The Effects of Immigration on Low-Skilled Native Workers in the US

Author: Joshua G Silver

May 5, 2017

Thesis Advisors:
Dr. James DeVault, Dr. Matthew Larsen, Dr. Caleb Gallemore

*Submitted in fulfillment of the requirements for Honors in Economics at Lafayette College

Abstract

Using data from the US Census's American Community Survey and Bureau of Labor Statistics' Current Population Survey, I estimate the impact of low-skilled immigrants on the employment of low-skilled native born workers in the non-tradable sector in the US. Specifically, I look at industries such as mining, construction, transportation, farming, fishing and forestry, maintenance, and extraction. These industries are the least vulnerable with respect to outsourcing (i.e. "shipping jobs overseas"). Therefore, a change in employment in these sectors should result from a change in the domestic labor supply rather than from labor being outsourced. The data are separated into foreign born and native born, and they are further separated by country of origin, educational attainment, and age of worker. I use a difference-in-differences model to determine the effects that immigrants have on the low-skilled American workers. The control group consists of Texas and South Dakota while the treatment group consists of Arizona and Georgia. These states are non-contiguous and have similar characteristics in terms of industries and labor composition, but the treatment group recently passed immigration reform, while the control group did not. The immigration reforms decreased the number of immigrants in the treatment states relative to the control states. Despite this, the empirical results from this paper find no evidence that low-skilled native workers in the treatment states benefitted from immigration reform.

Table of Contents

Introduction

One of the most controversial aspects of the US labor market is the role of immigrants in the labor force. The most pressing question regarding immigrants is whether they displace US workers and if so, to what extent and with what effect. The goal of the paper is to determine how immigrants impact native workers. Although there are numerous economic variables that can measure the effects of immigrant workers, the literature suggests that the most indicative variables are wages, total employment, and labor force participation. In this paper, I examine the effects that immigrants have on native workers' through wages, total employment, and labor force participation.

To determine these effects, this paper uses a natural experiment involving the immigration reform in Arizona and Georgia. In 2010 Arizona passed SB 1070, which will be referred to as the Arizona immigration reform bill. This reform is regarded as the first of the "omnibus immigration laws," named after the bill's all-encompassing and strict nature. In 2011 Georgia passed HB 87, which was based off of Arizona's bill, and is often regarded as being even more drastic. Both of these reforms share a similar purpose, which is to reduce the number of undocumented immigrants.

The study seeks to determine the effects that immigrants have on the most vulnerable workers in the US, low-skilled workers. Given that the US economy is currently outsourcing low-skilled jobs and transitioning to a high-skilled economy, low-skilled workers are experiencing higher levels of vulnerability with respect to job security and attainment. Additionally, when a company must make cut-backs, those with the lowest skill levels are usually the first to experience lay-offs or to be replaced by cheaper or alternative forms of labor. Thus, the study will focus on the effects that immigrants have upon the low-skilled native labor force. To more precisely identify this effect, attention is limited to the non-tradable sector because jobs in this sector cannot be outsourced or displace by imports. More specifically, by analyzing the non-tradable sector I will be able to better isolate the effects on workers due to immigration by eliminating possible confounding variables. Certain sectors lend themselves to outsourcing more than others; for example, industries like production and manufacturing are easily outsourced. However, industries like transportation, mining, etc. are less easily outsourced, and so they tend to last in the US labor markets. With respect to low-skilled labor, jobs can also be replaced with capital. This is more prevalent in goods markets than service markets due to the lower elasticity of labor demand in service markets vis a vis good markets. As a consequence, the focus in this paper is mainly on service industries and occupations.

Low skilled native workers are the most vulnerable group of US workers, for they are the first to be substituted for. Therefore, if immigrants have any effect on native workers, it should be shown through the substitution of low-skilled native workers. If the immigration reform has been successful, this should decrease the supply of low-skilled workers. Based on economic theory, this decrease in supply should cause an increase in the employment variables of the low-skilled native workers. So, if immigrants are truly substitutes for native workers this should be shown through the responses to the decrease in the supply of labor. However, if there are no effects on native workers, this would suggest that low-skilled native workers and immigrants are not substitutes. The overall purpose is to provide information on the true effects of immigrant workers on native workers, for this will allow for more educated policy decisions in the future. It will also help shape our opinions and understanding of immigrants and their entrance into the US labor force.

In order to analyze the effects of immigration on native workers, I use a difference-in-differences estimator. Arizona and Georgia serve as the treatment group, while Texas and South Dakota serve as the control group. The data is from the US Census' Current Population Survey (CPS). I use regression analysis to estimate the effect of treatment on wages, employment, and labor force participation to determine how native worker's employment variables are affected by immigration reform. The results show that immigration reform does not benefit native workers.

Background

As described briefly in the introduction, I assume that the immigration reform bills of Arizona and Georgia effectively reduced the number of immigrant workers in the respective treatment state. In order to confirm this assumption, I conducted a literature review and brief quantitative analysis. The literature review suggests that this assumption is reasonable. While the immigration reforms in Arizona and Georgia are relatively new, the existing literature suggests that the two reforms were successful at reducing the immigrant population and work force, particularly the undocumented workforce. It is important to note that measuring the number of undocumented immigrants is a taunting task, for many of them are hidden from formal population measurements and databases. That being said, undocumented immigrants tend to be the most vulnerable of workers/groups, so if any effect is seen on all immigrants it is reasonable to assume that undocumented immigrants experience the same or even larger effects.

Indeed, both Arizona and Georgia passed immigration reform with the expectation that the reforms would reduce the number of undocumented immigrants in their respective states. Since the Georgia immigration reform (ratified in 2011) was based off of the Arizona law (ratified in 2010), they share many of the same mechanisms and regulations. The reforms both focused on two main mechanisms, e-verify and the "show me your paper laws." E-verify is an employment process, and it requires companies to register every paid employee in a database. This database runs tests in order to determine the legal status of every worker. This causes many undocumented immigrants to lose their jobs and thus they migrate out of the state. The "show me your papers law" allows law enforcement to stop anyone they reasonable expect of being undocumented and demand that they show their legal papers. If one does not have the papers on them, the person is considered to be breaking the law and is arrested. Lastly, there is a third mechanism that is not directly in the laws, but has been shown to be a result of both laws; this mechanism is the process of "self deportation. (Sabia 2010; Orrenius and Zavodyn 2016 ; Lugo-Lugo and Bloodsworth-Lugo 2014 ; Picker 2013; Lyubansky, Harris, Baker, and Lippard 2013). Self deportation happens when an immigrant feels unwelcome, unsafe, and worse off in their current setting. Therefore, in order to avoid future trouble and formal deportation, the immigrants, especially undocumented immigrants, move under their own supervision. All of these processes leads to the deportation and outflow of immigrants. Therefore, these three mechanisms, paired with many other enforcement mechanisms, should, in theory, decrease the undocumented immigrant population. Since many of the undocumented immigrant workers are working as low-skilled laborers, this suggests that the low-skilled immigrant work force decreases in tandem with the implementation of the legislation.

Good (2013) conducted a review of omnibus immigration laws and their effect on the number of immigrants. He did so by reviewing states including, but not limited to, Arizona and Georgia, and he determined that omnibus immigration laws do create an immigrant outflow. He also found that immigration reform does not create a native inflow, which suggests that immigrants and natives are not perfect substitutes. Based on this work, it is safe to conclude that immigration reforms like those in Arizona and Georgia's do in fact reduce immigrant populations and future inflows.

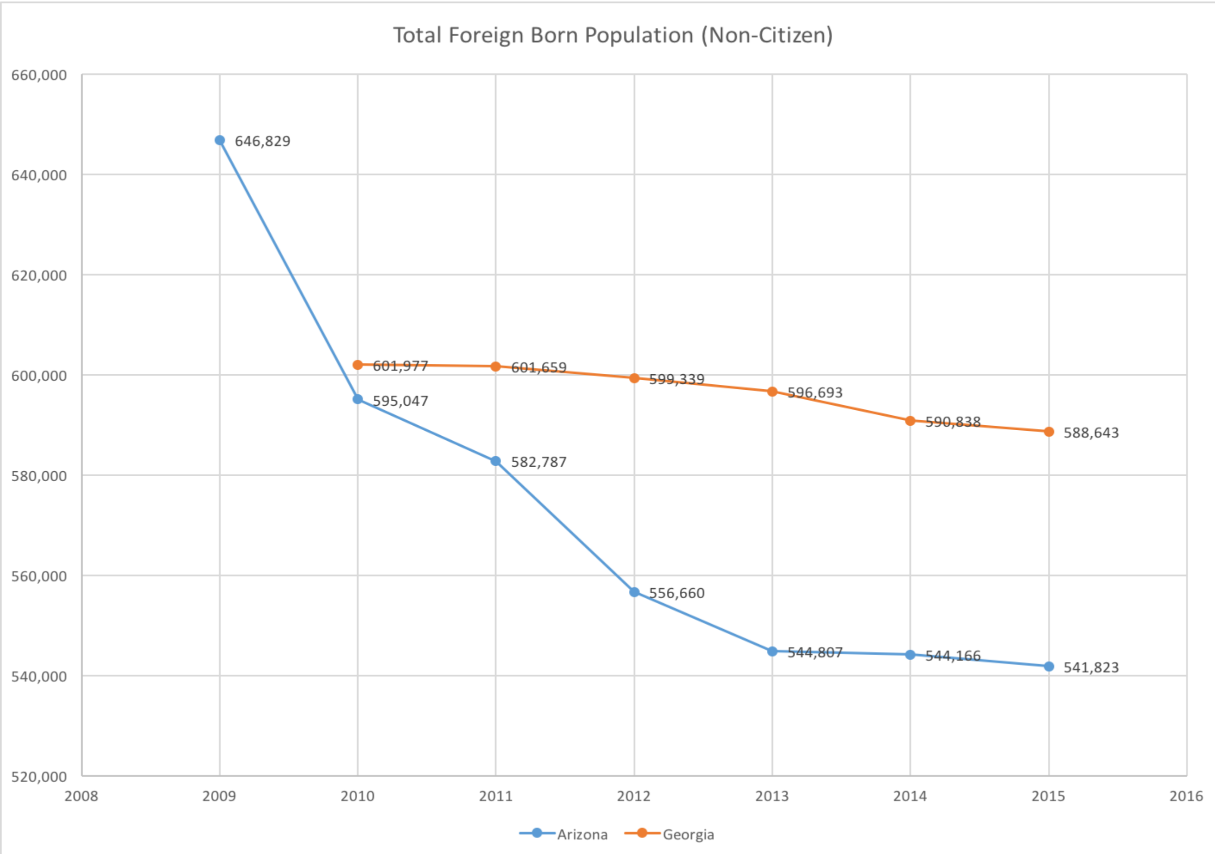
Prior to the SB 1070 immigration bill, Arizona instituted the Legal Arizona Workers Act (known as LAWA) in 2007. Amuedo-Dorantes and Lozano (2014) provided a review of LAWA and SB 1070's combined effectiveness. LAWA is not directly immigration reform, but it focused on creating an E-verify program in Arizona. SB 1070 used this platform, but made the enforcement more drastic and effective. They concluded that immigration flow did decrease in

Arizona as a result of these immigration bills. They were unable to determine the effects attributable to each respective bill, but they concluded that there was an overall incentive for immigrants to leave the state. Additionally, in their literature review, they noted that previous literature showed that immigration reforms like SB 1070 displace undocumented immigrants. To further this study, Hoekstra and Orozco-Aleman (2014) used a difference-in-differences estimate to calculate the percent of immigrants lost due to the the SB 1070 bill; they estimated that Arizona's immigrant population decreased by 30-70 percent as a result of SB 1070. Overall, the literature suggests that the post reform immigration outflow of Arizona increased, meaning the reform was successful at lowering the number of immigrants in the State.

Georgia ratified HB 87, which used Arizona's bill as a base and added additional laws and regulations in order to further control flows of undocumented immigrants. Good (2013) analyzes the effects of the "omnibus immigration laws" in Georgia, and he concludes that it caused an immigrant outflow. According to McKissick & Kane (2011), Georgia saw large labor shortages after the passage of HB 87, suggesting that the labor shortage was due to a reduction in undocumented workers. To further this argument, Young (2012) suggests that many businesses were hurt by the decrease in labor. Therefore, they adjusted their production to produce less, which limited the amount of jobs available to low-skilled labor. This decrease in labor demand should reduce wages and discourage immigrants from coming to or remaining in Georgia. Thus, the immigration reform successfully decreased the number of undocumented immigrants in Georgia.

Another crude measure of the number of undocumented workers can be obtained from the American Community Survey (ACS), which tracks the number of foreign born, non-citizen residents of a state (i.e. immigrants). The survey does not ask about legal status, so it should include both undocumented and documented immigrants. Given that the majority of the low-skilled immigrant workforce is made up of non-citizen immigrants, I graphed the trend of these immigrants using the ACS data. Figure 1 shows a decline in the immigrant populations of both Arizona and Georgia. The ACS data are only available from 2009-2015, but there is a consistent downward trend starting in 2010, which shows a decrease in the immigrant population for both states. Arizona saw a 16.2% decrease in the non-citizen immigrant population, and Georgia experience a 2.2% decrease in the non-citizen immigrant population. As noted earlier, it is hard to accurately measure the number of undocumented immigrants so since they are the most vulnerable group of immigrants it is reasonable to assume that they saw larger migration effects. These trends are consistent with the literature just mentioned as they show a decrease in the immigrant population.

Figure 1: Foreign Born (non-citizen) Populations of Arizona and Georgia, 2009-2015



*Not meant for replication, citation, or publication (partial or full) without the consent of the author

Literature Review

The most important question that the literature answers is through what mechanisms do immigrants affect the employment and wages of US native-born workers. In order to understand this, I first examine theoretical models in immigration economics. The first economic models that address immigration are the application of the Hecksher-Olin and Factor-Price Equalization models to labor economics. (Borjas 1989). Borjas sums up the Hecksher Olin model by noting that it states that countries export their relatively abundant goods. This is important to my research because for many countries their abundant good is labor. Since the thesis examines Arizona and Georgia, the largest immigrant population is from Mexico. Mexico has a relative abundance of low-skilled labor with respect to the United States. Therefore, this model states that Mexico should export its low-skilled labor to the US. The factor-price equalization model states that prices of labor (inputs) will equalize across countries. (Borjas, 1989) This model suggests that the wages of low-skilled immigrants and low-skilled native born workers will equalize over time. So, it would suggest that US workers' wages will decrease, while immigrant wages will increase until the two are equal. This provides a basic economic viewpoint of immigration; however, further studies suggest that the current labor markets in the US will not necessarily experience factor price equalization for immigrant and native wages.

In order to understand how immigrants, interact with native workers, we must examine the markets for immigrant labor and the patterns of immigration with respect to employment. Borjas (1989) and Chiswick (1978) both conclude that immigrants tend to assimilate to the host country over time. When Chiswick refers to assimilation he is not referring to the traditional definition of cultural assimilation, but rather economic assimilation. He noticed that immigrants initially have lower wages, and so this lower wage provides them more incentive to acquire human capital. Therefore, over time they attend school until they can compete in the labor market as a substitute for native workers. That is, in a span of 15 years they will normally acquire enough human capital to receive the same wage and skills as a native born worker. Borjas furthered this theory by introducing the idea of an “immigration market.” He claimed that there is a market that sorts out immigrants across cities. Immigrants research cities before they move, and so they use these markets to rationally determine which cities one should move to. Borjas argued that immigrants selectively choose location and the job/sectors entered. That is, immigration markets determine where the worker will be in the primary or secondary market, which sectors have the most job openings, and which locations are the best to migrate to based upon the current population in each area. Borjas furthers his argument stating that immigrants create their own labor market, so they tend to live in areas with a high density of immigrants. Lastly, he suggested that immigrants will assimilate (economic assimilation) to the labor market they enter into. Furthermore, Beranek (1984) and Duncan and Trejo (2012) both apply this idea of location selection to explain why it makes sense that immigrants do not affect native wages very much. They suggest that the market forces and knowledge of the immigrants encourages them only to enter markets where the labor demand is greater than the supply, so they take new jobs rather than substitute their labor for native workers' labor.

After determining how immigrants enter into US labor markets, it is important to understand how immigrants affect the wage structure in the US. Borjas (1997) determined that immigrants only affected the lowest level of low-skilled native born workers. He determined that the avenue through which immigrants are most likely to affect native workers is wages, but he also found that this effect is weak. Although traditional theories of supply and demand suggest that the influx of immigrants would increase the supply and thus lower the overall wage, Borjas did not notice any change to the overall wage structure in the US. This suggests that either low-skilled immigrant workers are not good substitutes for native born workers, or that the labor markets were not in equilibrium so they had a need for more workers. Additionally, Grossman (1982) found that immigrants have only a small, negative effect on the wages of native born workers. Furthermore, Johnson (1989) found that, in the long-run, any decrease in the wages of low-skilled native born workers was off-set by an increase in earnings for high-skilled native born workers. This suggests that low- skilled immigrants have minimal affects on the wages of native born workers

It is important to understand the structure of the low skilled labor markets before examining any changes. Berman, Bound, and Griliches (1994) suggest that low-skilled labor demand has been decreasing in the US for a long period of time. They note that this is due to a combination of factors, such as outsourcing, automation, increased access to education, and increased demand for high skilled labor. As a result, Autor and Dorn (2013) conclude that within the US, low-skilled labor has generally been shifting from goods markets to service markets. Production jobs have either been replaced by capital or outsourced to cheaper countries. Service jobs, on the other hand, require dexterity and flexibility. These skills have not yet been replaced by capital or outsourcing, so low-skilled labor has started to shift to the service industry.

Labor markets also have primary and secondary markets. Generally speaking, low-skilled immigrants conglomerate into secondary markets. (Enchautegui 1998, Carter 199, Wolla 2014) Secondary markets are informal labor markets; informal labor markets are uncontracted and unprotected. Due to the lower incentives and protection of the informal market, fewer native born workers enter this market. The secondary market tends to have riskier/less desired jobs and lower wages. Therefore, this suggests that low-skilled immigrants may not be competitors /substitutes for native-born workers. Illegal immigrants, in particular, cannot easily compete in formal labor markets, and so they are forced to work in secondary markets. Since many of the low-skilled immigrants are undocumented, it makes sense that they may not be in direct competition with native-born workers.

Data

This paper uses data from the Current Population Survey (CPS) in order to determine the effects of immigration on native workers' employment variables. The CPS is a monthly survey that is conducted by the United States Census Bureau and the Bureau of Labor Statistics. The CPS is cross-sectional data that elicits response from 60,000 Americans every month. Since the cross-sectional data is collected from multiple time periods, the sample forms a panel data set. I used the Integrated Public Use Microdata Series (IPUMS) database in order to extract the CPS data in a downloadable Stata format.

Data is collected from 2003 to 2016. The data is restricted by state of residence, educational level, industry, and occupation. Given these restrictions, my sample size is roughly 40,000 observations. It is important to note that this is survey data; therefore, there are some natural limitations on the data presented. First, it is based upon voluntary response, so sampling bias is possible. That being said, the US Census does a fairly reliable job of collecting accurate and representative data. However, since a significant portion of the low-skilled immigrant community consists of undocumented immigrants, sampling bias may exist. Although the CPS does not ask about legal status—suggesting that the responses are of both documented and undocumented immigrants—an undocumented immigrant may be more hesitant to respond to the survey. In order to control for this possible bias, only native workers are included in the regressions. Since the policy was ratified over 6 years ago, I examine the changes in native workers' incomes, employment, and Labor Force Participation (LFP) in order to determine the effect of the immigration reform on natives' employment variables.

Although the CPS data contains responses from a representative sample of the US and subsequently of each state, county, etc. in the US, restrictions were put on the data to limit the respondents to only consist of low-skill workers in the non-tradable sector. The initial restriction was by educational attainment. As shown in Table A12 (appendix), the CPS collects educational attainment by number of years in education. Therefore, I restricted the educational attainment to be 12 years—or its equivalent—of schooling or less. That is, a high school diploma or GED. Anyone who completed more years than this is not considered to be low-skilled and is subsequently dropped from the sample.

Secondly, restrictions were added for one's industry and occupation in order to further limit the sample to low-skilled workers. It is crucial to understand the different between one's industry and one's occupation. An industry reflects the sector, field, and overall area of business in which a worker is employed. An occupation reflects the nature of the work carried out by a worker, such as management, supervisor, executive, etc. For the scope of this study I restrict the industry to low-skilled non-tradable industries. As outlined in the appendix, the selected industries include mining, construction, transportation, maintenance, extraction, and various other service industries such as food and personal service. All of these industries are part of the non-tradable sector. The non-tradable sector is the sector that is not subject to outsourcing. Given that outsourcing a job results in less employment, it is crucial to isolate non-tradable sectors in order to control for the effect of outsourcing. That being said, I do add a few industries that would normally qualify as tradable, but are crucial to the state's economy. Those include jobs in farming. This industry is prominent in the two treatment states, and it is a sector with a lot of low-skilled labor. Therefore, I determined it was beneficial to keep this industry in the sample. With respect to occupation, I limit the data to people who held first-line supervisor jobs or below. Therefore, anyone who was classified as a manager or above is not included. I decided to keep first line supervisors because this position normally consists of workers who have worked in the field for a long time and earned promotions (usually those who started as lower level workers). Overall, the boundaries on industry and occupation make it more likely that respondents are working in low-skilled jobs.

These restrictions are only applied to the regressions for which wages are the dependent variable. Wages are the main variable of interest, but I also use labor force participation and employment as dependent variables. However, the restrictions on industry and occupation are not used for labor force participation and overall employment. If a respondent claims to be part of an industry and have an occupation then sampling bias might arise. Therefore, the main cut-off for LFP and employment is education. In the absence of industry controls, the sample for LFP and employment will no longer include just workers in the non-tradable sector. Since educational attainment and the skill levels of workers are highly correlated, it is reasonable to use educational attainment to limit the sample to low-skilled workers. To summarize, the regressions that use labor force participation and employment as dependent variables focus only on low-skilled workers independent of industry or occupation in order to control for possible sampling bias.

While the above restrictions are meant to limit the sample to low-skilled workers in the non-tradable sector, there are respondents who have salaries that are atypical for low-skilled occupations in this sector. Table 1 shows, however, that only a small minority of respondents fit this category. I consider anything less than 60,000 to be in the range of "normal" wages for a low-skilled worker. 60,000 would be at the higher end of low-skilled, but the traditional wage for low-skilled workers is around 25,000 as shown by the mean of the low-skilled wages in Table 1. A "normal" wage for the low-skilled labor force is considered to be anything less than 60,000.

The variation out of what is considered "normal" for low-skilled occupations in the non-tradable sector only exists among about five percent of the sample. 95% of the respondents are within the boundaries of what is considered typical for the low-skilled workers. Because the number of outliers is small, they are not likely to bias the results.

Table 1: Wage Percentiles of the Sample

Percent	**Percentiles**	**Smallest**		
1%	0	0		
5%	0	0		
10%	0	0	Obs	13,888
25%	8000	0	Sum of Wgt.	13,888
50%	19200		Mean	23468.82
		Largest	Std. Dev.	28796.83
75%	32000	562913		
90%	50000	595494	Variance	8.29E+08
95%	60000	1099999	Skewness	12.17986
99%	100000	1106999	Kurtosis	347.3445

Tables 2,3, and 4 contain summary statistics for the variables used in the analysis. The variables used are statecensus, hhincome, incwage, log_hhincome, log_incwage, relate, age, age2, sex, race, nativity, educ, empstat, employment, labforce, occ, ind, AZ, GA, SD, TX, AZ_DD, GA_DD, race_dummy, year, and xxyear. Statecensus is the variable that represents which state the respondent is from. Hhincome and incwage are two measure of income for the respondents, household income and individual income respectively; the log variables are the logarithmic transformations of the income variables. Relate measures whether the respondent is the head of household or not. Age is the respondent's age, and age2 is age squared. Sex is a dummy variable that takes a value of one if the respondent is male and zero otherwise. Race is a variable representing the race of each respondent. Nativity represents whether or not the respondent is foreign born. Educ represents the educational attainment of each respondent. Empstat and employment both measure whethere the respondent is employed or unemployed. Labforce represents the labor force participation, so it has a value of 1 if in the labor force and 0 if not. Occ represents the occupation of the individual and ind represents the industry of the respondent. Ind and Occ are not used in the regressions, but were used as to implement the restrictions I put on industry and occupation. The state acronyms are dummy variables for each state. The DD (AZ_DD and GA_DD) variables are the separate difference-in-differences estimators for each treatment state. Year is a variable that contains the numerical value of each year, such as 2009 or 2013, and xxyear are the year specific dummy variables.

Table 2: Summary Statistics of Variables Present in Wage Regressions

Variable	Obs	Mean	Std. Dev.	Min	Max
year	13,888	2009.458	3.942038	2003	2016
statecensus	13,888	69.42692	11.72794	45	86
hhincome	13,888	46082.99	42392.96	-14699	1130001
relate	13,888	101	0	101	101
age	13,888	41.00914	12.86234	15	85
age2	13,888	1847.178	1135.452	225	7225
sex	13,888	0.328773	0.4697842	0	1
race	13,888	135.8797	112.4437	100	830
nativity	13,888	2.588854	1.898413	0	5

educ	13,888	59.44297	20.42122	2	73
empstat	13,888	11.03442	3.561145	10	36
labforce	13,888	1.991143	0.093695	1	2
occ	13,888	6052.152	1806.837	3930	9750
race_dummy	13,888	0.1759793	0.3808162	0	1
ind	13,888	5166.711	3033.989	280	9090
incwage	13,888	23468.82	28796.83	0	1106999
log_hhincome	13,722	10.43436	0.9089011	0	13.93773
log_incwage	11,800	9.905591	0.8946852	1.098612	13.91716
AZ	13,888	0.1307604	0.3371502	0	1
GA	13,888	0.1851238	0.388412	0	1
SD	13,888	0.109663	0.3124805	0	1
TX	13,888	0.5744528	0.4944435	0	1
AZ_DD	13,888	0.0529954	0.2240324	0	1
GA_DD	13,888	0.062356	0.2418097	0	1
xxyear1	13,888	0.0666763	0.2494695	0	1
xxyear2	13,888	0.0644441	0.2455513	0	1
xxyear3	13,888	0.0733007	0.2606388	0	1
xxyear4	13,888	0.0746688	0.2628656	0	1
xxyear5	13,888	0.077549	0.2674701	0	1
xxyear6	13,888	0.0753888	0.2640272	0	1
xxyear7	13,888	0.0770449	0.2666723	0	1
xxyear8	13,888	0.0739487	0.2616969	0	1

xxyear9	13,888	0.0719326	0.2583856	0	1
xxyear10	13,888	0.0684764	0.2525707	0	1
xxyear11	13,888	0.0734447	0.2608744	0	1
xxyear12	13,888	0.0718606	0.2582663	0	1
xxyear13	13,888	0.0673243	0.2505918	0	1
xxyear14	13,888	0.0639401	0.244655	0	1

Table 3: Summary Statistics of Variables Present in Labor Force Participation Regressions

Variable	Obs	Mean	Std. Dev.	Min	Max
year	48,635	2009.42	3.957761	2003	2016
statecensus	48,635	68.58073	12.16756	45	86
hhincome	48,635	42833.04	46471.81	-14699	1701615
relate	48,635	101	0	101	101
age	48,635	48.58877	17.38935	15	85
age2	48,635	2663.252	1802.462	225	7225
sex	48,635	0.4967822	0.4999948	0	1
race	48,635	137.8391	109.2351	100	830
nativity	48,635	2.192392	1.757873	0	5
educ	48,635	59.51893	20.57798	2	73
empstat	48,635	19.89084	11.7791	10	36
labforce	48,635	0.6163874	0.4862703	0	1

occ	48,635	3368.098	3263.939	0	9840
ind	48,635	3327.722	3562.835	0	9890
incwage	48,635	16907.51	29904.94	0	1106999
log_hhincome	47,453	10.31023	0.9749867	0	14.34709
log_incwage	28,051	9.920086	0.9787497	0.6931472	13.91716
AZ	48,635	0.1246633	0.3303401	0	1
GA	48,635	0.1974915	0.3981104	0	1
SD	48,635	0.1294952	0.3357507	0	1
TX	48,635	0.54835	0.4976619	0	1
AZ_DD	48,635	0.0517323	0.2214883	0	1
GA_DD	48,635	0.0693328	0.2540218	0	1
race_dummy	48,635	0.2068058	0.4050192	0	1
xxyear1	48,635	0.0686543	0.2528679	0	1
xxyear2	48,635	0.0674411	0.250787	0	1
xxyear3	48,635	0.0730133	0.2601609	0	1
xxyear4	48,635	0.0767554	0.2662057	0	1
xxyear5	48,635	0.0751928	0.2637048	0	1
xxyear6	48,635	0.0751928	0.2637048	0	1
xxyear7	48,635	0.0742469	0.262175	0	1
xxyear8	48,635	0.0745554	0.2626752	0	1
xxyear9	48,635	0.0722114	0.2588402	0	1
xxyear10	48,635	0.0698674	0.254926	0	1
xxyear11	48,635	0.0710394	0.2568932	0	1

xxyear12	48,635	0.0702786	0.2556186	0	1
xxyear13	48,635	0.0680374	0.2518127	0	1
xxyear14	48,635	0.0635139	0.2438875	0	1

Table 4: Summary Statistics of Variables Present in Employment Regressions

Variable	Obs	Mean	Std. Dev.	Min	Max
year	30,108	2,009	4	2,003	2,016
statecensus	30,108	68	12	45	86
hhincome	30,108	50,894	48,617	-14,699	1,701,615
relate	30,108	101	0	101	101
age	30,108	42	13	15	85
age2	30,108	1,956	1,164	225	7,225
sex	30,108	0	0	0	1
race	30,108	137	112	100	830
nativity	30,108	2	2	0	5
educ	30,108	62	19	2	73
empstat	30,108	11	3	1	22
employment~y	30,108	1	0	0	1
labforce	30,108	2	0	0	2
occ	30,108	5,394	2,480	0	9,840
ind	30,108	5,321	3,108	0	9,890
incwage	30,108	26,664	33,730	0	1,106,999

log_hhincome	29,819	11	1	0	14
log_incwage	26,484	10	1	1	14
AZ	30,108	0	0	0	1
GA	30,108	0	0	0	1
SD	30,108	0	0	0	1
TX	30,108	1	0	0	1
AZ_DD	30,108	0	0	0	1
GA_DD	30,108	0	0	0	1
race_dummy	30,108	0	0	0	1
xxyear1	30,108	0	0	0	1
xxyear2	30,108	0	0	0	1
xxyear3	30,108	0	0	0	1
xxyear4	30,108	0	0	0	1
xxyear5	30,108	0	0	0	1
xxyear6	30,108	0	0	0	1
xxyear7	30,108	0	0	0	1
xxyear8	30,108	0	0	0	1
xxyear9	30,108	0	0	0	1
xxyear10	30,108	0	0	0	1
xxyear11	30,108	0	0	0	1
xxyear12	30,108	0	0	0	1
xxyear13	30,108	0	0	0	1
xxyear14	30,108	0	0	0	1

In order to measure income I used 2 different dependent variables: personal income and household income. Personal income (denoted incwage) equals the income and salary earned by the individual worker within a year; their salary is a result of their current employment and investments. Household income (denoted hhincome) equals the total annual income earned by the respondent and all other workers in his/her family. While using household data, the data could be biased if one of the family members works in a different industry, higher skilled job, etc. Since the data is restricted to head of household this will control for the possible bias; however, it is also reasonable to assume that the head of household is the highest earner within a family

I also used data that measured the labor force participation of each respondent. The variable I used in my regressions is derived from a pre-coded variable that contains the value of either 0, 1, or 2. Being labeled with a 0 means that the CPS does not have the data on that individual with respect to labor force participation. Therefore, for the purpose of this study's regressions those who were unknown were dropped from the data. The number of people labeled as unknown after the restrictions were enforced was very small, so the effect of excluding these respondents is likely small. Lastly, for the purpose of running a linear probability model, the values for LFP were recoded to take a value of one if the respondent is in the labor force and a value of zero if not.

To measure employment, I create a dummy variable using a pre-coded variable, known as "empstat". According to the IPUMS, "empstat" is coded between 0 and 36. However, since my model is specified for a linear probability regression, I create an alternative measure of employment called "employment_dummy." It takes a value of 0 if you are unemployed—defined by the Bureau of Labor Statistics (BLS) measure of unemployment. The BLS considers you unemployed if you are not currently employed, and you have actively sought employment in the past 4 weeks. Conversely, the employment dummy has a value of 1 if you are employed.

Two difference-in-differences estimators were created: one for Arizona (AZ_DD) and one for Georgia (GA_DD). These variables are the main independent variable of interest, for the estimated coefficients suggest the effects that immigrants have on native workers in treated states relative to the control group. Each of these estimators is an interactive independent variable that is the product of two dummy variables. The first dummy variable is a state dummy for the treatment group. The second dummy variable is a post variable that takes a value of 0 before the treatment occurred and a value of 1 after the treatment. Specifically, this cut-off year is 2010 in Arizona and 2011 in Georgia. Each interactive variable then takes a value of one if the state is a treatment state in the post-treatment period.

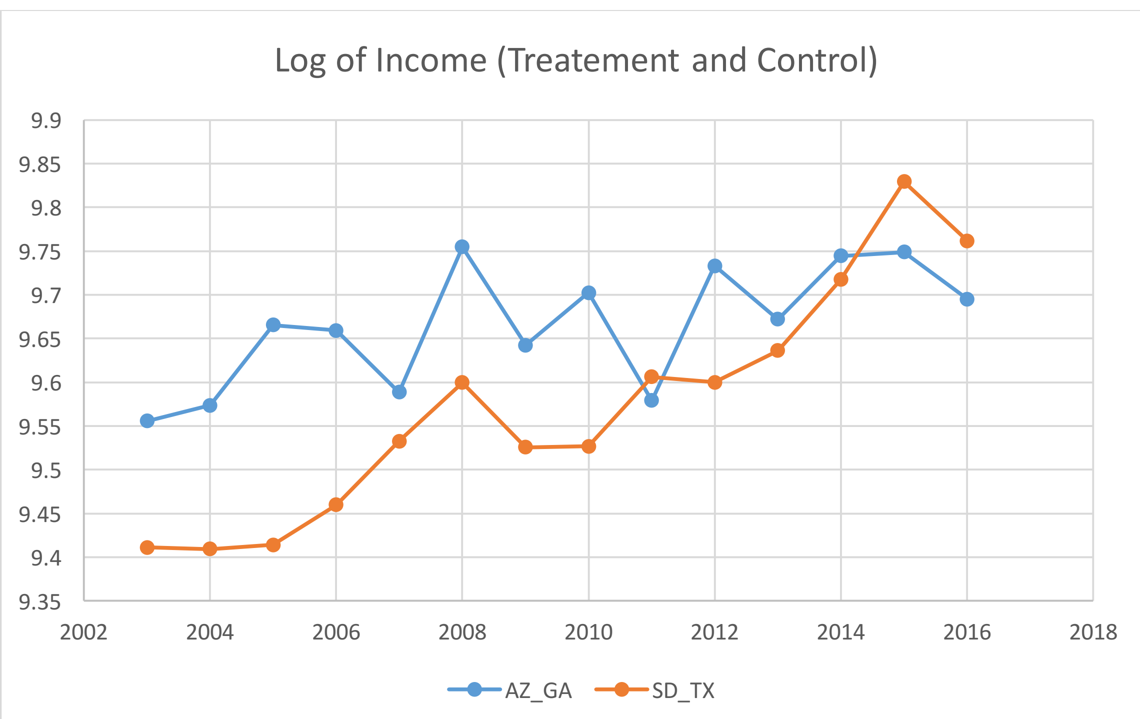
A race dummy (equal to 1 if non-white and 0 if white) was added to control for the fact that minorities tend to get paid lower wages than whites. Another variable used as a control in the regression was age—measured in number of years. As shown through the life-cycle model, age has a parabolic relationship with wage. This means that when you are young, age and wage have a positive relationship; however, once you reach a certain mid-life age, the relationship between age and wage starts to become become negative. Therefore, for the purpose of controls in my regression, I use both age and age^2. Economic theory also shows that one's sex has an effect on their wages. That is, men tend to get paid at higher rates than women do. This gap is due to discrimination in the workforce, and so it is essential to control for this difference. The sex variable is also a dummy variable; if you are male you are assigned a 0 and if you are female you are assigned a 1.

Not only is there a relationship between the individuals and employment variables, but also there is a relationship between time and employment variables. That is, different time periods have different rates of growth, different patterns, etc. Since the purpose of the regression is to determine the effects on employment variables holding all other effect constant, it is crucial to control for any and all factors than can predictably affect employment variables. So year dummies were added to the model to control for the time effects. Not only does time effect employment variables, but states can have different effects on employment variables. The states used in this difference-in-differences model have similar trends, which allows for the comparison. However, the overall size, growth, etc. of the economies varies and so it is necessary to control for state specific effects. Therefore, I added state-specific dummies to the model. Initially, I had added state specific trend variables to the model as well, but this caused problems with collinearity that caused a distortion of my data. Therefore, for the final regressions, these trends were not included.

Methodology

For the purpose of finding the effects of immigrants on native workers, I use a difference-in-difference estimator. Difference-in-differences regressions are only valid if they concur with the parallel trends assumption; that is, all of the states used had parallel trends before the treatment occurred. Only after the treatment occurred, did the trends differ. Thus, the control states act as a counterfactual for the treatment states had the treatment not occurred. Figure 2 shows a similarity of trends prior to the treatment followed by a change in trends after the treatment occurred in the respective states. This confirmation allows for the difference-in-differences estimator to accurately capture the change in the dependent variable as a result of the treatment group; this is due to the control groups acting as a counterfactual of sorts for Arizona and Georgia were they not to pass immigration reform.

Figure 2: Trends of Income in Treatment and Control States (year, log of income)

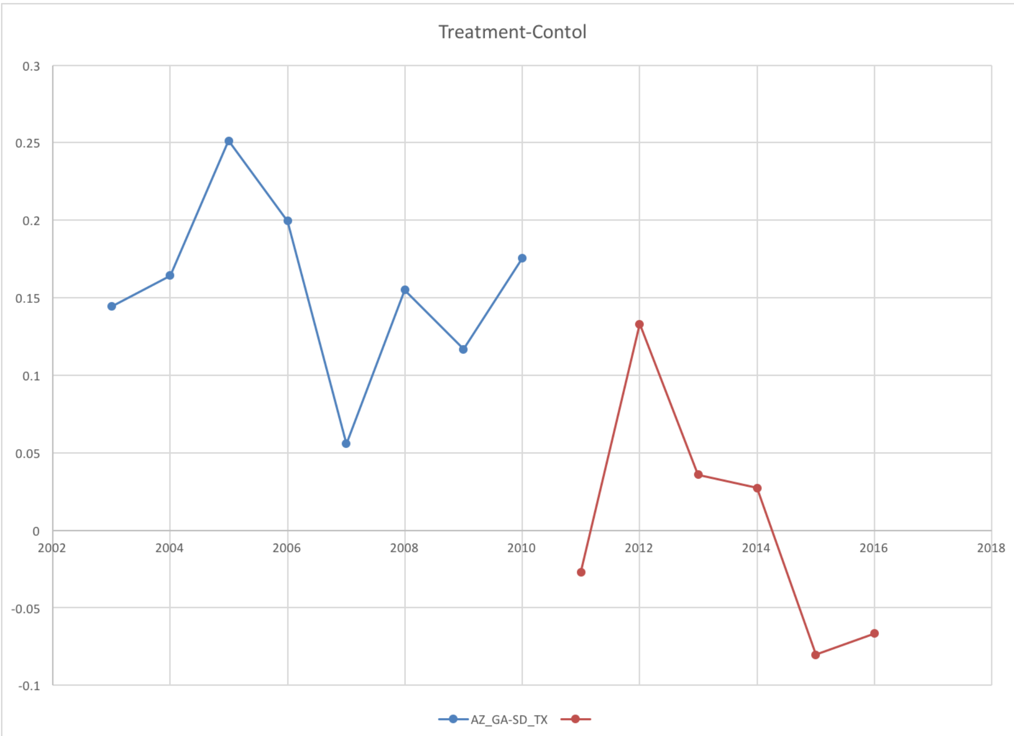


Key: AZ_GA= mean of Arizona and Georgia income (log*income); SD_TX = mean of South Dakota and Texas income (log*income)

*Not meant for replication, citation, or publication (partial or full) without the consent of the author

As discussed earlier, the treatment states are Arizona and Georgia, both of whom have recently acted immigration reform. The control states are Texas and South Dakota. These states were chosen for a variety of reasons. First, I wanted to select states that were non-contiguous with the treated states. That is, it is logical to assume that once immigrants were pushed out of treatment states, they would move to contiguous states. Therefore, Texas and South Dakota are viable states for comparison, for they are not-contiguous with either treatment state. Furthermore, the industry breakdown is similar in Arizona, Georgia, South Dakota, and Texas. In order to determine the validity of Texas and South Dakota as control groups, I graphed the difference in income by year between the Georgia and Texas/South Dakota and Arizona and Texas/South Dakota. The results are shown in Figure 3. There is a shift in trends in the treatment states compared to the control states, occurring at the start of each respective year of ratification. There is some variation in the data that distracts from a perfect trend distinction, but there is a shift in the data after the treatment year, which suggests that the parallel trends assumption is met.

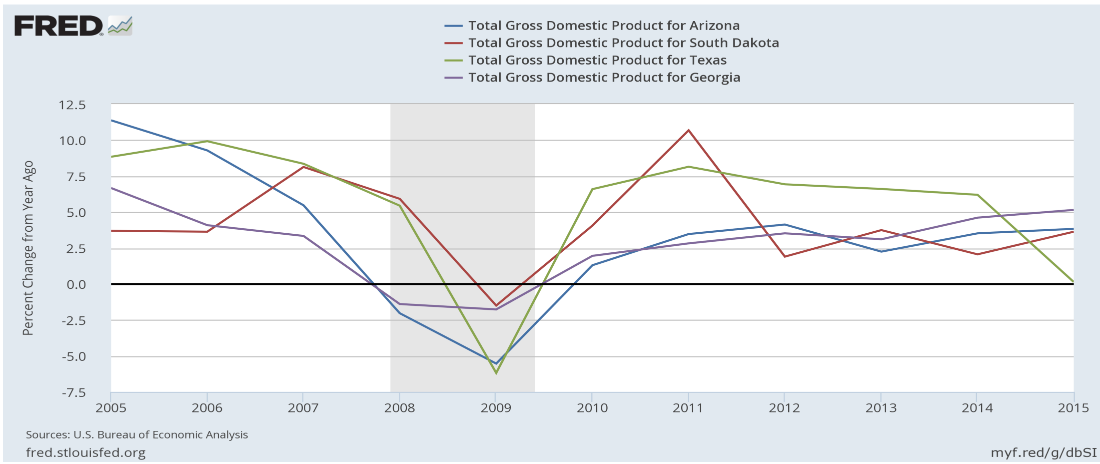
Figure 3: Difference in Treatment States and Control States income



Key: Graphed is the difference in the log of wages between the treatment states and control states. The log of income is on the y axis and the year is on the x axis. The treatment states' wages are averaged together and the control states' wages are averaged together.

As a robustness check, I ran all of the regression using all US border states and all US states as controls (shown in tables A5-A12, appendix); the regression coefficients had similar signs and magnitudes, which confirms the validity of the results. Additionally, this suggests that the original control group are well-selected. Lastly, as an additional validity test, the percent change in real GDP growth per year was graphed for all 4 states. As shown in Figure 4 the states follow similar patterns in changes in GDP. The numerical percentages are not the same, but the overall trends are comparable. South Dakota and Texas both share similar industries and GDP growth to Arizona and Georgia. That is, the break down of industries entered among the low-skilled workers is similar across the 4 states, so they serve as good states for this natural experiment. In conclusion, it is reasonable to assume that if the treatment had not occurred, then the control and treatment states would fit the parallel trends assumption.

Figure 4: GDP Growth Rates of Arizona, Georgia, Texas, and South Dakota



The equation to be estimated is

$$Y_{it} = \beta_1 TREAT_S + \beta_2 YEAR_t + \beta_3 DD_{St} + \beta X_{it} + \varepsilon$$

where i is a subscript representing the individual, s is a subscript representing the state, and t is a subscript representing the year. The dependent variables, Y include income, an employment dummy and a labor force participation dummy. Because the last two regressions have a dependent variable which is a dummy variable, they are estimated using a linear probability regression. The "treat" variable is a state dummy for each of the states included in the regression. This is to control for any effects that are consistently/structurally different across the states. A year dummy was also included in order to control for any economic effects, such as the great recession, that would have affected all states in a given year. The variable DD represent the difference-in-differences estimator, and are the product of the state and post-treatment dummy variables. The regressions were run separately for Arizona and Georgia, so in the regressions the Arizona DD was labeled AZ_DD and the Georgia DD was labeled GA_DD. Initially, I included state specific trends (State*year) in order to control for any endogenous trends within the state that are not representative of the differences caused by the immigration reform. However, the addition of this variable caused problems of collinearity. Therefore, these trends were eliminated from the model. Other controls were inserted such as state, race, sex, and age to control for their impact on the dependent variable. Since the purpose of this study is to examine the effects of immigration on the dependent variable and not the effects of race, sex, or age, it is crucial to include these variables as controls. This allows for the difference-in-differences coefficients to represent the changes due to immigrants while holding all other variables constant.

For the regressions, I used the natural log of the two income variables. Therefore, the regressions on wages are run as a log-linear regression. The reason for this is because numerical changes in one's income vary as one's income increases, and thus the marginal benefit of a dollar income is not constant. Transforming the variable to be the natural log of income controls for these variances in values and changes in income. This allows for me to determine the percent change in income, so the effects across all income levels are accurately represented.

It is important to note that there are a few limitations to the model. First, omitted variable bias might be present if excluded control variables have systemic effects on wages, employment, and labor force participation. For example, there could be discrimination that is immeasurable such as personality, work ethic, etc. Economic literature does not suggest any other major controls that should be included, so the controls in this regression are similar to those previously used in labor economics. Since this is a natural experiment there is an assumed level of randomness of subjects; therefore, those few possible sources of bias mentioned above should not cause any bias to occur in the regression coefficients.

Results

The results from this estimation are contained in tables 5, 6, and 7. They are analyzed individually in the following three sections: wages, LFP, and Employment. For each dependent variable and regression run, I ran a regression with both GA and AZ in the same equation. This was done to look for consistency across the regressions. By including both treatment states the other treatment group's information would be included in the regression. Therefore, the coefficients are not as reliable, but they can be used to test for consistency. Following the individual analysis, I will make overall arguments with respect to trends and conclusions.

Wages

Table 5 contains the results when wages are the dependent variable. In general, the difference-in-differences coefficient is negative for both states, indicating that the income of native low-skilled workers declined after the treatment (i.e. the immigration reform). Thus, there is no evidence that immigration reform increased the wages of low-skilled workers in treatment states. More specifically, I ran regressions with two different variables measuring wage. As outlined in the data section, one is the income earned by the individual and the other is the income of the individual's household. The main focus was on the variable representing the individual income of the head of household (labeled incwage), but the regressions for the household income (labeled hhincome) were included to check for robustness. The coefficient for the difference-in-differences variable in the incwage regression for Georgia is -.13 and is significant at the one percent level. This implies that the income of low-skilled native head of households was 13 percent lower after the immigration reform in Georgia. Similarly, the coefficient of the Georgia difference-in-differences variable in the hhincome regression is also negative and significant at the one percent level. This coefficient implies a 15.7 percent lower income for native workers' households after the treatment. As an additional robustness check, I conducted regressions using all border states and all US states as control groups and found very similar results. The results of the regressions can be seen in the appendix in Tables A5-A12 (see the appendix). Thus the results for Georgia's difference-in-differences estimator appear to be robust.

The Arizona difference-in-differences coefficients tells a similar story, but these coefficients aren't as statistically significant as those for Georgia. The coefficient on incwage suggests a 9.9% decrease post treatment, but this coefficient is only significant at a 13% percent level (i.e. with an 87% confidence level). The difference-in-differences coefficient is significant at the 2% level when hhincome is used as the dependent variable however, and indicates that native wages were 14.5% lower post treatment. It is important to note that the signs and magnitudes of the key coefficients are similar across both states, implying that the results are robust and that the wages of low-skilled native workers do not appear to increase (and may even decrease) after the number of immigrants is reduced.

Table 5: Wage Regression Results for Selected Variables

Independent Variables	**log_incwage (Georgia)**	**log_incwage (Arizona)**	**log_incwage (AZ+GA)**	**log_hhincome (Georgia)**	**log_hhincome (Arizona)**	**log_hhincome (AZ+GA)**
GA_DD	-0.134**		-0.133**	-0.157**		-0.160***
	(0.008)		(0.009)	(0.001)		(0.001)
AZ_DD		-0.0991	-0.0814		-0.145*	-0.142*
		(0.122)	(0.203)		(0.020)	(0.021)
race_dummy	-0.173***	-0.159***	-0.162***	-0.315***	-0.268***	-0.305***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age	0.0891***	0.0938***	0.0919***	0.0486***	0.0509***	0.0505***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age2	-0.000929***	-0.000988***	-0.000963***	-0.000443***	-0.000475***	-0.000463***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
sex	-0.641***	-0.666***	-0.641***	-0.354***	-0.359***	-0.356***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	6740	5977	7623	7827	6938	8841
p-values in parentheses						
="* p<0.05	** p<0.01	*** p<0.001"				

Employment

In addition to wages, the difference-in-differences estimator was run for employment as well. The results are contained in Table 6. The coefficient on the difference-in-differences estimator here is negative and statistically significant, suggesting that a reduction in the number of immigrants reduces employment of low-skilled native workers. The magnitude suggests that employment of low-skilled native workers was 2 percent lower after the immigration reforms. For Arizona, the coefficient on the difference-in-differences estimator is negative but not statistically significant, which suggests that a reduction in the number of immigrants has no significant effect on the employment of low-skilled native workers.

Table 6: Employment Regression Results for Selected Variables

Independent Variables	**Employment (Georgia)**	**Employment (Arizona)**	**Employment (AZ+GA)**
GA_DD	-0.0216*		-0.0227*
	(0.025)		(0.019)
AZ_DD		-0.0127	-0.0119
		(0.308)	(0.340)
race_dummy	-0.0585***	-0.0591***	-0.0564***
	(0.000)	(0.000)	(0.000)
age	0.00649***	0.00538***	0.00605***
	(0.000)	(0.000)	(0.000)
age2	-0.0000534***	-0.0000431***	-0.0000500***
	(0.000)	(0.000)	(0.000)
sex	-0.00483	0.00136	-0.00327
	(0.189)	(0.728)	(0.349)
N	19377	16920	21641
p-values in parentheses			
="* p<0.05	** p<0.01	*** p<0.001"	

Labor Force Participation

The results when labor force participation is the dependent variable are similar to those for wages and employment as can be seen in Table 7. In Georgia the results suggest that there was 4.4% lower labor force participation after the reform. The Georgia coefficient is significant at a 1% significance level. The difference-in-differences estimator for Arizona is statistically significant at the 6% level and indicates that labor force participation of low-skilled native workers was 2.7% lower after the immigration reform. Results for both states reinforce the conclusion that the presence of immigrant labor benefits low-skilled native workers.

Table 7: Labor Force Participation Regression Results for Selected Variables

Independent Variables	**LFP (Georgia)**	**LFP (Arizona)**	**LFP (AZ+ GA)**
GA_DD	-0.0444***		-0.0437***
	(0.000)		(0.000)
AZ_DD		-0.0272	-0.0248
		(0.057)	(0.081)
race_dummy	-0.0508***	-0.0766***	-0.0519***
	(0.000)	(0.000)	(0.000)
age	0.0240***	0.0250***	0.0240***
	(0.000)	(0.000)	(0.000)
age2	-0.000364***	-0.000372***	-0.000364***
	(0.000)	(0.000)	(0.000)
sex	-0.134***	-0.141***	-0.135***
	(0.000)	(0.000)	(0.000)
N	32403	28156	36411
p-values in parentheses			
="* p<0.05	** p<0.01	*** p<0.001"	

Controls

The controls in the regressions were not the main variables of interest, but the p-vaules and signs are important for determining validity of the regression and sample. In every regression the race dummy had a negative sign and was significant at a .1% level. This result is consistent with the economic literature on race. Similarly, for all the regressions, the coefficients on the age variables are significant at a .1% level and contain the hypothesized signs. Finally, the sign on the gender dummy is statistically significant and negative, which is consistent with existing literature on gender and wages. Overall, the main controls are statistically significant and have signs consistent with economic theory and previous empirical work, which confirms the validity of the sample.

Conclusion

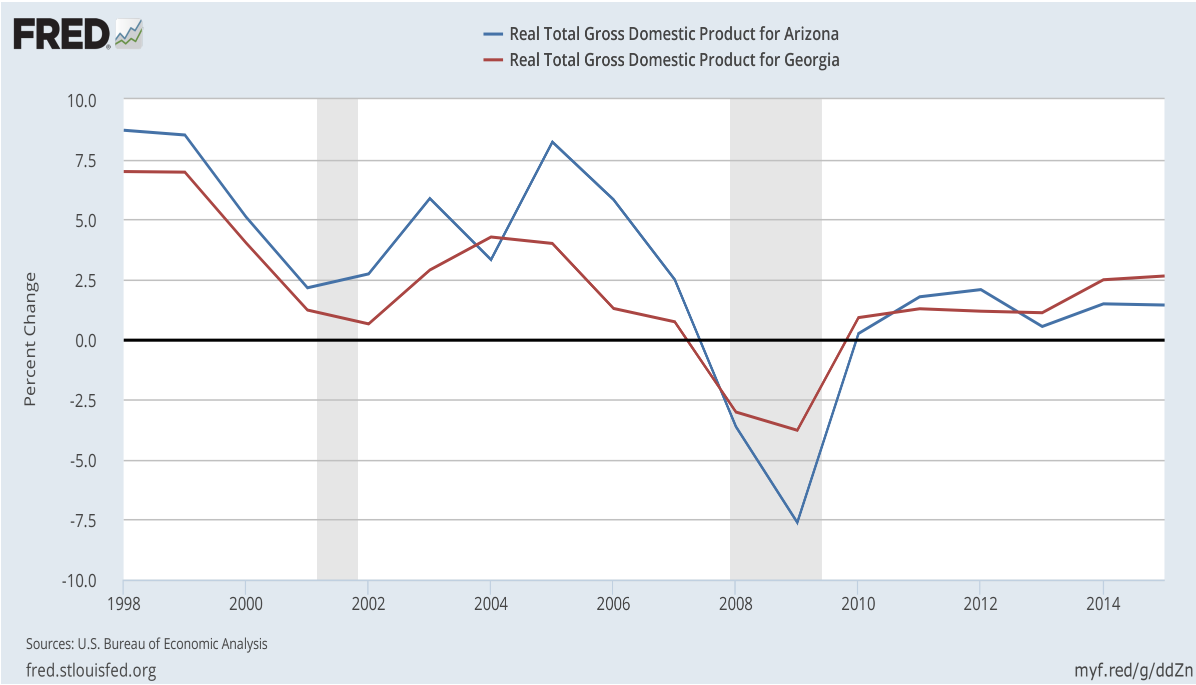
In summary, all of the differences-in-differences coefficients are negative. Since the coefficients are all negative, this suggests that the immigration reforms passed by Arizona and Georgie had no positive effect on the wages, labor force participation or employment of native workers in these states after immigration reform was enacted.

Discussion

One goal of the immigration reforms undertaken by Arizona and Georgia was to limit the number of undocumented immigrants in these states with the hope that this would benefit the local native workers who compete with immigrants. However, contrary to the goal of the policies, the results of this study suggest that the presence of immigrants has either no effect or a positive effect on the wages, LFP, and employment of low-skilled native workers. There are three main theories that can be applied to explain this relationship.

The first theory is that reductions in the immigrant workforces in the two treatment states were large enough to significantly reduce output and aggregate demand. This in turn implied reductions in wages, employment, and labor force participation in the treatment states. The decrease in the low-skilled labor force caused a decrease in economic growth that consequently decreased aggregate demand in the treatment states. As a result, low-skilled native workers, the most vulnerable of the native labor classes, saw a decrease in their wages, employment, and labor force participation. As a form of validation, I analyzed the GDP growth rates pre and post treatment, and in conjunction with this theory, there was an overall decrease in GDP growth rates post treatment dates. As shown in Figure 5, output in the treatment states has yet to return to pre-recession levels, whereas the control states have been able to return to pre-recession levels.

Figure 5: GDP Growth Rates of Arizona and Georgia



Another explanation for the positive impact of immigrants on low-skilled native workers involves complementarity between these two groups. In labor economics, workers can be complements or substitutes for one another. A substitute is a worker who fully or partially replaces another worker in skill, job, productivity, etc. Therefore, if two workers are substitutes they compete for the same jobs, and thus can have a positive cross elasticity of demand, which causes a negative relationship in the forms of employment, labor force participation, and wages. Conversely, workers can also be complements. Complementary workers are workers that have a negative cross elasticity of demand, which causes a positive relationship in the form of wages, employment, and labor force participation. If immigrants are complements to low-skilled native workers than a reduction in the number of immigrants after the treatment would adversely affect low-skilled native workers. However, Chiswick (2012) suggests that traditionally high-skilled natives are complements to low-skilled immigrants, but low-skilled native workers do not tend to be complements to low-skilled immigrants.

A third explanation relates to George Borja's "immigration markets." Borjas argues that the jobs immigrants take are disproportionately located in communities made up of immigrants. That is, immigrants selectively choose locations, create their own jobs, and participate in jobs in the secondary market. For example, this could include a Spanish-speaking waiter working in an immigrant-owned Spanish restaurant. Furthermore, Borjas suggests that immigrants only move when there is an opening for jobs in the local markets. Therefore, they would only work in the immigrant markets if there was a job opening already there. This theory can supplement the aggregate effects explanation and the complement explanation.

In addition to providing theoretical explanations for the results, it is important to analyze the limitations of the data and regression analysis. First, the difference-in-differences control states are not perfect matches, which could cause some noise in the results. That being said, this is a natural experiment, so it is impossible to expect a perfect comparison. In order to test the validity of the controls, regressions were run using all border states as controls and all states as controls. The results (shown in Tables A5-A12, see appendix) of these regressions showed the same signs and similar magnitudes in all regressions, implying that the results are robust; this suggest that the results do not depend on the choice of control states; that is, they are not a result of the control states, but rather a result of the immigration reform. One main restriction on the labor force participation and employment regressions is the inability to restrict the data to the non-tradable sector. This opens up the possibility that reductions in employment and labor force participation might be explained by factors such as higher imports or outsourcing that are not controlled for here. But the sample for the wage regressions is limited to the non-tradable sector, so these factors cannot explain the decline in wages experienced by native workers post treatment. That being said, the fact that the regressions continuously showed the same signs, suggest that there is an overall pattern occurring with respect to immigrants affecting native workers; they have either no effect or a positive benefit on native workers. Lastly, the CPS is a voluntary, self-reported set of data. Thus, there are sample biases that could occur. However, the US Census is effective at creating representative selections and samples, so the possible biases that could result are not likely to be great enough to explain the results. Lastly, since the sample used here includes only native workers, there is no need to worry about response biases due to undocumented immigrants.

References

1) Agiomirgianakis, George, and Athina Zervoyianni. "Macroeconomic equilibrium with illegal immigration." *Economic Modelling* 18, (January 1, 2001): 181-202. *ScienceDirect*, EBSCO*host*
2) Amuedo-Dorantes, C, and F Lozano. "ON THE EFFECTIVENESS OF SB1070 IN ARIZONA." *Economic Inquiry* 53, no. 1 (2014): 335-351. *Social Sciences Citation Index*, EBSCO*host*
3) Arrocha, William. "FROM ARIZONA'S S.B. 1070 TO GEORGIA'S H.B. 87 AND ALABAMA'S H.B. 56: EXACERBATING THE OTHER AND GENERATING NEW DISCOURSES AND PRACTICES OF SEGREGATION." *California Western Law Review* 48, no. 2 (Spring2012 2012): 245. *Supplemental Index*, EBSCO*host*
4) Autor, David H., and David Dorn. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *The American Economic Review*, 2013., 1553, *JSTOR Journals*, EBSCO*host*
5) BERANEK, WILLIAM. "The Illegal Alien Work Force, Demand for Unskilled Labor, and the Minimum Wage." *Journal Of Labor Research* 3, no. 1 (Winter82 1982): 89-99. *Business Source Index*, EBSCO*host*
6) BERMAN, E, J BOUND, and Z GRILICHES. "CHANGES IN THE DEMAND FOR SKILLED LABOR WITHIN UNITED-STATES MANUFACTURING - EVIDENCE FROM THE ANNUAL SURVEY OF MANUFACTURES." *Quarterly Journal Of Economics* 109, no. 2 (n.d.): 367-397.
7) Borjas, George J. "Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants." *Journal of Labor Economics*, 1985., 463, *JSTOR Journals*, EBSCO*host*
8) Borjas, George J. "Economic Theory and International Migration." *The International Migration Review*, 1989., 457, *JSTOR Journals*, EBSCO*host*
9) Borjas, George J., et al. "How Much Do Immigration and Trade Affect Labor Market Outcomes?." *Brookings Papers on Economic Activity*, 1997., 1, *JSTOR Journals*, EBSCO*host*
10) Borjas, George J. *Immigration economics*. n.p.: Cambridge, Massachusetts ; London, England : Harvard University Press, 2014., 2014. *Lafayette Library Catalog*, EBSCO*host*
11) Bruno, Andorra. "Unauthorized Aliens in the United States: Policy Discussion." *Congressional Research Service: Issue Brief* (May 2014): 1. *Publisher Provided Full Text Searching File*, EBSCO*host*
12) Card, David. "Is the New Immigration Really so Bad?." *The Economic Journal*, 2005., F300, *JSTOR Journals*, EBSCO*host*
13) Carter, Thomas J. "Illegal Immigration in an Efficiency Wage Model." *Journal Of International Economics* 49, no. 2 (December 1999): 385-401. *EconLit*, EBSCO*host*
14) Chiswick, Barry R. *Immigration: high Skilled vs. low skilled labor?*. No. 28. IZA Policy Paper, 2011.
15) Chiswick, Barry R. "The Effect of Americanization on the Earnings of Foreign-born Men." *Journal of Political Economy*, 1978., 897, *JSTOR Journals*, EBSCO*host*

16) Constant, Amelie, and Klaus F. Zimmermann. *International handbook on the economics of migration*. n.p.: Cheltenham, UK : Edward Elgar, [2013], 2013. *Lafayette Library Catalog*, EBSCO*host*
17) Duncan, Brian, and Stephen J. Trejo. "The Employment of Low-Skilled Immigrant Men in the United States." *The American Economic Review*, 2012., 549, *JSTOR Journals*, EBSCO*host*
18) Enchautegui, María E. "Low-Skilled Immigrants and the Changing American Labor Market." *Population and Development Review*, 1998., 811, *JSTOR Journals,* EBSCO*host*
19) Good, Michael. "Do Immigrant Outflows Lead to Native Inflows? An Empirical Analysis of the Migratory Responses to US State Immigration Legislation." *Applied Economics* 45, no. 28-30 (October 2013): 4275-4297. *EconLit*, EBSCO*host*
20) Grossman, Jean Baldwin. "The Substitutability of Natives and Immigrants in Production." *The Review of Economics and Statistics*, 1982., 596, *JSTOR Journals*, EBSCO*host*
21) Hagan, J, N Lowe, and C Quingla. "Skills on the Move: Rethinking the Relationship Between Human Capital and Immigrant Economic Mobility." *Work And Occupations* 38, no. 2 (n.d.): 149-178. *Social Sciences Citation Index*, EBSCO*host*
22) Hoekstra, Mark, and Sandra Orozco-Aleman. "Illegal Immigration, State Law, and Deterrence." *American Economic Journal: Economic Policy* 9, no. 2 (May 2017): 228-252. *EconLit*, EBSCO*host*
23) Howland, M, and D Nguyen. "The Impact of Immigration on Four Low-Wage Industries in the 1990s." *Economic Development Quarterly* 24, no. 2 (n.d.): 99-109. *Social Sciences Citation Index*, EBSCO*host*
24) Johnson, George E. "THE LABOR MARKET EFFECTS OF IMMIGRATION." *ILR Review* 33, no. 3 (April 1980): 331. *Publisher Provided Full Text Searching File*, EBSCO*host*
25) Lugo-Lugo, Carmen R., and Mary K. Bloodsworth-Lugo. "Containing (Un)American Bodies in Arizona." *Peace Review* 26, no. 2 (April 2014): 265-272. *SocINDEX with Full Text*, EBSCO*host*
26) Lyubansky, Mikhail, et al. "“One Day on the Red Hills of Georgia”: The Effects of Immigration Status on Latino Migrants' Experience of Discrimination, Utilization of Public Services, and Attitudes toward Acculturation." *Norteamérica* 8, no. Supplement (January 1, 2013): 85-117. *ScienceDirect*, EBSCO*host*
27) McKissick , John C., and Sharon P. Kane. "An Evaluation of Direct and Indirect Economic Losses Incurred by Georgia Fruit and Vegetable Producers in Spring 2011." *Center for Agribusiness and Economic Development*, November 2011. http://caes2.caes.uga.edu/center/caed/pubs/2011/documents/CR-11-01.pdf.
28) Orrenius, Pia, and Madeline Zavodny. "Do state work eligibility verification laws reduce unauthorized immigration?." *IZA Journal Of Migration* 5, no. 1 (March 10, 2016): 1. *Supplemental Index*, EBSCO*host*
29) Parrado, Emilio A., and William Kandel. "Industrial change, Hispanic immigration, and the internal migration of low-skilled native male workers in the United States, 1995–

2000." *Social Science Research* 40, (January 1, 2011): 626-640. *ScienceDirect*, EBSCO*host*

30) SABIA, DEBRA. "The Anti-Immigrant Fervor in Georgia: Return of the Nativist or Just Politics as Usual?." *Politics & Policy* 38, no. 1 (February 2010): 53-80. *Political Science Complete*, EBSCO*host*
31) Wachter, Michael L. "THE LABOR MARKET AND ILLEGAL IMMIGRATION: THE OUTLOOK FOR THE 1980s." *ILR Review* 33, no. 3 (April 1980): 342-354. *Business Source Index*, EBSCO*host*
32) Picker, Caroline. "Living in the Shadow of SB 1070: Organizing for Migrant Rights in Arizona." *Tikkun*, 2013., 47, *Literature Resource Center*, EBSCO*host*
33) Sarah Flood, Miriam King, Steven Ruggles, and J. Robert Warren. *Integrated Public Use Microdata Series, Current Population Survey: Version 4.0* [dataset]. Minneapolis, MN: University of Minnesota, 2015.
34) *Scott walla*
35) U.S. Bureau of Economic Analysis, Real Total Gross Domestic Product for Arizona [AZRGSP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/AZRGSP, May 3, 2017.
36) U.S. Bureau of Economic Analysis, Real Total Gross Domestic Product for Georgia [GARGSP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GARGSP, May 3, 2017.
37) U.S. Bureau of Economic Analysis, Real Total Gross Domestic Product for South Dakota [SDRGSP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/SDRGSP, May 3, 2017.
38) U.S. Bureau of Economic Analysis, Real Total Gross Domestic Product for Texas [TXRGSP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TXRGSP, May 3, 2017.
39) Young, Neely. "HB 87 TARGETS BUSINESS." *Georgia Trend* 27, no. 11 (July 2012): 10. *Supplemental Index*, EBSCO*host*

Appendix

Below are the parallel trend confirmations for all the treatment states. The graphs are set up by subtracting the mean logincwage for each treatment and control state. After determining the means, the mean of the treatment state is subtracted from the mean of the control state for every year and then graphed. The graphs, for the most part, show a change in trends following the treatment years.

Figure A1 (Georgia - Texas)

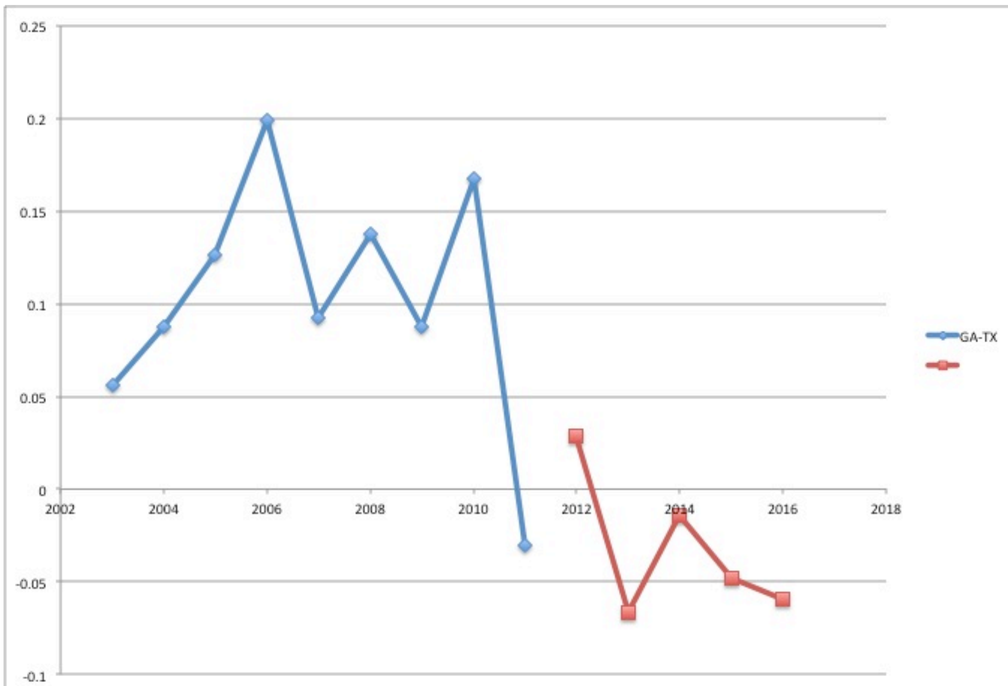


Figure A2 (Georgia – South Dakota)

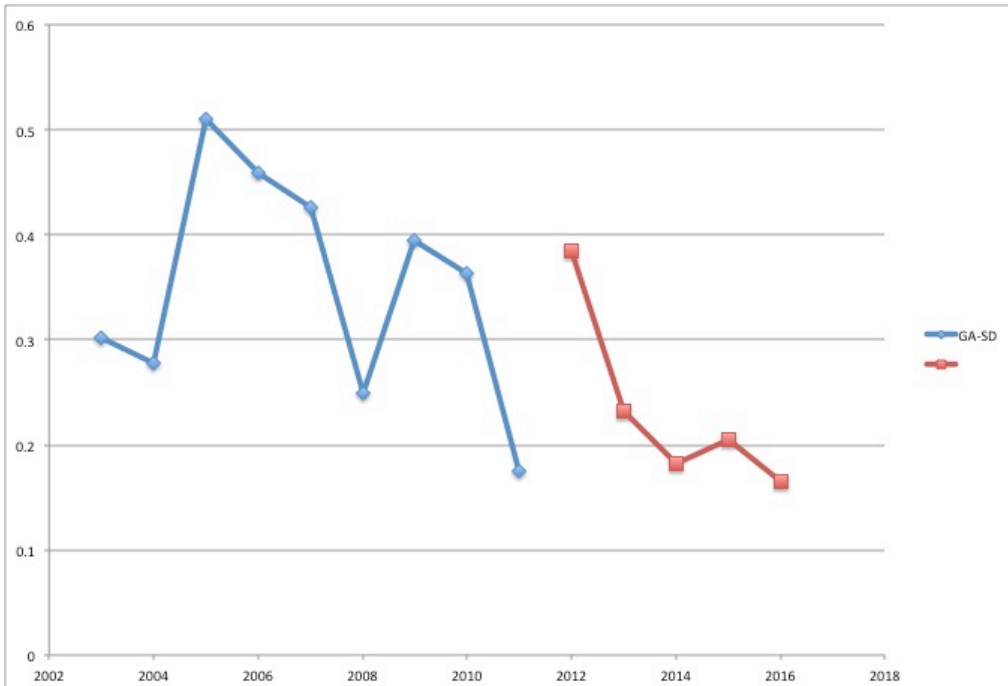


Figure A3 (Arizona – South Dakota)

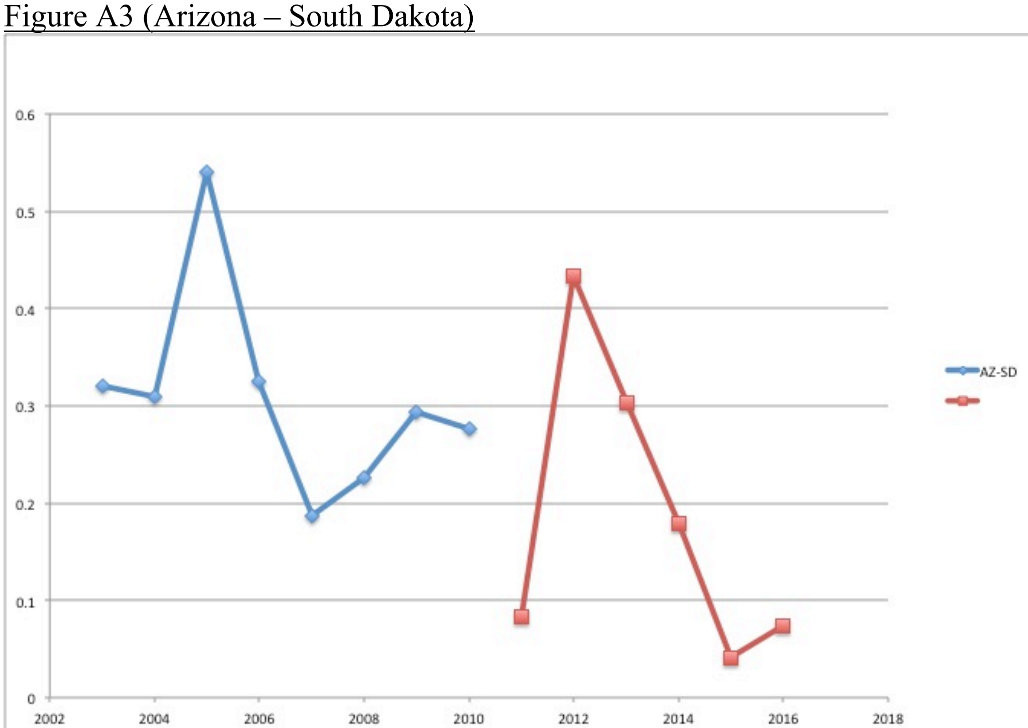
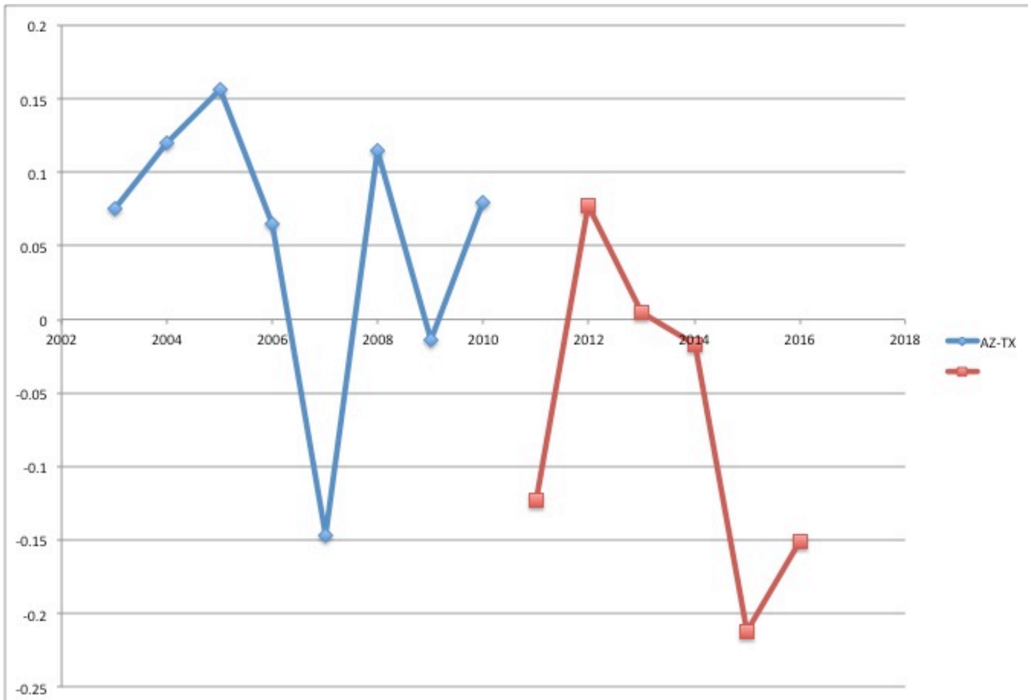


Figure A4: (Arizona-Texas)



Regressions:

Below are the full regression estimates for all variables, including every control. Log_incwage represents the regressions run on individual incomes for the head of household. Log_hhincome represents the log of the household's income for each household. LFP represents linear probability model on labor force participation. Lastly, employment represents the linear probability model on the employment dummy.

Table A5: Full Regression Results on "incwage"

Independent Variables	**log_incwage (Arizona)**	**log_incwage (Georgia)**	**log_incwage (AZ + GA)**
GA_DD	-0.134**		-0.133**
	(0.008)		(0.009)
AZ_DD		-0.0991	-0.0814
		(0.122)	(0.203)
AZ		0.126**	0.121**
		(0.006)	(0.009)
GA	0		0.207***
	(.)		(0.000)
SD	-0.211***	0	0
	(0.000)	(.)	(.)
TX	-0.127***	0.0818**	0.0831**
	(0.000)	(0.005)	(0.004)
xxyear1	-0.342***	-0.344***	-0.316***
	(0.000)	(0.000)	(0.000)
xxyear2	-0.315***	-0.282***	-0.286***
	(0.000)	(0.000)	(0.000)
xxyear3	-0.340***	-0.316***	-0.302***
	(0.000)	(0.000)	(0.000)
xxyear4	-0.294***	-0.273***	-0.265***
	(0.000)	(0.000)	(0.000)
xxyear5	-0.210***	-0.241***	-0.210***
	(0.001)	(0.000)	(0.000)
xxyear6	-0.148*	-0.142*	-0.133*
	(0.012)	(0.023)	(0.016)
xxyear7	-0.237***	-0.240***	-0.226***
	(0.000)	(0.000)	(0.000)
xxyear8	-0.278***	-0.249***	-0.238***
	(0.000)	(0.000)	(0.000)

xxyear9	-0.202***	-0.129*	-0.179**
	(0.001)	(0.033)	(0.001)
xxyear10	-0.221***	-0.217**	-0.191**
	(0.001)	(0.001)	(0.001)
xxyear11	-0.141*	-0.106	-0.111*
	(0.016)	(0.081)	(0.039)
xxyear12	-0.0971	-0.0512	-0.0566
	(0.107)	(0.418)	(0.305)
xxyear13	-0.0202	-0.0183	-0.00967
	(0.735)	(0.778)	(0.864)
xxyear14	0	0	0
	(.)	(.)	(.)
race_dummy	-0.173***	-0.159***	-0.162***
	(0.000)	(0.000)	(0.000)
age	0.0891***	0.0938***	0.0919***
	(0.000)	(0.000)	(0.000)
age2	-0.000929***	-0.000988***	-0.000963***
	(0.000)	(0.000)	(0.000)
sex	-0.641***	-0.666***	-0.641***
	(0.000)	(0.000)	(0.000)
_cons	8.616***	8.316***	8.331***
	(0.000)	(0.000)	(0.000)
N	6740	5977	7623
p-values in parentheses			
="* p<0.05	** p<0.01	*** p<0.001"	

*Not meant for replication, citation, or publication (partial or full) without the consent of the author

Table A6: Full Regression Results on "hhincome"

Independent Variables	**log_hhincome (Georgia)**	**log_hhincome (Arizona)**	**log_hhincome (AZ + GA)**
GA_DD	-0.157**		-0.160***
	(0.001)		(0.001)
AZ_DD		-0.145*	-0.142*
		(0.020)	(0.021)
AZ		0.0562	0.0567
		(0.192)	(0.186)
GA	0		0.0836*
	(.)		(0.021)
SD	-0.0855*	0	0
	(0.019)	(.)	(.)
TX	-0.107***	-0.0244	-0.0219
	(0.000)	(0.365)	(0.416)
xxyear1	-0.302***	-0.270***	-0.265***
	(0.000)	(0.000)	(0.000)
xxyear2	-0.315***	-0.265***	-0.269***
	(0.000)	(0.000)	(0.000)
xxyear3	-0.339***	-0.331***	-0.296***
	(0.000)	(0.000)	(0.000)
xxyear4	-0.270***	-0.229**	-0.225***
	(0.000)	(0.002)	(0.000)
xxyear5	-0.194**	-0.194**	-0.187**
	(0.002)	(0.004)	(0.002)
xxyear6	-0.106	-0.0792	-0.0793
	(0.091)	(0.236)	(0.174)
xxyear7	-0.219***	-0.183**	-0.195**
	(0.001)	(0.008)	(0.001)
xxyear8	-0.192**	-0.149*	-0.166**
	(0.003)	(0.033)	(0.006)
xxyear9	-0.204**	-0.178**	-0.179**
	(0.002)	(0.008)	(0.003)
xxyear10	-0.191**	-0.132	-0.128*
	(0.004)	(0.060)	(0.035)
xxyear11	-0.0821	-0.0721	-0.0548
	(0.196)	(0.300)	(0.352)
xxyear12	-0.0759	-0.0144	-0.0372

	(0.242)	(0.837)	(0.532)
xxyear13	-0.0778	-0.0559	-0.0456
	(0.238)	(0.434)	(0.452)
xxyear14	0	0	0
	(.)	(.)	(.)
race_dummy	-0.315***	-0.268***	-0.305***
	(0.000)	(0.000)	(0.000)
age	0.0486***	0.0509***	0.0505***
	(0.000)	(0.000)	(0.000)
age2	-0.000443***	-0.000475***	-0.000463***
	(0.000)	(0.000)	(0.000)
sex	-0.354***	-0.359***	-0.356***
	(0.000)	(0.000)	(0.000)
_cons	9.798***	9.644***	9.640***
	(0.000)	(0.000)	(0.000)
N	7827	6938	8841
p-values in parentheses			
="* p<0.05			

Table A7: Full Regression Results on Labor Force Participation

Independent Variables	LFP (Georgia)	LFP (Arizona)	LFP (Arizona and Georgia)
GA_DD	-0.0444***		-0.0437***
	(0.000)		(0.000)
AZ_DD		-0.0272	-0.0248
		(0.057)	(0.081)
AZ		-0.107***	-0.110***
		(0.000)	(0.000)
GA	-0.0721***		-0.0719***
	(0.000)		(0.000)
SD	0	0	0
	(.)	(.)	(.)
TX	-0.0839***	-0.0809***	-0.0838***
	(0.000)	(0.000)	(0.000)
xxyear1	-0.00233	0.0226	0.0167
	(0.838)	(0.089)	(0.160)
xxyear2	0	0.0285*	0.0206
	(.)	(0.035)	(0.089)
xxyear3	-0.0137	0.00111	0.00244
	(0.233)	(0.934)	(0.838)
xxyear4	-0.00794	0.00422	0.00589
	(0.485)	(0.753)	(0.619)
xxyear5	-0.00661	0.0117	0.00877
	(0.561)	(0.383)	(0.460)
xxyear6	-0.00538	0.0135	0.0131
	(0.642)	(0.318)	(0.274)
xxyear7	-0.00156	0.0144	0.0148
	(0.892)	(0.291)	(0.218)
xxyear8	-0.00949	0.0178	0.00778
	(0.414)	(0.195)	(0.520)
xxyear9	-0.0263*	0.00613	-0.00679
	(0.027)	(0.654)	(0.577)
xxyear10	-0.0189	-0.00238	-0.00507
	(0.125)	(0.863)	(0.673)
xxyear11	-0.0145	0.00561	-0.00122
	(0.234)	(0.683)	(0.918)
xxyear12	-0.00274	0.0229	0.0131

	(0.821)	(0.093)	(0.271)
xxyear13	-0.0169	-0.00292	0
	(0.185)	(0.839)	(.)
xxyear14	-0.0281*	0	-0.00511
	(0.031)	(.)	(0.681)
race_dummy	-0.0508***	-0.0766***	-0.0519***
	(0.000)	(0.000)	(0.000)
age	0.0240***	0.0250***	0.0240***
	(0.000)	(0.000)	(0.000)
age2	-0.000364***	-0.000372***	-0.000364***
	(0.000)	(0.000)	(0.000)
sex	-0.134***	-0.141***	-0.135***
	(0.000)	(0.000)	(0.000)
_cons	0.587***	0.543***	0.570***
	(0.000)	(0.000)	(0.000)
N	32403	28156	36411
p-values in parentheses			
="* p<0.05	** p<0.01	*** p<0.001"	

Table A8: Full Regression Results on Total Employment

Independent Variables	Employment (Georgia)	Employment (Arizona)	Employment (AZ + GA)
GA_DD	-0.0216*		-0.0227*
	(0.025)		(0.019)
AZ_DD		-0.0127	-0.0119
		(0.308)	(0.340)
AZ		0	-0.00499
		(.)	(0.534)
GA	0		0.0126*
	(.)		(0.045)
SD	-0.0134*	0.00427	0
	(0.033)	(0.596)	(.)
TX	-0.0122*	0.00506	0.000718
	(0.024)	(0.494)	(0.875)
xxyear1	-0.0164	-0.0174	-0.0205*
	(0.096)	(0.093)	(0.031)
xxyear2	-0.0143	-0.0172	-0.0164
	(0.147)	(0.098)	(0.082)
xxyear3	-0.0139	-0.0115	-0.0172
	(0.149)	(0.256)	(0.064)
xxyear4	-0.00307	-0.00247	-0.00604
	(0.743)	(0.804)	(0.504)
xxyear5	0.00162	-0.00738	-0.00453
	(0.861)	(0.461)	(0.614)
xxyear6	0.0129	0.0116	0.00639
	(0.143)	(0.214)	(0.456)
xxyear7	-0.0263**	-0.0300**	-0.0372***
	(0.008)	(0.005)	(0.000)
xxyear8	-0.0385***	-0.0415***	-0.0485***
	(0.000)	(0.000)	(0.000)
xxyear9	-0.0499***	-0.0498***	-0.0577***
	(0.000)	(0.000)	(0.000)
xxyear10	-0.0208*	-0.0201	-0.0268**
	(0.038)	(0.059)	(0.005)
xxyear11	-0.0367***	-0.0356**	-0.0427***
	(0.000)	(0.001)	(0.000)
xxyear12	-0.0106	-0.0113	-0.0172

	(0.275)	(0.269)	(0.067)
xxyear13	0	-0.00322	-0.00208
	(.)	(0.756)	(0.820)
xxyear14	0.00356	0	0
	(0.718)	(.)	(.)
race_dummy	-0.0585***	-0.0591***	-0.0564***
	(0.000)	(0.000)	(0.000)
age	0.00649***	0.00538***	0.00605***
	(0.000)	(0.000)	(0.000)
age2	-0.0000534***	-0.0000431***	-0.0000500***
	(0.000)	(0.000)	(0.000)
sex	-0.00483	0.00136	-0.00327
	(0.189)	(0.728)	(0.349)
_cons	0.803***	0.811***	0.806***
	(0.000)	(0.000)	(0.000)
N	19377	16920	21641
p-values in parentheses			
="* p<0.05	** p<0.01	*** p<0.001"	

As described in the results section, an additional robustness check the was run by using all the southern border states in US as controls and while using all US states as controls. They were run on the same dependent variables as the intial difference-in-differences estimators (just with different controls). Therefore, the variable names are the same. The results are posted below.

Border States

Table A5: Full Regression Results on "incwage" for All US Border States

Variable	**Incwage (Georgia)**	**Incwage (Arizona)**	**Incwage (AZ + GA)**
GA_DD	-0.11872242		-0.12006386
	0.0116		0.0106
GA	0.11873842		0.12623396
	0.0016		0.0011
AZ_DD		-0.08004212	-0.0718327
		0.1936	0.2429
AZ		(omitted)	0.02554843
			0.5925
race_dummy	-0.21852309	-0.21903378	-0.21205453
	0	0	0
age	0.08644922	0.08850487	0.08812297
	0	0	0
age2	-0.00088758	-0.0009134	-0.00090865
	0	0	0
sex	-0.64690663	-0.66017467	-0.64712962
	0	0	0
xxyear1	-0.1595406	-0.17733999	-0.15644588
	0.0001	0.0001	0.0001
xxyear2	-0.12940363	-0.13037248	-0.12470953
	0.0012	0.0025	0.0013
xxyear3	-0.1460998	-0.15217081	-0.1365572
	0.0003	0.0004	0.0004
xxyear4	-0.0994005	-0.10669677	-0.09462629
	0.0115	0.0131	0.0134
xxyear5	-0.01232833	-0.04669152	-0.02504111
	0.7607	0.29	0.5258
xxyear6	0.04685552	0.03223806	0.04339042
	0.2363	0.4602	0.2586

*Not meant for replication, citation, or publication (partial or full) without the consent of the author

xxyear7	0.00155429	-0.01525715	-0.00765687
	0.969	0.7304	0.8451
xxyear8	-0.0316243	-0.02908914	-0.0224406
	0.4447	0.522	0.5794
xxyear9	(omitted)	0.01930313	(omitted)
		0.6644	
xxyear10	0.01262175	(omitted)	0.01507638
	0.7756		0.7248
xxyear11	0.07679115	0.08052886	0.08098998
	0.0655	0.07	0.0437
xxyear12	0.10638423	0.11410455	0.11751593
	0.014	0.0136	0.0048
xxyear13	0.12108151	0.10368519	0.11912193
	0.0035	0.021	0.0033
xxyear14	0.15622121	0.13941214	0.14957388
	0.0001	0.0015	0.0002
xxstate1	-0.10840587	-0.10076887	-0.09882304
	0.0047	0.009	0.0104
xxstate2	(omitted)	(omitted)	(omitted)
xxstate3	-0.03692065	-0.02853593	-0.0297495
	0.3239	0.4585	0.4388
xxstate4	(omitted)	0.00963092	0.00773082
		0.8127	0.8488
xxstate5	-0.11475716	-0.10627793	-0.10572938
	0.0035	0.0076	0.0079
xxstate6	0.01930895	0.02826789	0.02652543
	0.6085	0.4709	0.4973
xxstate7	-0.02542089	-0.01704963	-0.01662346
	0.4975	0.6551	0.6629
xxstate8	-0.01830127	-0.01103154	-0.00940042
	0.5641	0.7315	0.7698
xxstate9	-0.00990338	(omitted)	(omitted)
	0.8071		
xxstate10	(omitted)	0.02684841	(omitted)
		0.5738	
_cons	8.3494287	8.3185892	8.3089645
	0	0	0

Table A6: Full Regression Results on “hhincome” for All US Border States

Variable	**HH_GA**	**HH_AZ**	**HH_AZ_GA**
GA_DD	-0.1339851		-0.13783183
	0.0025		0.0018
GA	0.09182287		0.13192922
	0.0101		0
AZ_DD		-0.13173608	-0.1315413
		0.0255	0.0255
AZ		0.10437815	0.08907361
		0.0191	0.0145
race_dummy	-0.36447016	-0.35535475	-0.36241596
	0	0	0
age	0.04774355	0.04883547	0.04858552
	0	0	0
age2	-0.00042731	-0.00044212	-0.00043675
	0	0	0
sex	-0.37078874	-0.37567847	-0.37153355
	0	0	0
xxyear1	-0.17042418	-0.18936044	-0.14576511
	0	0	0
xxyear2	-0.14396392	-0.1541682	-0.1190694
	0.0002	0.0001	0.0007
xxyear3	-0.16830187	-0.19745211	-0.14414721
	0	0	0.0001
xxyear4	-0.10928957	-0.12272165	-0.08005637
	0.006	0.0027	0.026
xxyear5	-0.02081598	-0.05469994	-0.01221661
	0.5746	0.1503	0.7168
xxyear6	0.04090304	0.0183951	0.06275629
	0.2826	0.6377	0.0666
xxyear7	-0.00400241	-0.01537071	0.01066746
	0.9158	0.6932	0.7548
xxyear8	-0.01066354	-0.02119136	0.00714807
	0.78	0.5964	0.8408
xxyear9	-0.01807521	-0.03973065	(omitted)
	0.6387	0.3106	
xxyear10	(omitted)	(omitted)	0.03981643
			0.2839
xxyear11	0.06155198	0.03373643	0.0844418
	0.1164	0.4059	0.0212
xxyear12	0.07150648	0.06996971	0.09989958

	0.0702	0.085	0.0064
xxyear13	0.06436101	0.04332928	0.08569727
	0.1	0.2803	0.0183
xxyear14	0.12461883	0.09489634	0.1317637
	0.0024	0.024	0.0005
xxstate1	-0.00682946	0.04807669	
	0.8469	0.1815	
xxstate2	(omitted)	(omitted)	
xxstate3	-0.11857423	-0.0656303	
	0.001	0.0791	
xxstate4	(omitted)	0.05274947	
		0.1661	
xxstate5	-0.07810528	-0.02336709	
	0.0243	0.5115	
xxstate6	-0.03356586	0.0189638	
	0.3298	0.5994	
xxstate7	-0.03679766	0.01723669	
	0.3033	0.6409	
xxstate8	-0.023824	0.03057013	
	0.4201	0.3183	
xxstate9	-0.05548551	(omitted)	
	0.1445		
xxstate10	(omitted)	(omitted)	
_cons	9.5710749	9.5179014	9.4931271
	0	0	0

Table A7: Full Regression Results on Employment for All US Border States

Variable	**EMP_Georgia**	**EMP_Arizona**	**EMP_AZ +GA**
GA_DD	-0.01797003		-0.01838931
	0.0473		0.0424
GA	0.01481446		0.0176487
	0.0329		0.0305
AZ_DD		-0.00792159	-0.0073046
		0.5106	0.5439
AZ		-0.00078333	(omitted)
		0.927	
race_dummy	-0.05667498	-0.05696688	-0.05584338
	0	0	0
age	0.00743057	0.00691238	0.00711641
	0	0	0
age2	-0.00006135	-0.0000565	-0.00005883
	0	0	0
sex	-0.00745713	-0.00462339	-0.00643726
	0.006	0.0988	0.0147
xxyear1	0.01188284	0.01458478	0.01785224
	0.1023	0.0505	0.0128
xxyear2	0.01962876	0.02154578	0.02617003
	0.006	0.0033	0.0002
xxyear3	0.01541337	0.01983303	0.0217673
	0.0329	0.0074	0.0022
xxyear4	0.02481486	0.02853122	0.03150699
	0.0005	0.0001	0
xxyear5	0.02340999	0.02157103	0.02858521
	0.0011	0.0037	0.0001
xxyear6	0.02895643	0.03056275	0.03425082
	0	0	0
xxyear7	-0.00474146	-0.00383753	-0.00224823
	0.5388	0.631	0.7689
xxyear8	-0.01934962	-0.01824236	-0.01625219
	0.0159	0.0282	0.041
xxyear9	-0.02604504	-0.02333071	-0.02220256
	0.0019	0.0068	0.0072
xxyear10	(omitted)	0.00347568	0.00506011
		0.6691	0.5167
xxyear11	-0.00432378	(omitted)	(omitted)
	0.5872		
xxyear12	0.01238971	0.01509079	0.01691925
	0.105	0.0541	0.0252
xxyear13	0.00902106	0.00989731	0.01647662

	0.2249	0.1967	0.0239
xxyear14	0.02179993	0.02333092	0.02813777
	0.0025	0.0016	0.0001
xxstate1	0.00220372	0.00414263	0.00544555
	0.7392	0.5186	0.491
xxstate2	(omitted)	(omitted)	(omitted)
xxstate3	-0.00218918	-0.00011422	0.0004945
	0.7533	0.9868	0.9526
xxstate4	(omitted)	0.00211713	0.00260701
		0.7729	0.7639
xxstate5	-0.00120671	0.00085145	0.00165716
	0.8612	0.8999	0.8398
xxstate6	0.0043461	0.00636621	0.0068611
	0.5325	0.3562	0.4096
xxstate7	0.01256315	0.01443045	0.01534981
	0.0654	0.0316	0.0602
xxstate8	0.00415852	0.0059144	0.00713009
	0.4743	0.2937	0.3278
xxstate9	-0.00183725	(omitted)	0.00085366
	0.8021		0.9205
xxstate10	(omitted)	(omitted)	(omitted)
_cons	0.7396008	0.74691158	0.7392213
	0	0	0

Table A8: Full Regression Results on Labor Force Participation for All US Border States

Variable	LFP_Georgia	LFP_Arizona	LFP_AZ_GA
GA_DD	-0.03575819		-0.035413
	0.0005		0.0006
GA	0.06382002		0.03852832
	0		0.0001
AZ_DD		-0.01903433	-0.01785316
		0.1644	0.1918
AZ		(omitted)	(omitted)
race_dummy	-0.04881012	-0.0570223	-0.04931023
	0	0	0
age	0.02046785	0.02078642	0.02069713
	0	0	0
age2	-0.00032909	-0.00033117	-0.00033132
	0	0	0
sex	-0.12966763	-0.13239874	-0.13024393
	0	0	0
xxyear1	0.01568816	0.00715638	0.01410315
	0.0621	0.4021	0.0888
xxyear2	0.03238658	0.0261942	0.03086659
	0.0002	0.0025	0.0002
xxyear3	0.02441031	0.01303053	0.02039643
	0.0044	0.1359	0.0156
xxyear4	0.01904204	0.00555372	0.01447402
	0.0272	0.5291	0.088
xxyear5	0.02147889	0.01103347	0.01772569
	0.0132	0.2135	0.0379
xxyear6	0.02350461	0.01300998	0.02134972
	0.0073	0.1456	0.0133
xxyear7	0.02125641	0.00880232	0.01820962
	0.0151	0.326	0.0346
xxyear8	0.01032204	0.00310556	0.00789717
	0.2429	0.732	0.3639
xxyear9	0.00429776	0.00012536	0.00220246
	0.6321	0.9891	0.8022
xxyear10	0.00485343	-0.0066009	(omitted)
	0.5911	0.4774	
xxyear11	(omitted)	-0.01019982	-0.00456941
		0.2676	0.6028
xxyear12	0.00769719	(omitted)	0.00473255
	0.3878		0.5877
xxyear13	0.00218332	-0.00993164	-0.00066852

*Not meant for replication, citation, or publication (partial or full) without the consent of the author

	0.7997	0.2616	0.9369
xxyear14	-0.00545255	-0.01255844	-0.00615794
	0.5255	0.1517	0.4639
xxstate1	0.13764209	0.11100863	0.11233275
	0	0	0
xxstate2	(omitted)	(omitted)	(omitted)
xxstate3	0.01432197	-0.0098007	-0.0110879
	0.0579	0.3147	0.2547
xxstate4	(omitted)	-0.02310987	-0.02532426
		0.022	0.0119
xxstate5	0.02260907	-0.00294138	-0.00285105
	0.0037	0.7645	0.7714
xxstate6	0.03314989	0.00970012	0.00773751
	0	0.3293	0.4357
xxstate7	0.04579191	0.02090873	0.02047704
	0	0.0352	0.0391
xxstate8	0.05480989	0.02926769	0.02950856
	0	0.0009	0.0008
xxstate9	0.01143409	-0.01433036	-0.01402898
	0.171	0.1628	0.1717
xxstate10	(omitted)	(omitted)	(omitted)
_cons	0.49975427	0.52780658	0.52325171
	0	0	0

All US States as Controls

Table A9: Full Regression Results on "incwage" Using All US States as a Control Group

Variable	Wages_Georgia	Wages_Arizona	Wages_AZ_GA
GA_DD	-0.07806462		-0.07819915
	0.0787		0.0782
GA	0.04110224		0.03351331
	0.2847		0.4436
AZ_DD		-0.02366071	-0.0226799
		0.6914	0.7036
AZ		-0.07582915	-0.07426424
		0.1497	0.1581
race_dummy	-0.2135707	-0.213617	-0.21183574
	0	0	0
age	0.09899951	0.09945443	0.09917146
	0	0	0
age2	-0.00103957	-0.0010452	-0.00104177
	0	0	0
sex	-0.64427814	-0.64656873	-0.64431687
	0	0	0
xxyear1	-0.24040973	-0.19041158	-0.18832972
	0	0	0
xxyear2	-0.22703619	-0.17449185	-0.1745732
	0	0	0
xxyear3	-0.21504578	-0.16273348	-0.16194989
	0	0	0
xxyear4	-0.18956416	-0.13771932	-0.13714696
	0	0	0
xxyear5	-0.13637873	-0.0893896	-0.08673288
	0	0	0
xxyear6	-0.11403905	-0.06438466	-0.06228134
	0	0.0004	0.0005
xxyear7	-0.12353937	-0.07369128	-0.0733124
	0	0.0001	0.0001
xxyear8	-0.17592848	-0.12312823	-0.12202745
	0	0	0
xxyear9	-0.15729048	-0.10236084	-0.10540609
	0	0	0
xxyear10	-0.13684544	-0.08628265	-0.08471036
	0	0	0
xxyear11	-0.09222949	-0.03906014	-0.03948745

	0	0.0407	0.0357
xxyear12	-0.05418825	(omitted)	(omitted)
	0.0063		
xxyear13	-0.01560904	0.03368702	0.0353169
	0.4242	0.0819	0.0638
xxyear14	(omitted)	0.04928119	0.0499623
		0.0135	0.011
xxstate1	-0.26845091	-0.27753268	-0.27544248
	0	0	0
xxstate2	-0.00475252	-0.01383545	-0.0116916
	0.9001	0.7535	0.7905
xxstate3	-0.17688401	-0.18579983	-0.18373625
	0	0	0
xxstate4	-0.06702568	-0.07571823	-0.07386979
	0.1303	0.1273	0.1366
xxstate5	-0.05132726	-0.06018436	-0.0583563
	0.1932	0.1851	0.1984
xxstate6	-0.04132177	-0.05028794	-0.04852197
	0.3056	0.2743	0.2912
xxstate7	-0.03996708	-0.04885492	-0.04712769
	0.2573	0.2415	0.2581
xxstate8	0.08556067	0.07698254	0.07851527
	0.0249	0.0808	0.0747
xxstate9	-0.11117484	-0.12000683	-0.11820611
	0.0012	0.0033	0.0038
xxstate10	-0.16740551	-0.17630234	-0.17453801
	0	0	0
xxstate11	-0.097785	-0.10654794	-0.10483326
	0.0076	0.013	0.0144
xxstate12	0.00205884	-0.00671045	-0.00511246
	0.9526	0.8702	0.9008
xxstate13	-0.14683063	-0.15583316	-0.1540033
	0.0001	0.0003	0.0003
xxstate14	-0.12946953	-0.13827277	-0.13642597
	0.0006	0.0017	0.0019
xxstate15	-0.08131846	-0.09036534	-0.08831376
	0.0423	0.0491	0.0543
xxstate16	-0.14440003	-0.15330165	-0.15132645
	0.0001	0.0005	0.0006
xxstate17	-0.06181735	-0.07077369	-0.06896068
	0.102	0.1064	0.1154
xxstate18	-0.11630652	-0.12530306	-0.1232976
	0.0024	0.0048	0.0055
xxstate19	-0.17032019	-0.17921976	-0.17733241
	0	0.0001	0.0001

xxstate20	-0.17943522	-0.1882706	-0.1863188
	0	0	0.0001
xxstate21	-0.12254348	-0.13131695	-0.12960563
	0.0021	0.0039	0.0044
xxstate22	0.06105175	0.05223698	0.05375663
	0.1047	0.2298	0.2162
xxstate23	0.07318604	0.06428679	0.06572594
	0.0578	0.1449	0.1359
xxstate24	0.00824354	(omitted)	(omitted)
	0.8618		
xxstate25	-0.08228089	-0.09116561	-0.08970964
	0.0312	0.0376	0.0407
xxstate26	-0.19015461	-0.19918048	-0.19703863
	0	0	0
xxstate27	-0.14746356	-0.15615727	-0.15478407
	0.0001	0.0003	0.0003
xxstate28	-0.09645491	-0.10509202	-0.10398903
	0.0106	0.015	0.0161
xxstate29	(omitted)	(omitted)	(omitted)
xxstate30	-0.06529371	-0.07387312	-0.07243072
	0.0539	0.0672	0.0725
xxstate31	-0.17039859	-0.17925025	-0.17740533
	0	0	0
xxstate32	-0.11915843	-0.12782166	-0.12621578
	0.0014	0.0031	0.0035
xxstate33	-0.10615669	-0.11497084	-0.11362995
	0.0061	0.0094	0.0102
xxstate34	-0.06310288	-0.07162173	-0.07054032
	0.1211	0.118	0.1235
xxstate35	-0.17889945	-0.18763466	-0.18597438
	0	0	0
xxstate36	-0.04644929	-0.05511917	-0.05392756
	0.2369	0.2153	0.2252
xxstate37	-0.08633543	-0.09507558	-0.09354085
	0.0253	0.032	0.0348
xxstate38	-0.08062981	-0.08958983	-0.08773801
	0.0132	0.023	0.0258
xxstate39	-0.20677244	-0.21549507	-0.2136278
	0	0	0
xxstate40	-0.13102002	-0.14014648	-0.13799426
	0.0011	0.0024	0.0027
xxstate41	0.07549055	0.06632548	0.0685816
	0.0394	0.123	0.1104
xxstate42	-0.05470065	-0.06365535	-0.06173448

	0.1621	0.1582	0.1707
xxstate43	-0.0752241	-0.08374123	-0.08210881
	0.0688	0.0743	0.0799
xxstate44	(omitted)	(omitted)	(omitted)
xxstate45	(omitted)	-0.00902539	-0.00693442
		0.849	0.8836
xxstate46	0.11991665	0.11107495	0.11267668
	0.0008	0.0083	0.0074
xxstate47	-0.01613559	-0.02513805	-0.02320948
	0.6878	0.5843	0.6132
xxstate48	-0.14096742	-0.14993552	-0.14793308
	0.0009	0.0018	0.0021
xxstate49	0.02106395	0.01205465	0.01402853
	0.5312	0.765	0.7277
xxstate50	0.07924811	0.07005468	0.07192761
	0.0494	0.1269	0.1169
xxstate51	0.22204548	0.21350199	0.21399348
	0	0	0
_cons	8.3076622	8.2580002	8.2595737
	0	0	0

Table A10: Full Regression Results on "hhincome" Using All US States as a Control Group

Variable	HH_Georgia	HH_Arizona	HH_AZ+GA
GA_DD	-0.09463969		-0.09505827
	0.0232		0.0226
GA	0.14977068		0.15067585
	0.0003		0.0003
AZ_DD		-0.08352521	-0.08353469
		0.1443	0.1442
AZ		0.1007055	0.1008335
		0.0409	0.0405
race_dummy	-0.37216868	-0.37021492	-0.37023363
	0	0	0
age	0.05336256	0.0535903	0.0535143
	0	0	0
age2	-0.00049044	-0.00049341	-0.00049204
	0	0	0
sex	-0.33296971	-0.33343612	-0.33355806
	0	0	0
xxyear1	-0.20586994	-0.20543498	-0.2048802
	0	0	0
xxyear2	-0.1823032	-0.18055296	-0.18097027
	0	0	0
xxyear3	-0.18385507	-0.18487645	-0.18290493
	0	0	0
xxyear4	-0.14131285	-0.13966127	-0.13969937
	0	0	0
xxyear5	-0.08448656	-0.08667294	-0.08675493
	0	0	0
xxyear6	-0.07568418	-0.07667352	-0.07476834
	0	0	0
xxyear7	-0.08045598	-0.07900403	-0.0812561
	0	0	0
xxyear8	-0.12129444	-0.12033316	-0.12111579
	0	0	0
xxyear9	-0.12546178	-0.1265628	-0.12605751
	0	0	0
xxyear10	-0.09864641	-0.09520703	-0.09537563
	0	0	0
xxyear11	-0.07890939	-0.08081125	-0.0783245
	0	0	0

xxyear12	-0.04938902	-0.04622665	-0.04785897
	0.005	0.0091	0.0062
xxyear13	(omitted)	(omitted)	(omitted)
xxyear14	0.03013097	0.02760517	0.0272125
	0.1022	0.1373	0.1372
xxstate1	0.01666896	0.01796316	0.01801013
	0.6748	0.6515	0.6503
xxstate2	0.25509235	0.25644518	0.25650132
	0	0	0
xxstate3	0.10373015	0.10512601	0.10514672
	0.011	0.0101	0.01
xxstate4	0.27357643	0.27501811	0.2750352
	0	0	0
xxstate5	0.19511589	0.196305	0.19640748
	0	0	0
xxstate6	0.27958922	0.28071557	0.28079391
	0	0	0
xxstate7	0.1324163	0.1334673	0.13355368
	0.0007	0.0007	0.0006
xxstate8	0.35681838	0.35797176	0.35793067
	0	0	0
xxstate9	0.15050264	0.15180765	0.15175645
	0.0001	0	0
xxstate10	0.04828129	0.04947079	0.04947955
	0.2013	0.1908	0.1903
xxstate11	0.03679579	0.03803932	0.03810048
	0.3712	0.3556	0.3545
xxstate12	0.16007773	0.1611704	0.1612099
	0	0	0
xxstate13	0.07824865	0.07936738	0.07945642
	0.0468	0.0439	0.0435
xxstate14	0.15244075	0.15369812	0.15370381
	0.0001	0.0001	0.0001
xxstate15	0.20201595	0.20318349	0.20329434
	0	0	0
xxstate16	0.12164176	0.12302422	0.12304539
	0.0019	0.0017	0.0017
xxstate17	0.11505194	0.116173	0.1162841
	0.0036	0.0033	0.0033
xxstate18	0.08063678	0.08189861	0.08193399
	0.0449	0.0418	0.0415
xxstate19	0.06323221	0.064521	0.06457091
	0.1281	0.1208	0.1202

xxstate20	0.04880083	0.0501907	0.05013833
	0.2365	0.2238	0.2239
xxstate21	0.07000592	0.07127763	0.07127526
	0.0884	0.083	0.0828
xxstate22	0.2353149	0.23630382	0.23634309
	0	0	0
xxstate23	0.32427608	0.32508552	0.32507348
	0	0	0
xxstate24	(omitted)	(omitted)	(omitted)
xxstate25	0.17736441	0.17821414	0.17823066
	0	0	0
xxstate26	-0.02003706	-0.01859086	-0.01856343
	0.6239	0.6494	0.6496
xxstate27	0.02380322	0.02481299	0.02481423
	0.5455	0.5288	0.5286
xxstate28	0.01333961	0.01408059	0.01410655
	0.743	0.7294	0.7288
xxstate29	(omitted)	(omitted)	(omitted)
xxstate30	0.06763631	0.06877879	0.06878819
	0.0724	0.0679	0.0677
xxstate31	-0.05281884	-0.05158481	-0.05151352
	0.1938	0.2048	0.205
xxstate32	-0.0141504	-0.01296068	-0.01286369
	0.7259	0.7483	0.7499
xxstate33	-0.05450402	-0.05370651	-0.05362165
	0.1959	0.2026	0.2032
xxstate34	0.07008307	0.07086494	0.07093917
	0.101	0.0973	0.0969
xxstate35	-0.0113642	-0.01015017	-0.01007298
	0.782	0.8049	0.8063
xxstate36	0.0348627	0.03559538	0.03570111
	0.3931	0.3834	0.3818
xxstate37	0.03488175	0.03596712	0.03604095
	0.407	0.3928	0.3916
xxstate38	0.04720806	0.04839683	0.04853078
	0.2001	0.1894	0.1878
xxstate39	0.01122243	0.01273589	0.01281816
	0.7879	0.7603	0.7586
xxstate40	0.07429884	0.07555289	0.07574513
	0.0704	0.0661	0.0651
xxstate41	0.17042578	0.1717938	0.17185404
	0	0	0

xxstate42	0.15193618	0.15305621	0.15321908
	0.0003	0.0003	0.0003
xxstate43	0.00892459	0.01025532	0.01035124
	0.8387	0.8152	0.8134
xxstate44	(omitted)	(omitted)	(omitted)
xxstate45	0.26456915	0.26582679	0.26601441
	0	0	0
xxstate46	0.23274222	0.23376803	0.23387479
	0	0	0
xxstate47	0.20356518	0.20473664	0.20489357
	0	0	0
xxstate48	0.06343046	0.06470929	0.06484536
	0.1559	0.148	0.1469
xxstate49	0.19747121	0.19861158	0.19881064
	0	0	0
xxstate50	0.30336718	0.30424106	0.30438662
	0	0	0
xxstate51	0.5399607	0.5400925	0.54007288
	0	0	0
_cons	9.4544768	9.4491418	9.44947
	0	0	0

Table A11: Full Regression Results on Employment Using All US States as a Control Group

Variable	EMP_Georgia	EMP_Arizona	EMP_AZ_GA
GA_DD	-0.01678861		-0.01690301
	0.0529		0.0513
GA	-0.00152358		0.06260893
	0.8132		0
AZ_DD		-0.00629425	-0.00623204
		0.5918	0.5954
AZ		-0.01929763	0.04478647
		0.0187	0
race_dummy	-0.05691534	-0.05693021	-0.05667338
	0	0	0
age	0.00688988	0.0067878	0.00682999
	0	0	0
age2	-0.00005575	-0.0000548	-0.00005528
	0	0	0
sex	0.00097192	0.00157624	0.00107285
	0.4349	0.2083	0.3858
xxyear1	0.00519183	-0.0022704	0.00478672
	0.0925	0.4625	0.1186
xxyear2	0.00808658	0.00046153	0.00784251
	0.0088	0.8812	0.0105
xxyear3	0.00789618	0.00077868	0.00757893
	0.0108	0.8017	0.0138
xxyear4	0.01528956	0.00804028	0.01505961
	0	0.0085	0
xxyear5	0.01819111	0.01007169	0.01763713
	0	0.001	0
xxyear6	0.00747961	-0.0003038	0.00712462
	0.0177	0.9235	0.023
xxyear7	-0.03660714	-0.04467755	-0.03739701
	0	0	0
xxyear8	-0.0562586	-0.0643415	-0.05688191
	0	0	0
xxyear9	-0.04161265	-0.04913114	-0.04231063
	0	0	0
xxyear10	-0.02721002	-0.03473303	-0.02757232
	0	0	0
xxyear11	-0.0222601	-0.02950223	-0.02285978
	0	0	0
xxyear12	-0.00572638	-0.01324486	-0.00628435
	0.0936	0.0001	0.064

xxyear13	(omitted)	-0.00778233	(omitted)
		0.0217	
xxyear14	0.0077393	(omitted)	0.00754082
	0.0217		0.0239
xxstate1	-0.04803588	-0.04793223	0.01621779
	0	0	0.0739
xxstate2	-0.01736135	-0.01724425	0.0469072
	0.0038	0.004	0
xxstate3	-0.03116935	-0.0310616	0.03308732
	0	0	0.0003
xxstate4	-0.03619941	-0.03614007	0.02802237
	0	0	0.0036
xxstate5	-0.05715415	-0.05710192	0.00706413
	0	0	0.4672
xxstate6	-0.04200959	-0.04193859	0.02223097
	0	0	0.0164
xxstate7	-0.03625157	-0.03619859	0.02793449
	0	0	0.0011
xxstate8	-0.03713534	-0.03704711	0.02707169
	0	0	0.0032
xxstate9	-0.02981877	-0.02973929	0.03440319
	0	0	0
xxstate10	-0.04274547	-0.04267206	0.02144927
	0	0	0.0118
xxstate11	-0.04421099	-0.04416949	0.01996836
	0	0	0.0257
xxstate12	-0.04689515	-0.04684053	0.0172799
	0	0	0.0477
xxstate13	-0.05706321	-0.05698343	0.00712389
	0	0	0.4231
xxstate14	-0.04054365	-0.04046947	0.02366943
	0	0	0.0077
xxstate15	-0.0407535	-0.04065945	0.02348443
	0	0	0.0104
xxstate16	-0.01637932	-0.01629142	0.04787073
	0.0056	0.0058	0
xxstate17	-0.03273138	-0.03269059	0.03144335
	0	0	0.0005
xxstate18	-0.01799707	-0.01790813	0.04620105
	0.0052	0.0055	0
xxstate19	-0.01283558	-0.0127577	0.05138735
	0.033	0.034	0
xxstate20	-0.00902872	-0.00893212	0.05520919

	0.1359	0.1401	0
xxstate21	-0.01978935	-0.01975387	0.04438424
	0.0024	0.0024	0
xxstate22	-0.01583915	-0.01578762	0.04832387
	0.0133	0.0136	0
xxstate23	-0.01592006	-0.01584151	0.04825644
	0.0134	0.0139	0
xxstate24	-0.06400053	-0.06400667	(omitted)
	0	0	
xxstate25	-0.0153829	-0.01533852	0.04877183
	0.0127	0.013	0
xxstate26	-0.04803443	-0.04791969	0.01617427
	0	0	0.0796
xxstate27	-0.02583856	-0.02577777	0.0383013
	0	0	0
xxstate28	-0.02554991	-0.0254689	0.03858033
	0.0001	0.0001	0
xxstate29	(omitted)	(omitted)	(omitted)
xxstate30	-0.01709315	-0.01707026	0.04706431
	0.0021	0.0021	0
xxstate31	-0.04109243	-0.04102586	0.02311247
	0	0	0.0115
xxstate32	-0.03123133	-0.03116867	0.03292329
	0	0	0.0003
xxstate33	-0.01871387	-0.01863734	0.04538954
	0.0043	0.0045	0
xxstate34	-0.016559	-0.01648065	0.04751902
	0.0179	0.0185	0
xxstate35	-0.0175241	-0.01744465	0.04662385
	0.0065	0.0067	0
xxstate36	-0.0123619	-0.01229913	0.05170192
	0.0594	0.0607	0
xxstate37	-0.00350991	-0.00346531	0.06061546
	0.581	0.5858	0
xxstate38	-0.01128477	-0.01124963	0.05288086
	0.0302	0.0307	0
xxstate39	-0.02364653	-0.02359246	0.04051185
	0.0005	0.0006	0
xxstate40	-0.02913671	-0.02907838	0.03503785
	0	0	0.0002
xxstate41	-0.01475011	-0.01465546	0.0494568
	0.0162	0.0169	0

xxstate42	-0.0216443	-0.02160249	0.04254182
	0.0007	0.0007	0.000
xxstate43	-0.01888324	-0.01884961	0.04524114
	0.006	0.0061	0
xxstate44	(omitted)	(omitted)	(omitted)
xxstate45	(omitted)	(omitted)	0.06413985
			0
xxstate46	-0.03651029	-0.03650777	0.02762045
	0	0	0.0033
xxstate47	-0.04080852	-0.04076772	0.02335048
	0	0	0.0138
xxstate48	-0.06154729	-0.06146593	0.00265771
	0	0	0.7911
xxstate49	-0.04812848	-0.04809283	0.01601307
	0	0	0.0582
xxstate50	-0.05311709	-0.05302156	0.0110185
	0	0	0.263
xxstate51	0.03433508	0.03441686	0.09839066
	0	0	0
_cons	0.780158	0.78994024	0.71794733
	0	0	0

Table A12: Full Regression Results on Labor Force Participation Using All US States as a Control Group

Variable	**LFP_Georgia**	**LFP_Arizona**	**LFP_AZ + GA**
GA_DD	-0.03649513		-0.03649501
	0.0002		0.0002
GA	-0.02773067		-0.02767785
	0.0005		0.0006
AZ_DD		-0.0215683	-0.02136466
		0.1057	0.109
AZ		-0.06711387	-0.06743325
		0	0
race_dummy	-0.06254579	-0.06476884	-0.06253095
	0	0	0
age	0.02187501	0.02194865	0.02190093
	0	0	0
age2	-0.0003425	-0.00034303	-0.00034275
	0	0	0
sex	-0.1124257	-0.11273826	-0.11274545
	0	0	0
xxyear1	0.01270229	0.01223063	0.01244859
	0.0005	0.0009	0.0006
xxyear2	0.01804851	0.01789502	0.01791227
	0	0	0
xxyear3	0.01263379	0.01152962	0.01199523
	0.0007	0.0022	0.0013
xxyear4	0.01553534	0.01414999	0.01470001
	0	0.0002	0.0001
xxyear5	0.01845998	0.01762915	0.0177917
	0	0	0
xxyear6	0.01682985	0.0159197	0.01650696
	0	0	0
xxyear7	0.01882351	0.01760964	0.01827748
	0	0	0
xxyear8	0.01403703	0.01386423	0.01355978
	0.0003	0.0003	0.0004
xxyear9	0.00711393	0.00745497	0.0067448
	0.069	0.0576	0.0827
xxyear10	0.00348388	0.0025212	0.00264985
	0.3782	0.5259	0.4999
xxyear11	0.00062787	-0.00009674	-0.00019424
	0.8745	0.9807	0.9608

*Not meant for replication, citation, or publication (partial or full) without the consent of the author

xxyear12	-0.00118491	-0.00162668	-0.00159801
	0.7669	0.6856	0.6873
xxyear13	-0.00672459	-0.0080718	-0.00710866
	0.0931	0.0452	0.074
xxyear14	(omitted)	(omitted)	(omitted)
xxstate1	-0.06199319	-0.06205647	-0.06195306
	0	0	0
xxstate2	0.00334627	0.00326565	0.00339452
	0.6598	0.6675	0.6552
xxstate3	-0.00931894	-0.00940044	-0.00929111
	0.2385	0.2344	0.2399
xxstate4	-0.05074909	-0.05071057	-0.05071474
	0	0	0
xxstate5	-0.03829427	-0.03824438	-0.03823697
	0	0	0
xxstate6	-0.01413024	-0.01391458	-0.0140625
	0.0704	0.0748	0.0717
xxstate7	-0.06998344	-0.06958057	-0.06993967
	0	0	0
xxstate8	-0.00324016	-0.00290164	-0.00320973
	0.6755	0.7077	0.6783
xxstate9	-0.03663019	-0.03644359	-0.03659017
	0	0	0
xxstate10	-0.03323711	-0.03297189	-0.03320396
	0	0	0
xxstate11	-0.03659327	-0.03639211	-0.0365666
	0	0	0
xxstate12	-0.01122659	-0.01079271	-0.01119213
	0.1075	0.1218	0.1086
xxstate13	-0.05690117	-0.0565494	-0.05687852
	0	0	0
xxstate14	0.01694417	0.01705702	0.01698065
	0.0189	0.0181	0.0186
xxstate15	0.01215279	0.01220376	0.01220726
	0.1032	0.1018	0.1017
xxstate16	0.02416279	0.0241526	0.02421036
	0.001	0.001	0.001
xxstate17	-0.04092365	-0.0406428	-0.04087247
	0	0	0
xxstate18	0.03147574	0.03159363	0.03148491
	0.0001	0.0001	0.0001
xxstate19	0.04408048	0.04418766	0.04411435
	0	0	0

xxstate20	0.04381466	0.04383178	0.0438404
	0	0	0
xxstate21	0.00552917	0.00575745	0.00556413
	0.4901	0.4724	0.4874
xxstate22	-0.01753244	-0.0169889	-0.01748222
	0.0246	0.0294	0.025
xxstate23	0.00170039	0.00245492	0.00176659
	0.8239	0.748	0.8171
xxstate24	-0.05067094	-0.04869185	-0.05059857
	0	0	0
xxstate25	-0.01830732	-0.01765236	-0.01824798
	0.0154	0.0195	0.0157
xxstate26	-0.15564513	-0.15571972	-0.15565887
	0	0	0
xxstate27	-0.04342653	-0.04274966	-0.04339698
	0	0	0
xxstate28	-0.04214523	-0.04127831	-0.04210859
	0	0	0
xxstate29	(omitted)	(omitted)	(omitted)
xxstate30	-0.03478869	-0.03437187	-0.03474406
	0	0	0
xxstate31	-0.10831359	-0.10821853	-0.10827574
	0	0	0
xxstate32	-0.07838569	-0.07804333	-0.07835897
	0	0	0
xxstate33	-0.07705983	-0.07629545	-0.0770632
	0	0	0
xxstate34	-0.09052801	-0.08950298	-0.09052382
	0	0	0
xxstate35	-0.07069709	-0.07031702	-0.07069686
	0	0	0
xxstate36	-0.05784415	-0.0569171	-0.05785564
	0	0	0
xxstate37	-0.0469651	-0.04642285	-0.04693793
	0	0	0
xxstate38	-0.03978284	-0.03944321	-0.03973527
	0	0	0
xxstate39	-0.03969351	-0.03957193	-0.03969665
	0	0	0
xxstate40	(omitted)	(omitted)	(omitted)
xxstate41	0.01273656	0.01272365	0.01274442
	0.0997	0.1	0.0994

xxstate42	-0.01070046	-0.01055042	-0.01065387
	0.1696	0.1757	0.1714
xxstate43	-0.08238695	-0.08208031	-0.08238661
	0	0	0
xxstate44	(omitted)	(omitted)	(omitted)
xxstate45	-0.01511061	-0.01503581	-0.01508351
	0.086	0.0875	0.0865
xxstate46	-0.01865406	-0.01826209	-0.018624
	0.02	0.0228	0.0202
xxstate47	-0.02962302	-0.02944255	-0.02960414
	0.0002	0.0003	0.0002
xxstate48	-0.053285	-0.0532179	-0.05326725
	0	0	0
xxstate49	-0.0660889	-0.06570343	-0.06603368
	0	0	0
xxstate50	-0.02648121	-0.02584333	-0.02648589
	0.0018	0.0023	0.0018
xxstate51	0.01613744	0.01775849	0.01618897
	0.0546	0.0345	0.0538
_cons	0.55916422	0.55790674	0.55918518
	0	0	0

Below are the figures mentioned in the methodology section depicting the breakdown of variables used to restrict the respondents to the low-skilled industry.

Education: The cut off for education was 12 years or less, given the groups listed below.

Table A13: Education Coding from IPUMS

Code	**Label**
0	NIU or no schooling
1	NIU or blank
2	None, preschool, or kindergarten
10	Grades 1, 2, 3, or 4
11	Grade 1
12	Grade 2
13	Grade 3
14	Grade 4
20	Grades 5 or 6
21	Grade 5
22	Grade 6
30	Grades 7 or 8
31	Grade 7
32	Grade 8
40	Grade 9
50	Grade 10
60	Grade 11
70	Grade 12
71	12th grade, no diploma
72	12th grade, diploma unclear
73	High school diploma or equivalent
80	1 year of college
81	Some college but no degree
90	2 years of college
91	Associate's degree, occupational/vocational program
92	Associate's degree, academic program
100	3 years of college
110	4 years of college
111	Bachelor's degree
120	5+ years of college
121	5 years of college
122	6+ years of college
123	Master's degree

124	Professional school degree
125	Doctorate degree

Industry: These are the industries determined to be part of the low-skilled workforce. They are coded with respect to the IPUMS coding, so the industry coding is linked here (https://cps.ipums.org/cps-action/variables/IND#codes_section)

ind==0280|ind==0370|ind==0380|ind==0390|ind==0470|ind==0490|ind==0770|ind==6070|ind==6080|ind==6090|ind==6170|ind==6180|ind==6190|ind==6270|ind==6280|ind==6290|ind==6380|ind==6390|ind==7680|ind==7690|ind==7770|ind==7780|ind==7790|ind==8470|ind==8580|ind==8590|ind==8660|ind==8670|ind==8680|ind==8690|ind==8770|ind==8780|ind==8880|ind==8970|ind==8980|ind==8990|ind==9070|ind==9090|ind==1190|ind==1270|ind==4070|ind==4080|ind==4090|ind==4170|ind==4180|ind==4195|ind==4265|ind==4270|ind==4280|ind==4290|ind==4370|ind==4380|ind==4390|ind==4470|ind==4480|ind==4490|ind==4560|ind==4570|ind==4580|ind==4670|ind==4680|ind==4690|ind==4770|ind==4780|ind==4795|ind==4870|ind==4880|ind==4890|ind==4970|ind==4980|ind==4990|ind==5070|ind==5080|ind==5090|ind==5170|ind==5180|ind==5190|ind==5275|ind==5280|ind==5295|ind==5370|ind==5380|ind==5390|ind==5470|ind==5480|ind==5490|ind==5570|ind==5580|ind==5590|ind==5591|ind==5592|ind==5670|ind==5680|ind==5690|ind==5790|ind==7970|ind==7980|ind==7990|ind==8070

Occupation: These are the occupations determined to be part of the low-skilled workforce. The, too, are coded with respect to the IPUMS coding system, so the occupational coding is linked here. (https://cps.ipums.org/cps-action/variables/OCC#codes_section)

occ==3840|occ==3860|occ==3930|occ==3940|occ>=4020&occ<=4460|occ>=4500&occ<=4760|occ==4830|occ==4840|occ==4850|occ>=4940&occ<=5110|occ==5160|occ==5300|occ>=5500&occ<=5900|occ==5940|occ>=6040&occ<=6110|occ>=6220&occ<=6520|occ==6700|occ==6710|occ>=6730&occ<=6810|occ>=6930&occ<=7855|occ>=7920&occ<=8550|occ>=8760&occ<=8830|occ>=8850&occ<=8965|occ>=9120&occ<=9150|occ==9260|occ>=9350&occ<=9750