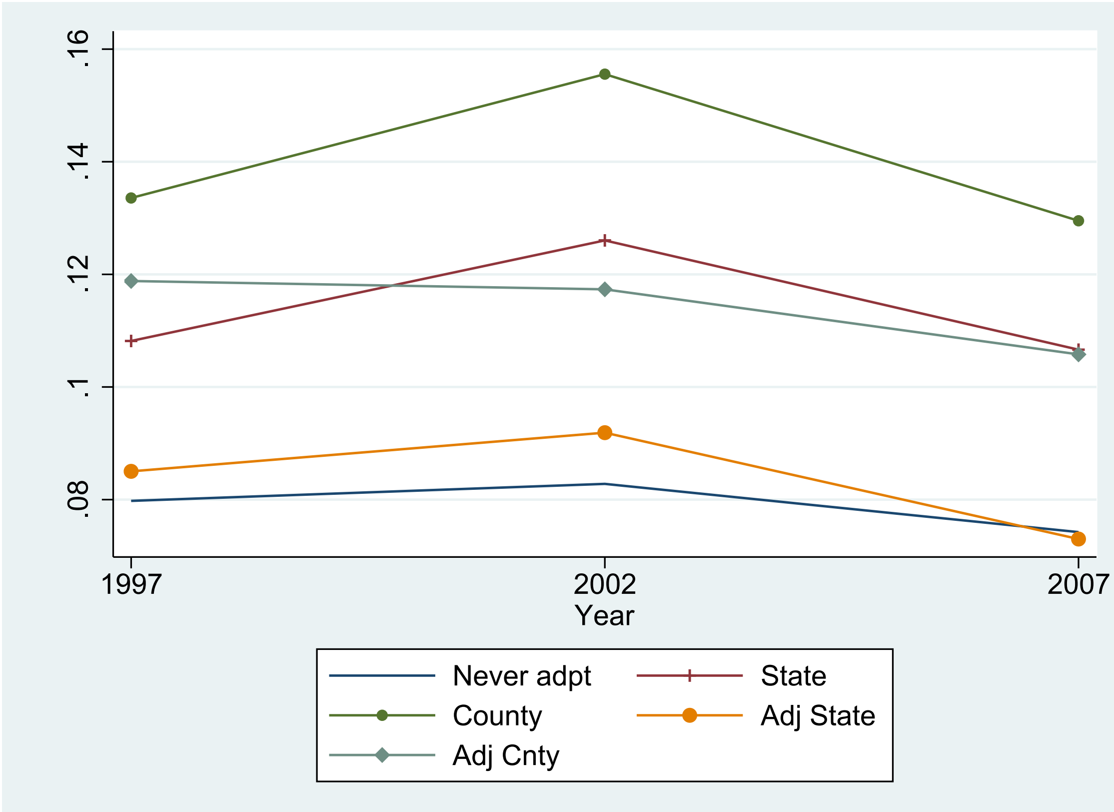

Figure 3: Share of hired labor expense on total production expense

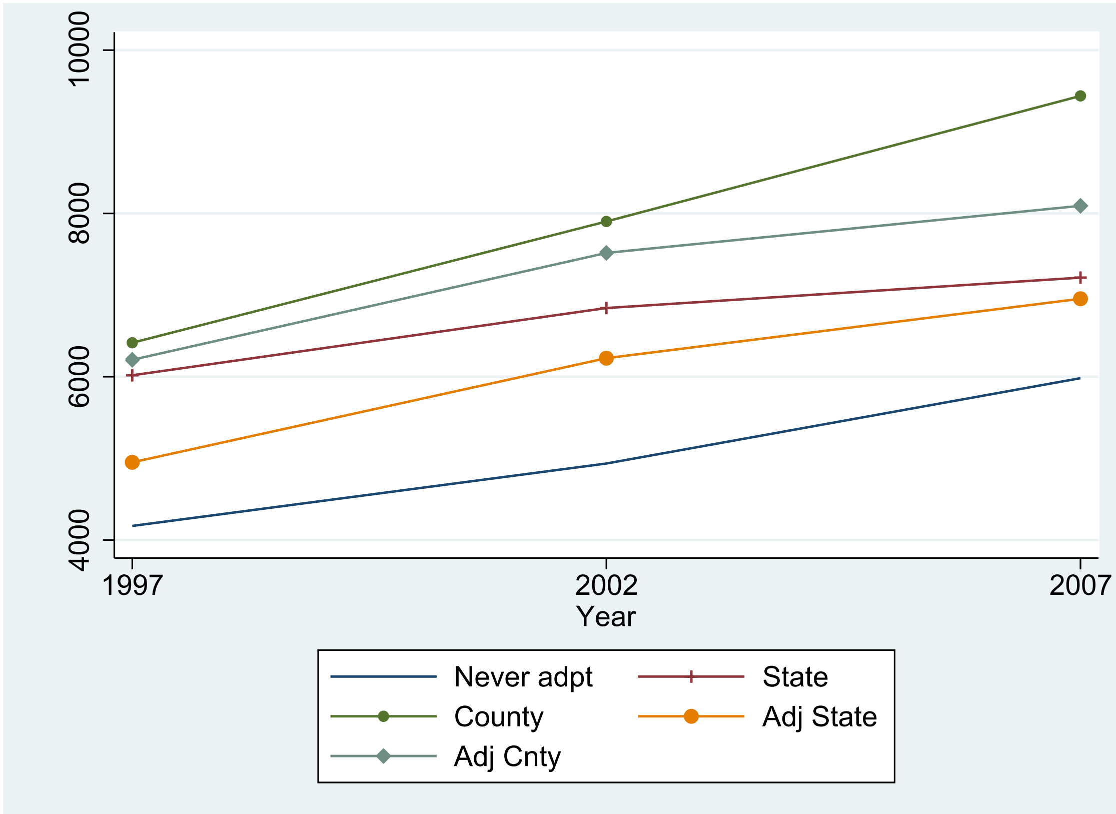

Figure 4: Expense per hired worker (dollars)

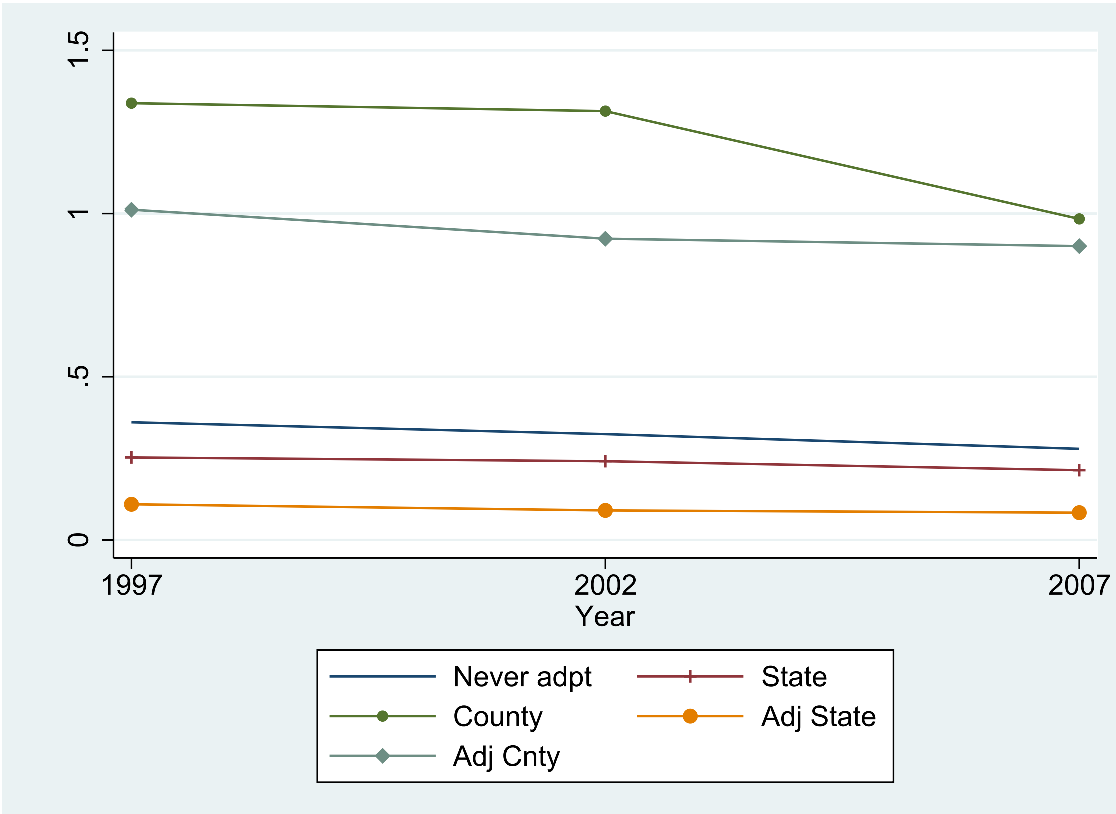

Figure 5: Number of hired workers per unit of land

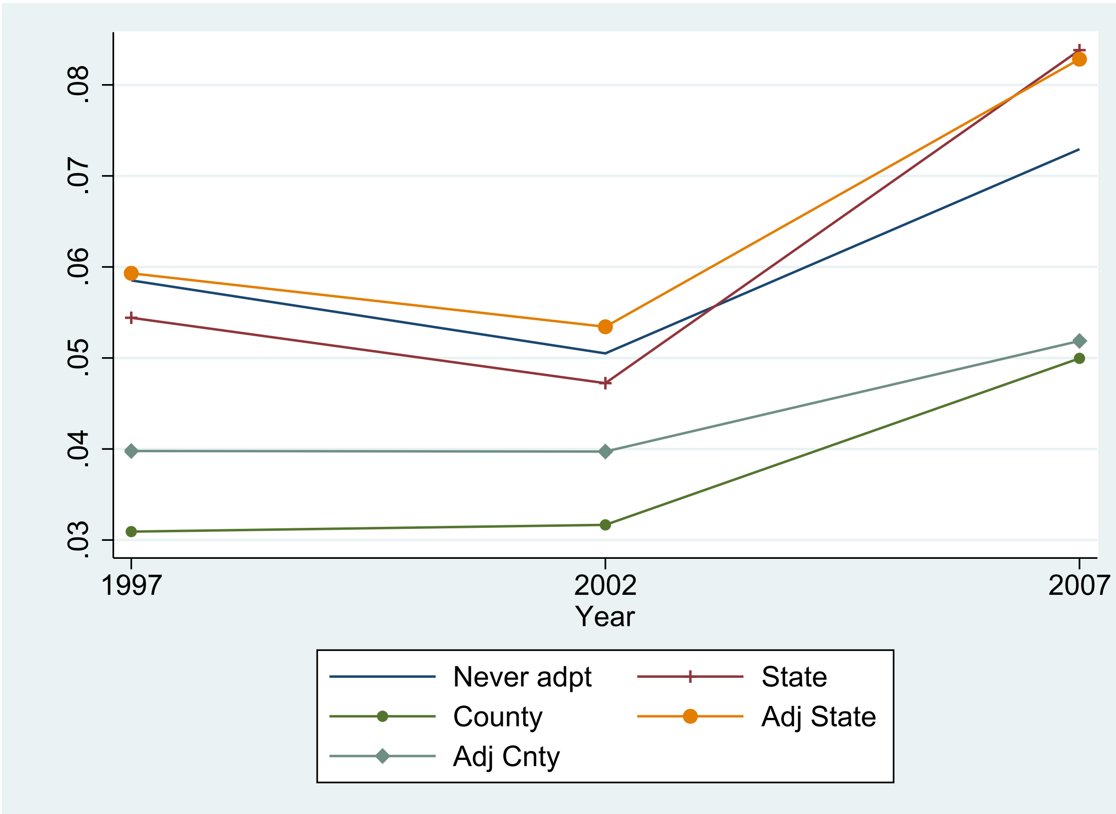

Figure 6: Share of fuel expense on total production expense

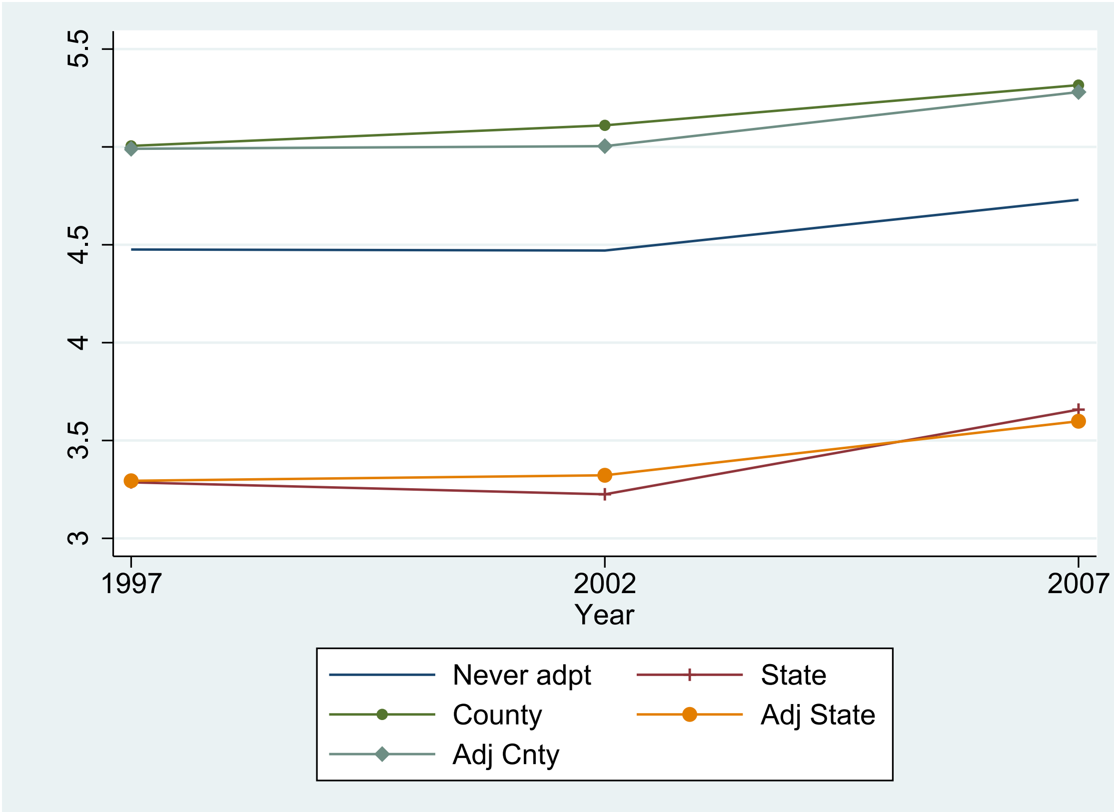

Figure 7: Log machine value per unit of land

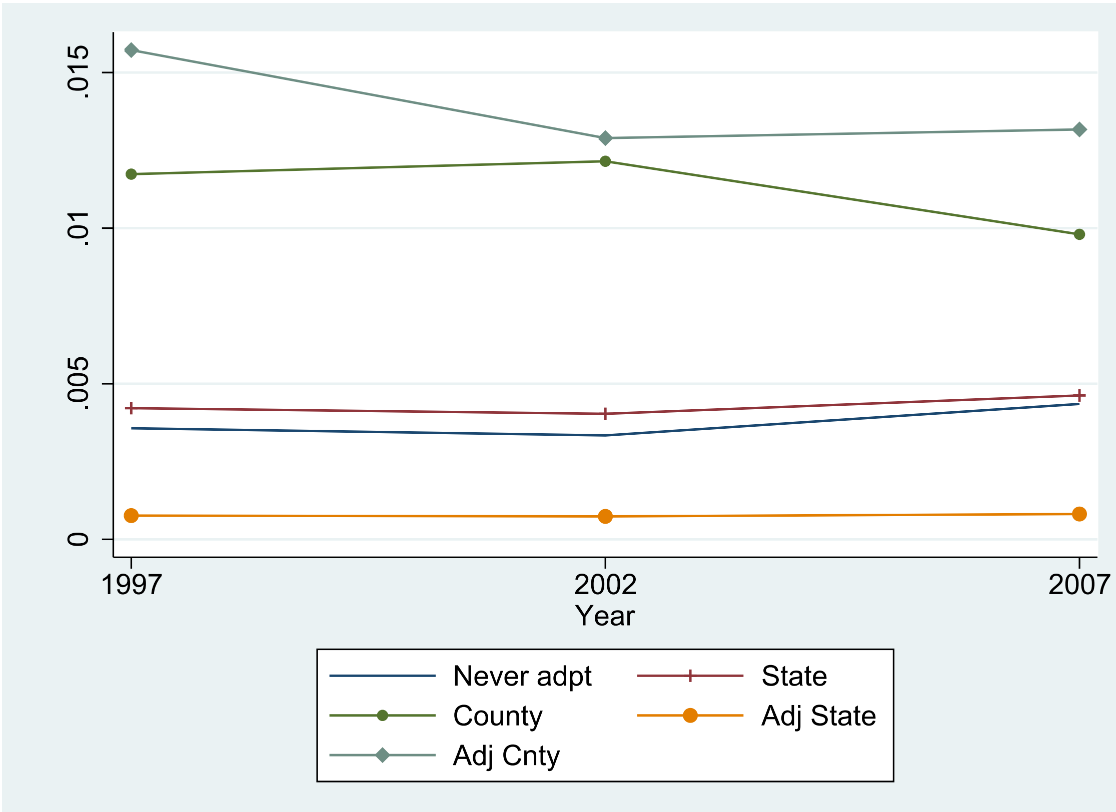

Figure 8: Share of vegetables acres per unit of land

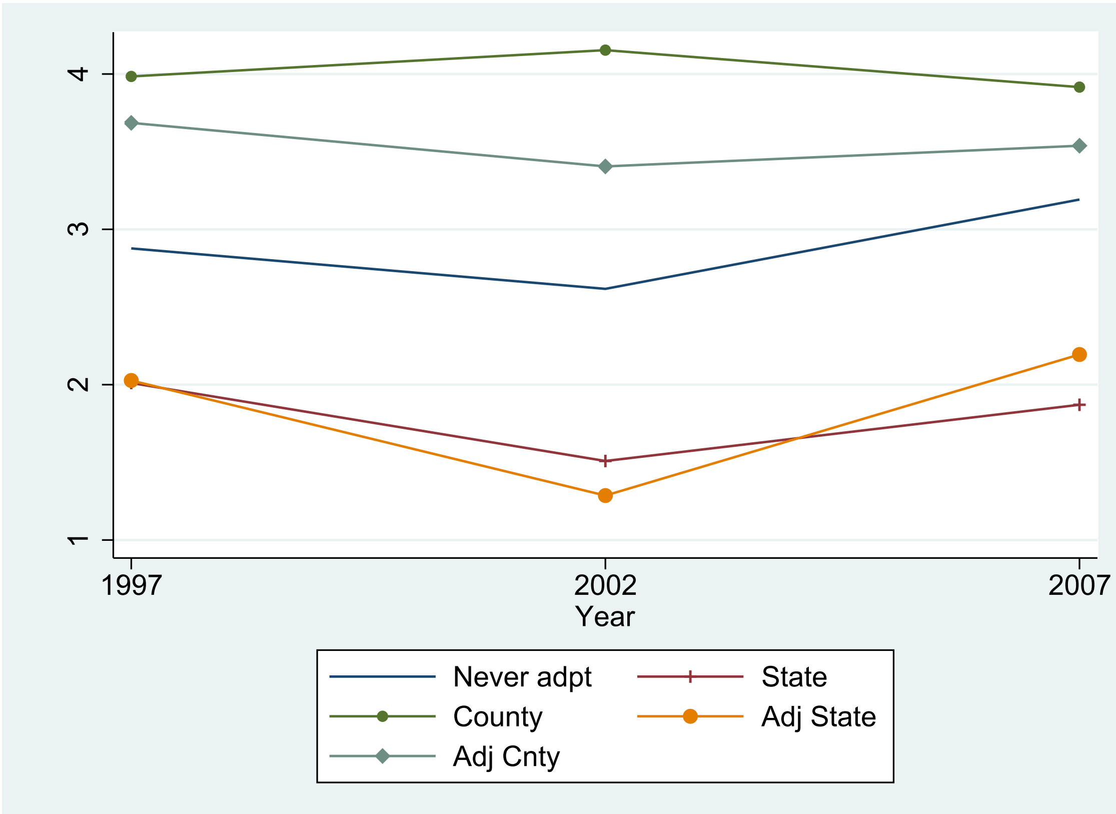

Figure 9: Log farm income per acre available each year

8 Appendix

Table 15: 287(g) Contracts Signed

State	Law Enforcement Agency	Support	Date
Alabama	Alabama Department of Public Safety	Task Force	10-Sep-03
Arizona	Arizona Department of Corrections	Jail Enforcement	16-Sep-05
Arizona	Arizona Department of Public Safety	Jail/Task Force	15-Apr-07
Colorado	Colorado Department of Public Safety	Task Force	29-Mar-07
Florida	Florida Department of Law Enforcement	Task Force	2-Jul-02
Georgia	Georgia Department of Public Safety	Task Force	27-Jul-07
New Mexico	New Mexico Department of Corrections	Jail Enforcement	17-Sep-07
Arizona	Maricopa county	Combo	14-Mar-08
Arkansas	Benton County Sheriff's Office	Jail/Task Force	26-Sep-07
Arkansas	City of Springdale Police Department	Task Force	26-Sep-07
Arkansas	Rogers Police Department	Task Force	25-Sep-07
Arkansas	Washington County Sheriff's Office	Jail/Task Force	26-Sep-07
California	Los Angeles County Sheriff's Office	Jail Enforcement	1-Feb-05
California	Orange County Sheriff's Office	Jail Enforcement	2-Nov-06
California	Riverside County Sheriff's Office	Jail Enforcement	28-Apr-06
California	San Bernardino County Sheriff's Office	Jail Enforcement	19-Nov-05
Colorado	El Paso County Sheriff's Office	Jail Enforcement	17-May-07
Florida	Collier County Sheriff's Office	Jail/Task Force	6-Aug-07
Georgia	Cobb County Sheriff's Office	Jail Enforcement	13-Feb-07
North Carolina	Alamance County Sheriff's Office	Jail Enforcement	10-Jan-07
North Carolina	Cabarrus County Sheriff's Office	Jail Enforcement	2-Aug-07
North Carolina	Gaston County Sheriff's Office	Jail Enforcement	22-Feb-07
North Carolina	Mecklenburg County Sheriff's Office	Jail Enforcement	27-Feb-06

Oklahoma	Tulsa County Sheriff's Office	Jail/Task Force	6-Aug-07
South Carolina	York County Sheriff's Office	Jail Enforcement	16-Oct-07
Tennessee	Davidson County Sheriff's Office	Jail Enforcement	21-Feb-07
Virginia	Herndon Police Department	Task Force	21-Mar-07
Virginia	Prince William-Manassas Regional Jail	Jail Enforcement	9-Jul-07
Virginia	Rockingham County Sheriff's Office	Jail Enforcement	25-Apr-07
Virginia	Shenandoah County Sheriff's Office	Jail/Task Force	10-May-07
North carolina	City of Durham Police Department	Task force	1-Feb-08
Georgia	Whitfield County Sheriff's Office	Jail enforcement	4-Feb-08
Ohio	Butler County Sheriff's Office	Jail/task force	5-Feb-08
Maryland	Frederick County Sheriff's Office	Jail/task force	6-Feb-08
Virginia	Prince William County Police Department	Task force	26-Feb-08
Virginia	Prince William County Sheriff's Office	Task force	26-Feb-08
Georgia	Hall County Sheriff's Office	Jail/task force	29-Feb-08
Virginia	Manassas Police Department	Task force	5-Mar-08
Arizona	City of Phoenix Police Department	Jail/task force	10-Mar-08
Arizona	Pima County Sheriff's Office	Jail/task force	10-Mar-08
Arizona	Pinal County Sheriff's Office	Jail/task force	10-Mar-08
Arizona	Yavapai County Sheriff's Office	Jail/task force	10-Mar-08
Virginia	Manassas Park Police Department	Task force	10-Mar-08
Florida	Bay County Sheriff's Office	Task force	15-Jun-08
Missouri	Missouri State Highway Patrol	Task force	25-Jun-08
North carolina	Henderson County Sheriff's Office	Jail enforcement	25-Jun-08
North carolina	Wake County Sheriff's Office	Jail enforcement	25-Jun-08
South carolina	Beaufort County Sheriff's Office	Task force	25-Jun-08
Tennessee	Tennessee Highway Patrol / Department of Safety	Task force	25-Jun-08
Virginia	Loudoun County Sheriff's Office	Task force	25-Jun-08

Florida	Jacksonville Sheriff's Office	Jail enforcement	8-Jul-08
Texas	Farmers Branch Police Department	Task force	8-Jul-08
Texas	Harris County Sheriff's Office	Jail enforcement	20-Jul-08
New jersey	Hudson County Department of Corrections	Jail enforcement	11-Aug-08
Texas	Carrollton Police Department	Jail enforcement	12-Aug-08
Texas	Carrollton Police Department	Jail enforcement	12-Aug-08
Texas	Carrollton Police Department	Jail enforcement	12-Aug-08
Nevada	Las Vegas Metropolitan Police Department	Jail enforcement	8-Sep-08
Nevada	Las Vegas Metropolitan Police Department	Jail enforcement	8-Sep-08
Minnesota	Minnesota Department of Public Safety	Task force	22-Sep-08
Utah	Washington County Sheriff Office	Jail enforcement	22-Sep-08
Utah	Weber County Sheriff's Office	Jail enforcement	22-Sep-08
Connecticut	City of Danbury Police Department	Task force	15-Oct-09
Delaware**	Delaware Department of Corrections	Jail enforcement	15-Oct-09
Georgia	Gwinnett County Sheriff's Office	Jail enforcement	15-Oct-09
New jersey	Monmouth County Sheriff's Office	Jail enforcement	15-Oct-09
Arizona	Florence Police Department	Jail/task force	21-Oct-09
South carolina	Charleston County Sheriff's Office	Jail enforcement	9-Nov-09
Arizona	City of Mesa Police Department	Jail/task force	19-Nov-09
South carolina	Lexington County Sheriff's Office	Jail enforcement	19-Aug-10

Table 16: Raids from the Immigration and Customs Enforcement Agency (ICE)

State	City	County	Date
Colorado	Greely town	Weld County	12- 01- 06
Nebraska	Grand Island	Hall County	12 -01- 06
Massachusetts	New Bedford	Bristol County	03- 01- 07
Pennsylvania	East Stroudsburg	Monroe County	07 -01 -07
North Carolina	Tar Heel	Bladen County	01 -01- 07
Arkansas	Arkadelhpia	Clark County	06 -27 -05
New York	New Haven	Oswego County	06- 01- 07
Iowa	Postville	Allamake county	1-May-08
Mississipi	Postville	Clayton County	12-May-08
Mississipi	Laurel	Jones county	12-May-08