Political Posturing vs. Reality on the Ground: E-Verify and the Employment of Undocumented Immigrants

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Abstract

Illegal immigration has been a central issue in American politics. On January 10, 2024, during a U.S. presidential debate, former South Carolina Governor Nikki Haley emphasized her stance against illegal immigration by passing "the toughest immigration law in the country" and cited her early enforcement of E-Verify to ensure the legal status of workers. In contrast, she criticized Florida Governor Ron DeSantis for only recently adopting E-Verify, suggesting it was a political maneuver for his presidential run. In this paper, we explore the impact of these state mandates enforcing E-Verify on undocumented immigrant employment and find that these restrictive immigration policies often fail to achieve their stated objectives. Our research shows that E-Verify mandates are effective in reducing undocumented employment only in Arizona and Alabama, while failing in all other states. In these states, selective enforcement and exemptions that are designed to spare key industries effectively reduce these seemingly restrictive immigration policies, particularly those passed during election cycles, to political posturing aimed at gaining electoral favor, rather than delivering meaningful immigration reform as promised.

Keywords: political posturing, immigration reform, undocumented immigrants, E-Verify, labor market

JEL codes: J15, J18, J43, J48

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1 Introduction

Immigration reform has consistently been at the forefront of political discourse in the United States. Key historical actions, such as the 1950s military operation aimed at forcefully deporting undocumented immigrants, the Immigration and Nationality Act of the 1960s, which established a preference system for skilled immigrants, and the 1986 Immigration Reform and Control Act (IRCA), which made it illegal to hire undocumented immigrants, have significantly shaped the country's immigration policy. The post-9/11 era marked a further intensification of border security and surveillance, leading to the creation of the Department of Homeland Security in 2002, which further restricts illegal immigration. More recently, during Donald Trump's presidency, the debate on illegal immigration was again brought to the center of public attention, characterized by proposals for border walls and stringent actions against sanctuary cities. The conflicts at the border and overcrowded detention centers under Biden's administration have further deepened divisions between political isles over immigration. These evolving policies, especially acute in border states (González-Carriedo 2016), have fueled a contentious national debate.

A prevailing argument surrounding immigration reform is the protection of domestic jobs. Established as a mechanism to deter employers from hiring undocumented workers, E-Verify serves as a pivotal tool for validating the work authorization status of employees and controlling unauthorized employment in the United States. E-Verify is an internet-based system that allows employers to instantly verify the employment eligibility of newly hired workers. The utilization of E-Verify witnessed a substantial increase post-2009, particularly after the imposition of a mandate for its usage by federal contractors (E-Verify 2024). This directive marked a pivotal shift, reflected in the increase in participating employers from approximately 227,000 in the 2000s to over 1.2 million by 2023 (E-Verify 2024). While it remains mostly voluntary for private employers to

participate, there has been a legislative shift in some regions; specifically, nine states have enacted mandates that require both public and private sector employers to verify the legal status of their workforce.

This policy shift aligns with broader patterns observed in the formation of restrictive immigration policies, which are often driven by political ideologies, public opinions, and economic welfare considerations, among others (Milner and Tingley 2011; Gilligan 2015; Miller 2016). Republican parties, in particular, have historically prioritized illegal immigration in their political agenda, especially with conservatives being more likely to pass legislation enhancing strict immigration enforcement (Tichenor 2009; Fennelly, Pearson, and Hackett 2015). However, the reality on the ground is that these immigration reforms are often moderated by electoral or economic concerns (Natter, Czaika, and de Haas 2020; Commins and Wills 2017; Tichenor 2009), which potentially results in ineffective policies.

Past literatures have highlighted the role of political posturing in shaping policy outcomes, and suggest legislators often advocate for immigration policies that offer electoral benefits (Ward and Gabel, 2019). Fox and Stephenson (2011) further argue that political posturing driven by electoral considerations results in bold and irresponsible policies, which could weaken the quality and effectiveness of the immigration reforms. A policy like the E-Verify mandate is a prime example of how ideology is challenged by economic and political realities, resulting in state-level reforms that achieve little and serve primarily as political posturing to gain electoral support from conservative voters.

To illustrate, this study first examines the effects of E-Verify on undocumented employment using a synthetic control approach, and then discuss the differences in policy design to explore the reasons behind the ineffectiveness of reforms in some states. We find significant reductions of

undocumented employment in Arizona and Alabama, where severe penalties and broad enforcement are in place. In contrast, other E-Verify mandating states introduce exemptions or adopt phased implementation approaches, intentionally sparing key sectors that heavily rely on undocumented labor, leaving the policies with little to no impact on labor market. We argue that these immigration policies, often moderated to minimize economic impact, serve as a prime example of how legislations spurred by political ideology are diluted by economic concerns and donor interests. And for policies passed during election cycles, they function more as posturing to gain electoral support rather than offering meaningful solutions to the issue.

This study advances the political economy literature by addressing the issue of undocumented immigrants, one of the major challenges at the heart of American politics, and demonstrating how it has been approached in the political battlegrounds and how policy outcomes are altered by political agendas and economic realities. By examining the impacts, policy design, and political intent, we unwrap the complex landscape of immigration reform. The article is organized as follows: The next section provides an overview of undocumented immigration, partisan views on immigration reform, and the background and examination of the E-Verify program. This is followed by a description of the data and methodology, including key descriptive statistics. The subsequent sections present the main findings and robustness checks. Finally, the paper concludes with our discussions.

2 Background

The 1965 Immigration and Nationality Act shifted U.S. immigration policy by prioritizing educated, skilled labor and setting country-specific limits on the number of legal immigrants (Keyes, 2013). These changes led to an increase in undocumented migration, particularly from Mexico. In

the U.S., demand for low-skilled labor comes from labor-intensive sectors like agriculture, construction, and hospitality, which are low-wage industries that benefit from an increasing supply of low-skilled immigrant labor (Commins and Wills 2017) The growing dependence on undocumented workers has complicated efforts to implement immigration reform, deepening partisan divisions on the issue.

2.1 Undocumented Immigrants and Workforce

The 2024 Pew Research estimates indicated that the undocumented immigrant population had reached 11 million in 2022, marking the first sustained increase since a long term decline between 2007 and 2019 (Passel and Krogstad 2024). According to the report, the demographic composition of undocumented immigrants has seen significant changes. In 2007, nearly 57% of the undocumented population was of Mexican origin, but by 2022, this proportion had decreased to 37%. Meanwhile, the share of immigrants from regions such as Central America and Asia has steadily increased over the past decades. Geographically, undocumented immigrants are primarily concentrated in California, Texas, Florida, and New York (Moslimani and Passel 2024).

In 2022, around 8.3 million undocumented immigrants made up about 5% of the U.S. work force, a slight decline from the peak of 5.4% in 2007 (Moslimani and Passel 2024). The report highlights a large portion of these workers are low-skilled and have lower levels of education compared to native workers, with many employed in labor-intensive sectors like agriculture (17%), construction (13%), and hospitality (9%).

Labor shortages are a key driver of demand for undocumented workers in agriculture (Richards 2018; Huang, Guan, and Hammami 2022), construction (Han et al. 2008; Karimi et al. 2018), and hospitality (Choi, Woods, and Murrmann 2000). Due to their labor-intensive and physically

demanding nature, seasonal demands, among other factors, these sectors have struggled to find sufficient native-born workers, leading employers to increasingly rely on undocumented workers to fill the gaps.

2.2 Partisan Views on Immigration Reform

Undocumented immigration has been a polarized issue between democrats and conservatives in the U.S. (Tichenor 2009; Fennelly, Pearson, and Hackett 2015). Political ideology and interest make partisan views divided. For democrats, the issue of reform is focused on the social welfare of undocumented immigrants, and often more open to the pathway to citizenships (Tichenor 2009). As for conservatives, many tend to favor stricter enforcement, protectionism and increasing boarder security, and associate undocumented immigration with job replacement, criminality, and an overburdened welfare system (Tichenor 2009). What both parties can agree on is the country's economic reliance on undocumented workers.

During the mid-2000s, economic anxieties from the Great Recession, coupled with the looming 2008 presidential election, fueled heated discussions around undocumented workers and job competition. At the national level, the 2007 Comprehensive Immigration Reform Act, supported by President George W. Bush, collapsed in the U.S. Senate, and comprehensive reforms have not occurred to date. The political gridlock prevented such reforms at the federal level, prompting states to implement their own enforcement policies, including employment protection acts such as E-Verify mandates (Shannon 2010; Gray and Shimshack 2011; Newton 2012).

2.3 State E-Verify Mandates

The E-Verify program was first introduced under the 1996 Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) (U.S. Government Publishing Office 1996). It provided a

voluntary mechanism for employers to validate the work authorization status of their employees. In 2007, this initiative was rebranded as E-Verify, and it underwent significant enhancements in the following years, including the adoption of photo matching and facial recognition technologies to enhance the accuracy of verifications (E-Verify 2022). It has evolved into a critical component of U.S. government immigration control policies.

Despite its national scope, the implementation and impact of E-Verify have been anything but uniform. State-level decisions to mandate or resist E-Verify are deeply intertwined with political ideologies and agendas. Figure 1 shows the timeline of states passing such mandates, with most of these mandates being passed between 2007 and 2011, in the southern United States with republican controls.



Figure 1. Timeline of States Passing E-Verify Mandates

Arizona's Legal Arizona Workers Act is the first state-level mandate to restrict undocumented employment. Historically tough on immigration, Arizona followed the 'Legal Arizona Workers Act' with the passage of the 'Show Me Your Papers' law in 2010, further tightening its immigration enforcement. Following Arizona's initiative, other states have soon followed suit in enacting their own version to restrict undocumented employment. Mississippi enacted the ‘Mississippi Employment Protection Act’ in 2008. During the 2010 midterm election and before the 2012 presidential election, several states including Utah, Alabama, Georgia, North Carolina, South Carolina, and Tennessee joined the wave of state legislation on immigration. The timing and clustering of these laws suggest a regional response to the ongoing debates over immigration policy (Gray and Shimshack 2011), which intensify during election cycles.

In 2023, amidst the early stages of the 2024 presidential election cycle and shortly before Governor Ron DeSantis entered the race, Florida passed Senate Bill 1718 on immigration, mandating E-Verify and a series of measures widely seen as harsh and controversial (Olazagasti 2024). This move suggests a strategic anticipation of immigration emerging as a central issue in the forthcoming election. The pattern of legislation timing, closely paralleling national election cycles, suggests that these states may be positioning themselves to demonstrate a commitment to stricter immigration policies. This timing highlights the interplay between political maneuvering and policy enactment, as policymakers often face stronger incentives to influence public perception and election outcomes closer to election periods (Martinez 2009).

2.3.1 Policy Scope and Exemptions

While these mandates are presumably designed to prevent the employment of undocumented immigrants, certain employers or types of employees may be exempt, limiting the policy's impact on undocumented employment. As outlined in Table 1, the scope of these practices varies, as states

may define 'employer' and 'employee' differently, thus altering who must comply and whose work authorization status needs to be verified.

Table 1. Comparison of E-Verify Mandates: Policy Scope and Exemption

State	Bill	Policy Scope	Exemptions	Phased Timeline
Alabama	HB 56	All employers are required to verify the employment authorization of all employees and continued employment of unauthorized aliens is prohibited.	None specified	None specified
Arizona	Legal Arizona Workers Act (HB 2779)	All employers are required to verify the employment authorization of all *new* employees.	None specified	None specified
Mississippi	Employment Protection Act (SB 2988)	All businesses or persons issuing a W-2 or 1099 form to an employed person must verify the employment authorization of all *new* employees.	None specified	- July 1, 2008: Public entities, contractors, 250+ employees - July 1, 2009: 100–249 employees - July 1, 2010: 30–99 employees - July 1, 2011: All employers
South Carolina	Illegal Immigration Reform Act (SB 20)	All employers required to verify the employment authorization of all *new* employees.	None specified	None specified
Georgia	Illegal Immigration Reform and Enforcement Act (HB 87)	Private employers with *more than 10* employees must verify the employment authorization of all *new* employees who works ≥35 hours/week.	Employers with 10 or fewer employees exempted.	- Jan. 1, 2012: 500+ employees - July 1, 2012: 100–499 employees - July 1, 2013: 10–99 employees
Utah	Private Employer Verification Act (SB 251)	All private employers required to verify the employment authorization of *new employee*s.	Employers with 15 or fewer employees exempted.	None specified
North Carolina	Protect North Carolina Workers Act (HB 36)	Employers with *25 or more* employees required to use E-Verify for all *new employee*s.	Employers with 25 or fewer employees and employees hired for less than nine months exempted.	- Oct. 1, 2012: 500+ employees - Jan. 1, 2013: 100–499 employees - July 1, 2013: 25+ employees
Tennessee	Tennessee Lawful Employment Act (HB 1378)	Employers with *six or more* employees must verify the employment authorization of all *new employee*s.	Employers with six or fewer employees exempted.	None specified

References: Alabama HB658 2012; Arizona HB2745 2008; Georgia HB87 2011; Florida SB1718 2023; Tennessee SB1378 2011; North Carolina HB36 2011; South Carolina SB20 2012; Utah HB0116 2011; Mississippi SB2988 2008

Within these mandates, there are also notable exemptions for smaller employers in four states: Tennessee exempts those with 6 or fewer employees; Georgia, with 10 or fewer; Utah, with 15 or fewer; North Carolina, with 25 or fewer. Besides the number of employees, North Carolina also exempts the verification of employees whose term of employment is less than nine months, effectively excluding temporary and seasonal workers, such as those in agriculture, a major industry of unauthorized employment. Similar to North Carolina, Florida specifies that the law only applies to 'permanent employees'. However, since this term is not defined within the law, it could be interpreted as exempting temporary and seasonal workers or even more broadly (Florida SB1718 2023).

Stringent E-Verify mandates could critically deplete labor force in key sectors, and thus disrupt the state's economy. Due to these considerations, certain high-impact sectors like agriculture are often intentionally excluded from E-Verify mandates. These sectors rely heavily on undocumented workers, contributing significantly to state GDP but frequently consisting of large proportions of small operations that fall below exemption thresholds. In agriculture, for example, small family farms make up nearly 90% of all U.S. farms, with over half utilizing less than the equivalent of one full-time worker, and fewer than 12% employing more than five full-time equivalents (Hoppe 2017). States like North Carolina exemplify this approach, with specific exemptions for seasonal workers that align with the state's agricultural production cycles. Similarly, Florida's mandate applies only to permanent employees, leaving seasonal or temporary agricultural workers unregulated by E-Verify requirements.

Lawmakers may also exempt certain employers to gain the necessary support from industries to pass the legislation. Notably, sectors such as agriculture, which possess formidable lobbying power, may advocate for exemptions. In addition, small businesses often face administrative and

financial challenges in complying with regulatory mandates. E-Verify mandates demand more than a one-time setup and require ongoing effort in verifying compliance, which can be especially burdensome for small businesses and the enforcement bodies. Lawmakers, recognizing the potential impact of these burdens, may exempt smaller employers to alleviate these challenges. These concerns prevent states from enacting stringent laws, resulting in less impactful immigration reform.

Of the eight states included in the analysis, three states implemented E-Verify mandates with a phased approach: Mississippi, Georgia, and North Carolina (Table 1). These phased approaches suggest that these states aimed to mitigate immediate economic shocks and provide employers with more time to adjust to the new regulations. However, this gradual rollout may also have reduced the law's overall effectiveness, as delayed implementation could allow employers to continue relying on undocumented labor in the interim, potentially weakening enforcement and the intended reduction in unauthorized employment.

2.3.2 TIMELINE

Arizona's Legal Workers Act, passed in 2007, was the first state-level mandate to restrict undocumented employment. That same year, the 2007 Comprehensive Immigration Reform Act failed in the U.S. Senate, prompting states like Arizona to address the national issue at the state level. Arizona's early action marked a landmark shift, and the first shot fired by the state stunned the communities of undocumented immigrants and their families in Arizona as well as the general public nationally. Three years later, Arizona's "Show Me Your Papers" law was then signed in 2010. It was initially set to take effect 60 days after its passing, but key provisions faced legal challenges. The U.S. Supreme Court upheld the requirement for police to check immigration status

during lawful stops in June 2012, it struck down provisions that criminalized undocumented immigrants seeking employment.

Following Arizona, other states quickly emulated its approach, taking immigration policies into their own hands. During this period of rapid growth in undocumented immigration from Mexico, Arizona—as the only border state in our analysis—served as a primary entry point. By making the first move, Arizona curbed the accelerating settlement of undocumented workers within its borders and has since shown the most significant reduction in undocumented employment following the adoption of E-Verify.

Before the 2012 presidential election, several states, including Utah, Alabama, Georgia, North Carolina, South Carolina, and Tennessee, had all enacted state immigration legislation, challenging the federal government's control over immigration policy (Gray and Shimshack 2011). Although these states are not on the U.S.-Mexico border, they had become secondary hubs for undocumented immigrants, experiencing significant growth in immigrant population during the 2000s. This shift was partly driven by stricter immigration enforcement in traditional gateway states like Arizona and the increased demand for low-cost labor in southern industries such as agriculture, construction, and food services (Shannon 2010; Newton 2012). Consequently, public support for more restrictive immigration policies grew, intensifying public debate on immigration reform leading into the 2012 election cycle.

2.3.3 Varying Degree of Penalties

Penalties for E-Verify non-compliance vary significantly across states, reflecting a broad spectrum of enforcement measures. While fines are a common penalty and typically increase with repeat offenses, the suspension or revocation of business licenses is another prevalent consequence. However, this approach may have limited impact on many agricultural businesses, as more than 85%

of U.S. farms operate as sole proprietorships and do not register business licenses with the state (USDA-NASS, n.d.). This is a critical distinction because these legislative penalties for E-Verify non-compliance, such as license suspension or revocation, are often not applicable to unregistered farms, reducing the policy's reach in sectors such as agriculture where undocumented labor is prevalent.

Arizona and Alabama stand out in their severity of penalties. Arizona imposes some of the strictest measures, including potential felony charges for non-compliance and fines ranging from $2,500 to $150,000, depending on the violation's severity. By comparison, Tennessee imposes fines ranging from $500 to $2,500 per violation, not exceeding $10,000 in total. Other states, however, do not specify the amount of fines in their legislation. Alabama also enforces substantial penalties; upon conviction, "the entity or employer is liable for a penalty equal to 10 times the business expense deduction claimed..." These harsher penalties signal a stronger commitment to enforcement.

3 Data

The data utilized in this study are micro-level data sourced from the American Community Survey (ACS-IPUMS), encompassing eighteen years from 2002 to 2019. The ACS, conducted annually by the U.S. Census Bureau, provides a rich repository of detailed demographic, social, economic, and housing information. This extensive dataset facilitates our in-depth analysis of individual-level attributes, which is crucial for identifying likely undocumented immigrants. Data from the COVID-19 years starting 2020 were excluded due to significant participation drops and experimental adjustments made by the ACS during this period. Our analysis includes data from all 50 states and the District of Columbia.

Demographic and employment details such as race, age, gender, citizenship, educational attainment, employment status, weekly hours worked, and yearly wage income are compiled for each individual from the IPUMS dataset. Hourly wage rates are calculated by dividing annual income by total hours worked in the year, then adjusted for inflation using the Consumer Price Index (CPI). These individual-level data are then aggregated at the state level. Additionally, annual state-level GDP per capita data were sourced from the Bureau of Economic Analysis (BEA), and unemployment rates from the Bureau of Labor Statistics (BLS).

3.1 Likely Undocumented Immigrant Identification

Given the clandestine nature of undocumented immigration, direct measures to accurately identify this population are challenging. Consequently, researchers often rely on indirect methodologies and assumptions based on observable characteristics. To identify the undocumented population, Warren and Passel (1987) developed the "residual" methodology, which the DHS uses to estimate the undocumented population. They calculated the expected number of legal immigrants in the U.S. by tracking green cards issued, applying mortality tables, and accounting for temporary foreign-born residents. Passel later extended this method to identify undocumented immigrants at the individual level in survey data, distinguishing legal from undocumented immigrants using various demographic traits. Borjas (2017) adapted this methodology to classify individuals as legal or undocumented without using probabilistic sampling. One such method, detailed in Borjas (2017), involves the use of exclusion criteria to infer the likelihood of an individual being undocumented. This paper adopts Borjas (2017)'s approach in deducing the undocumented status for its direct application of the residual approach to survey microdata and its ability to provide clear classifications. The criteria are listed in the Appendix.

Borjas (2017) applied this method to the Current Population Surveys and estimated that approximately 5% of the population are likely undocumented immigrants (LUI). This paper adapts the method to identify LUI population in the ACS dataset between 2002 to 2019. Our findings align with this estimate. Figure 2 presents the percentage of likely undocumented immigrants (LUI) and legal immigrants in the dataset from 2002 to 2019. It shows the share of undocumented immigrants fluctuated between 4% and 6%, peaking in the early 2000s, particularly in 2004, before experiencing a steady decline starting in 2010. In contrast, there has been a steady increase in the share of legal immigrants, rising from just above 7% in 2002 to nearly 11% by 2019. These trends are consistent with national patterns reported by the Pew Research Center in 2019.

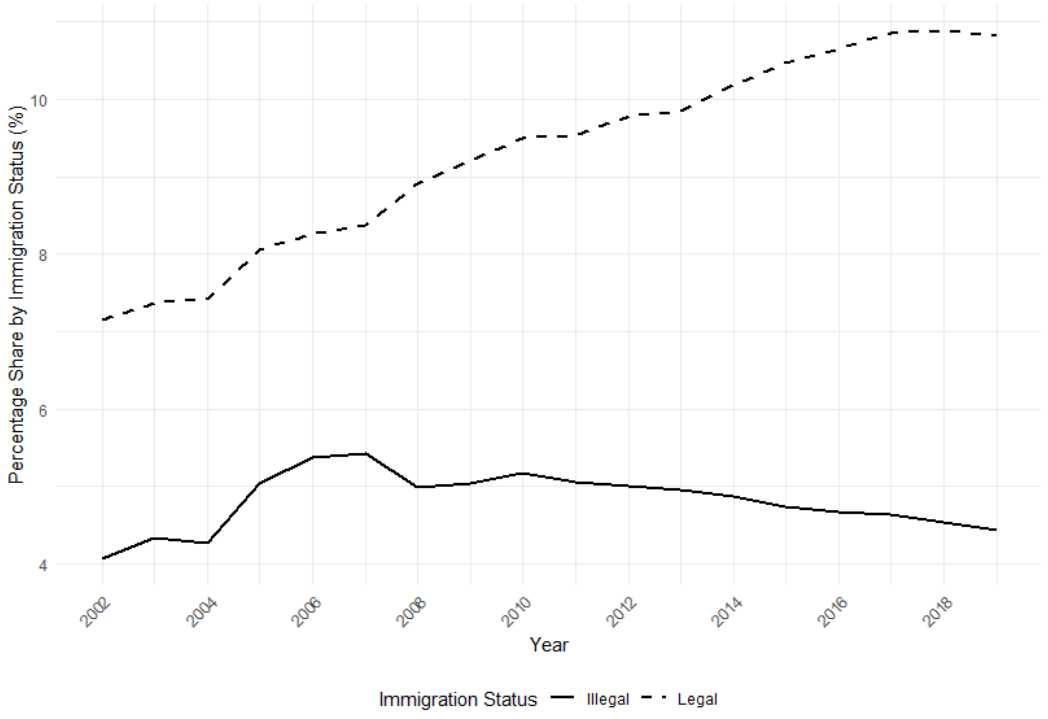


Figure 2. Percentage of Likely Undocumented and Legal Immigrants, 2002-19.

3.2 Descriptive Evidence

Table 1 provides summary statistics for the variables of interest and the control variables for undocumented, legal, and natives for the eight E-Verify mandating states, as well as the average

across the states without E-Verify mandates that includes 42 states and Washington DC. Even though we are only interested in the undocumented population, it's important to compare the three groups and validate the identification method before empirical analysis.

The variable of interest is the total number of employed LUI at the state level in logarithmic form. As E-Verify is designed to check unauthorized employment status, the direct impact of mandating this verification system is presumably to restrict undocumented employment. For predictors, we included demographic variables, as well as economic and development indicators for each state. These include race, age, sex, educational attainment, and total number of immigrants, along with economic indicators such as GDP per capita and the unemployment rate. Experience is estimated by subtracting the number of years of highest completed education from age, following the approach proposed by Ottaviano and Peri (2012).

The descriptive evidence presented in Table 2 aligns with national estimates of population dynamics. The table first highlights the wage disparities among LUI, legal immigrants, and native workers. It shows that undocumented immigrants earn the lowest average hourly wages—approximately 25% less than native workers and 29% less than legal immigrant workers, who earn the highest. This aligns with previous research, which finds that undocumented workers generally earn lower wages compared to both legal immigrants and native workers (Borjas and Tienda 1993; Borjas 2017). This wage gap is largely attributed to socioeconomic factors, particularly differences in education (Borjas 2017). Regarding age, the average for working-age LUI is the lowest, followed by natives, and then legal immigrants. The majority of undocumented workers are male and Hispanic, reflecting the national demographic profile of this group. Education levels also differ significantly. Undocumented immigrants typically have the lowest educational attainment compared to legal immigrants and natives. In terms of work experience, legal immigrants possess the

highest average, followed by natives, while undocumented immigrants have the least. Table 2 also contrasts the employment figures between states that mandate E-Verify and those that do not. In mandating states, the average total employment figures for both undocumented and legal workers are generally lower than those in non-mandating states, although other patterns remain consistent across both groups.

Table 2. Summary Statistics of Dependent and Control Variables for Likely Undocumented Immigrants, Legal Immigrants and Natives, 2002-19.

	E-Verify Mandating States			Donor Group		
	LUI	Legal	Native	LUI	Legal	Native
Outcome variable (before transformation)						
Avg total employment	15,003	21,092	363,477	22,444	45,905	368,588
Control variables (before transformation)						
Hourly wage	18.98	26.55	25.41	23.09	30.38	28.66
	(90.30)	(90.86)	(88.83)	(59.56)	(119.54)	(100.77)
Employment rate	90.30%	90.86%	88.83%	90.58%	91.51%	89.19%
Avg age	37.33	44.80	41.98	37.23	44.78	42.01
	(10.90)	(12.15)	(13.82)	(10.86)	(12.08)	(13.77)
Male	65.72%	52.65%	51.31%	60.92%	51.55%	51.39%
Hispanic	64.74%	28.83%	3.96%	55.26%	35.59%	8.14%
Education						
No degree	39.17%	14.58%	7.82%	33.52%	17.60%	5.98%
High-school Diploma	23.42%	20.76%	26.79%	22.22%	20.42%	26.56%
At least Some College	37.41%	64.65%	65.39%	44.26%	61.98%	67.45%
Experience	17.53	23.61	22.53	18.83	25.56	22.70
	(10.63)	(12.42)	(13.65)	(11.15)	(12.36)	(13.77)
Number of observations	132,890	185,461	3,272,099	1,065,467	2,156,972	17,769,428

Notes: the sample considers people of working age, 18-65 years old. Hourly wage is deflated. E-Verify mandating states exclude Florida.

Table 3 reveals key insights into the employment sectors of LUI in states with E-Verify mandates and the rest of the states. The primary industries include Construction, Restaurants and Other Food Services, Manufacturing, and Agriculture. These sectors are characterized by a high demand

for low-skilled manual labor. The aggregated data align with national estimates suggesting that most undocumented immigrants are employed in construction, agriculture, and hospitality (S. Passel and Cohn 2016). Notable differences in the industrial composition of the workforce between mandating states and the comparison group highlight regional variations and emphasize the necessity for analyzing the policy's impact within each state's unique context.

Table 3. Industry Statistics of Likely Undocumented Immigrants in Eight E-Verify Mandate States and Donor Group, 2002-19.

	Construction	Restaurants and food services	Manufacturing	Agriculture	Other business and services
Alabama	1,086 (18.79%)	623 (10.78%)	1,242 (21.48%)	256 (4.43%)	2,574 (44.53%)
Arizona	5,043 (18.37%)	2,833 (10.32%)	2,541 (9.26%)	1,429 (5.21%)	15,606 (56.85%)
Georgia	6,649 (18.36%)	3,328 (9.19%)	5,151 (14.22%)	1,479 (4.08%)	19,605 (54.14%)
Mississippi	408 (16.79%)	250 (10.29%)	477 (19.63%)	140 (5.76%)	1,155 (47.53%)
North Carolina	6,188 (20.36%)	3,041 (10.01%)	4,947 (16.28%)	2,423 (7.97%)	13,789 (45.38%)
South Carolina	2,022 (22.71%)	926 (10.40%)	1,332 (14.96%)	496 (5.57%)	4,127 (46.36%)
Tennessee	2,188 (19.34%)	1,264 (11.17%)	1,644 (14.53%)	577 (5.10%)	5,639 (49.85%)
Utah	1,160 (14.18%)	976 (11.93%)	1,329 (16.25%)	324 (3.96%)	4,391 (53.68%)
Average of Donor Group	2,891 (9.67%)	2,402 (10.24%)	2,934 (14.13%)	1,280 (6.53%)	14,798 (59.43%)

Notes: Industry and occupation classifications are based on the Standard Occupational Classification (SOC) system and the North American Industry Classification System (NAICS) codes: "Agriculture" includes SOC codes 451010-452099 and 537064("H-2A Wage Rates & SOC Codes Explained" 2024), and NAICS codes 0170-0290. "Construction" is categorized by NAICS code 770. "Restaurants and Other Food Services" corresponds to NAICS code 8680. "Manufacturing" spans NAICS codes 1070-3990. All other industries and occupations are grouped into "Other Business and Services."

4 Examine Parallel Trends

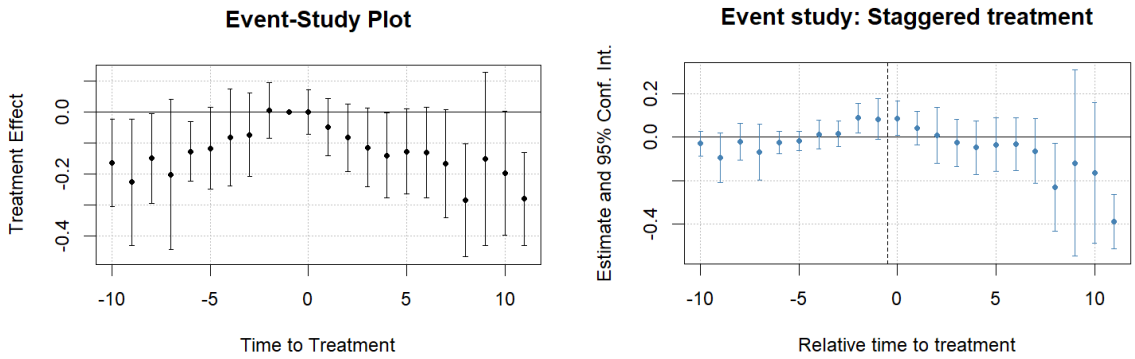
Studies often use difference-in-differences (DID) to identify the average treatment effects of policies. To assess the validity of the parallel trends assumption, a prerequisite for employing the generalized difference-in-differences approach, we focus on the event-study model as specified in equation (1):

$$Y_{st} = \alpha + \sum_{\tau=t-t_d} \beta_\tau (I_\tau * D_s) \; + \Omega X'_{st} + \gamma_t + \delta_s + \varepsilon_{st} \tag{1}$$

where s indexes states and t indexes years. Specifically, t_d represents the enactment year of E-Verify for each treated state, and τ defines the event time relative to the policy implementation. The coefficients β_τ capture the effect of the E-Verify mandate in the years leading up to and following its enactment, allowing us to assess both pre-treatment trends and post-treatment effects. The outcome variable Y_{st} is the level of LUI employment in state s and year t. The model includes state fixed effects (δ_s) and year fixed effects (γ_t) to control for unobserved time-invariant state characteristics and time trends. Additionally, $X_{st}^{'}$ is a vector of time-varying state-level covariates, including demographic and economic controls such as race, sex, educational attainment, work experience, state GDP, unemployment rate, the percentage of total immigrants in the state population, and total state employment. These covariates account for potential confounders that could affect both the adoption of E-Verify and the outcome variable. The analysis includes 8 treated states that implemented E-Verify mandates during the study period and 43 untreated control states. We cluster standard errors at the state level, allowing for correlation of errors within states over time.

The event-study coefficients, plotted in Figure 3, reveal deviations in pretreatment trends between the treatment and control groups, indicating a violation of the parallel trends assumption.

These findings are robust across multiple empirical specifications, including a two-way fixed effects model and a two-staged difference-in-differences (DID) model (Gardner, 2022). Both approaches consistently indicate a violation of the parallel trends assumption in specific pretreatment periods, suggesting that the treatment and control groups exhibited divergent trends prior to the implementation of the policy.



(a) (b)

Figure 3. Event studies of equation (1): (a) TWFE specification; (b) two-staged DID specification

Given the violation of the parallel-trend assumption, the generalized difference-in-differences approach is not appropriate for estimating the average treatment effect of E-Verify in this context. As a result, we adopt an alternative empirical strategy: the synthetic control method (SCM). This method constructs a weighted combination of control units that closely replicates the pretreatment characteristics and trends of the treated unit, thereby addressing the limitations of DID when parallel trends are not satisfied. The SCM is particularly advantageous in this study, as it allows us to analyze a single treated unit, a feature that is well-suited to the heterogeneous effects arising from variations in policy design and enforcement across states.

To further enhance the robustness of our findings, we supplement the synthetic control analysis with the synthetic difference-in-differences (SDID) approach, a novel methodology that integrates the strengths of DID and SCM. This dual approach enables us to construct synthetic controls that

more precisely match pretreatment outcomes while mitigating concerns related to imperfect fit. The doubly robust inference design of SDID ensures that our estimates are less sensitive to potential misspecification. Together, these methods offer a rigorous framework for estimating the causal effects of E-Verify.

5 Synthetic Control Approach

Our main analysis employs the synthetic control approach proposed by Abadie and Gardeazabal (2003), and Abadie, Diamond, and Hainmueller (2010) to construct counterfactuals for states mandating the use of E-Verify. The synthetic control method stands as a robust statistical tool in policy evaluation (Bohn, Lofstrom, and Raphael 2015). This approach involves creating a synthetic version of the treatment group (in this case, states with E-Verify mandates) by using a weighted combination of control units (states without such mandates) that closely resemble the pre-intervention characteristics of the treatment group. The primary advantage of the synthetic control method lies in its ability to approximate the counterfactual scenario - what would have happened in the absence of policy intervention (Abadie 2021). This is achieved by matching the treatment group with a synthetic counterpart that mirrors its attributes before the policy implementation, allowing us to isolate the policy effect in each implementing state and analyze its specific impact on employment outcomes.

Synthetic control is implemented by first choosing a weighting vector W^*that minimizes the difference between the treated and the synthetic control group preintervention:

$$W_j^* = argmin(X_j - X_0 W)' V (X_j - X_0 W) \quad (2)$$

subject to the restrictions that weights are nonnegative and sum to one (Abadie, Diamond, and Hainmueller 2010). X_j represents the set of k predictors of the variable of interest Y_j, which is total

employment of LUI in logarithm form in this case, for state j. X_0 contains the predictor values of the states that are in the donor pool. For the treated group, we have eight states and the rest of the states without E-Verify mandates are in the donor pool. For predictors, we included demographic variables as well as economic and development indicators for each state. Matrix V is positive definite with diagonal elements defining the relative importance of each of the k predictors. Given the set of weights, W_j^*, the composed synthetic control of the outcome becomes:

$$Y^S{}_j = W_j^* Y_0 \tag{3}$$

where $Y^S{}_j$ stands for the composed synthetic outcomes, which is the sum of the weighted outcomes of the states in the donor pool, represented by Y_0 for each year preintervention and postintervention.

The method is particularly advantageous in this case to eliminate confounding effect as we navigate the heterogeneity when the same policy is applied to different states with different population and economic dynamics. Employing the synthetic control approach in our study enables us to evaluate the E-Verify mandates' effects individually. Then the minimization process in equation (2) is conducted individually for the eight states to find W_j^*.

5.1 Empirical Methodology

The individual-level data are weighted using sample weights and aggregated by year at the state level before entering the synthetic control process. Predictors include race, age, sex, educational attainment, and total number of immigrants, as well as economic indicators such as GDP per capita and unemployment rate. Package Synth is deployed to apply the synthetic control approach in R.

We estimate the impact of the E-Verify mandate on the total employment of LUI in the

mandating states. A difference-in differences (DD) estimate of the employment outcome is taken as the measure of the average treatment effect, comparing the pre and postintervention of both the treated group and its synthetic control (Bohn, Lofstrom, and Raphael 2015). While the synthetic control method constructs a counterfactual by matching pre-treatment characteristics, it is particularly sensitive to the quality of this match. By incorporating DID, we account for potential differential trends between the treated and synthetic control groups, reducing potential bias and enhancing the robustness of the causal estimate. This estimate reflects the percentage changes in the total employment post-mandates, as shown below:

$$DD_j = (Y_j^{post} - Y_j^{S,post}) - (Y_j^{pre} - Y_j^{S,pre}) \quad (4)$$

where Y_j^{post} and Y_j^{pre} represent the average of log total employment of LUI for each treated state j, post and pre-intervention, $Y_j^{S,post}$ and $Y_j^{S,pre}$ represent the corresponding values for the synthetic control for each treated state. In our analysis, the period from 2002 up until the year each state passed its E-Verify mandate is considered the pre-intervention phase. This approach aligns with most states, where the laws were passed and implemented in the early to mid-part of the following calendar year. For instance, in Alabama, the years leading up to and including 2011 constitute the pre-treatment era, with 2012 marking the commencement of the post-treatment phase. However, exceptions exist, such as Tennessee and Mississippi, where the laws were both passed and became effective mid-year in 2011 and 2008, respectively. To ensure consistency across states, we adopt the same rule: treating the year of passage as the pre-intervention phase and the subsequent year as the start of the post-intervention period. In a robustness check, we assign the treatment year to the year of passage rather than implementation to account for any anticipatory effects that may influence employment outcomes.

5.2 Inference

To assess the significance of the treatment effects in states with E-Verify mandates, we apply the permutation test as proposed by Abadie, Diamond, and Hainmueller (2010). This involves randomly reassigning the treatment status among the states in the donor pool to generate a distribution of "placebo effects". Specifically, we calculate the ratio of the root mean square prediction error (RMSPE) post-treatment (R_j^{post}) and pre-treatment (R_j^{pre}) for each treated state and corresponding unit in the donor pool, the equation for calculating the RMSPE is:

$$R_j = \left(\frac{1}{T} \sum_{0}^{t} \left(Y_{jt} - \hat{Y}_{jt}^{S} \right)^2 \right)^{1/2} \tag{5}$$

where Y_{jt} represents the actual outcome for unit j that is treated at time t, and $\hat{Y}_{jt}^{S}$ is the estimated outcome generated by the remaining units from the donor pool. Therefore, R_j^{pre} and R_j^{post} measure the pre and post intervention fit, and the ratio r_j serves as the test statistic for evaluating the impact of the policy, according to the methodology outlined by Abadie, Diamond, and Hainmueller (2010). The ratio is calculated as:

$$r_j = \frac{R_j^{pre}}{R_j^{post}} \tag{6}$$

P-values are calculated by comparing the test statistic for each treated state with the corresponding permutation distribution of r_j using a one-sided test. This test statistic measures the relative fit of the post-treatment model compared to the pre-intervention model. Abadie, Diamond, and Hainmueller (2010) suggest that placebo states with poorly matched pre-treatment trends could be discarded. However, this approach can be subjective; our method mitigates this potential

bias. This inference technique does not assume a specific form for the error term, which enhances robustness and analytical flexibility. Additionally, employing a one-sided test can significantly enhance statistical power, as noted by Abadie, Diamond, and Hainmueller (2010).

6 Results

The results demonstrate varied impacts of E-Verify mandates on the employment of undocumented immigrants across different states. The DD estimates of the treatment effects and the estimated gaps in employment pre- and post-mandate are presented in Table 4. These gaps represent the average differences in the logarithm of total likely undocumented immigrant employment between the treated states and their synthetic controls. For states like Alabama and Arizona, the effects on employment reduction are statistically significant, whereas they are non-significant in all other states. Details on the permutation test results are provided in the Appendix.

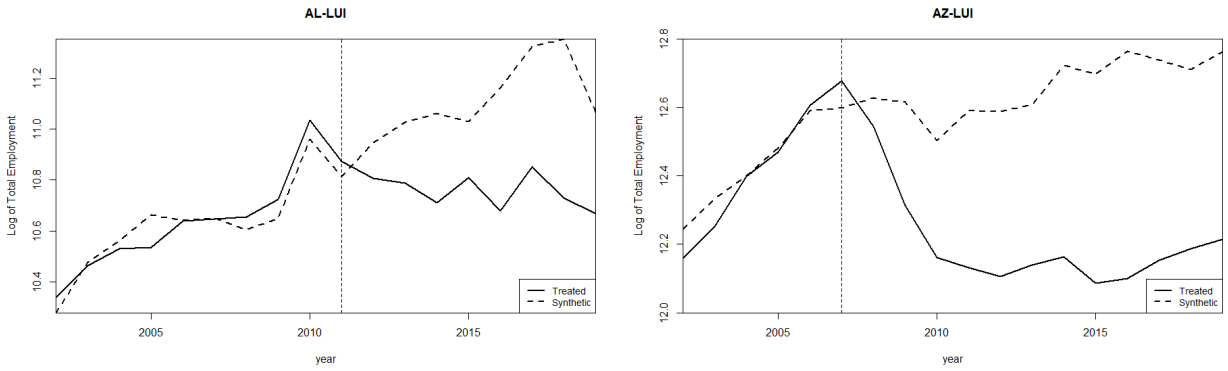
Table 4. Estimated Impact of E-Verify Mandate on the Employment of Likely-Undocumented Immigrants

	Pre-treatment gap	Post-treatment gap	DD estimate of treatment effect	p-value (one-tail test)
Alabama	0.014	-0.3679	-0.382***	0.000
Arizona	-0.015	-0.469	-0.455**	0.023
Georgia	-0.001	0.003	0.004	0.977
Mississippi	-0.006	-0.084	-0.078	0.581
North Carolina	-0.013	0.074	0.088	0.465
South Carolina	0.008	0.049	0.041	0.953
Tennessee	0.007	0.076	0.069	0.279
Utah	0.000	0.055	0.056	0.163

Notes: Predictors include Hispanic percentage, age, educational attainment, years of experience, log of hourly wage, state unemployment rate, log of state GDP, log of the state's total immigrant population, and log of the state's total employment. Aggregations are weighted using ACS individual sample weights. Significance levels: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$.

6.1 Significant Reduction of Undocumented Employment in Alabama and Arizona

Alabama and Arizona stand out for their broad enforcement and severe penalties for employers that knowingly employ unauthorized immigrants. Both states experienced a significant decrease in the total employment of LUI following the implementation of the E-Verify mandates, with decreases of 38.2% and 45.5%, respectively, as detailed in Table 4. Figure 3 illustrates the synthetic control estimates of the mandate's impact in these two states. The synthetic control for Alabama is primarily composed of North Dakota and Texas, with substantial weights of 0.368 and 0.321, respectively, followed by Arkansas and Oklahoma, with weights of 0.197 and 0.114. For Arizona, the synthetic control is predominantly composed of Texas, with a weight of 0.664, alongside Colorado, Wyoming, and Montana contributing weights of 0.160, 0.115, and 0.061. The dotted vertical line indicates when the policy was enacted which starts the post-enactment years. The significant reduction in LUI employment post-mandate indicates the effectiveness of the policy's implementation in both states.



(a) (b)

Figure 4. Total Employment (Log) of Likely Undocumented Immigrants (LUI) between Treated States without Exemptions and Synthetic States, 2002-2019: (a) Alabama and Synthetic Alabama; (b) Arizona and Synthetic Arizona.

6.2 Limited Impact of E-Verify Mandates in Other States

The insignificant results observed in six other states are expected, given their bill designs and implementations, which reveals a narrower scope, phased approach, and milder penalties—all factors that likely reduce the impact of these reforms. Figure 4 shows that there is no clear trend indicating a reduction in LUI employment in these states post mandates. While the employment effects for LUI are mostly negative in these states, they are not statistically significant.

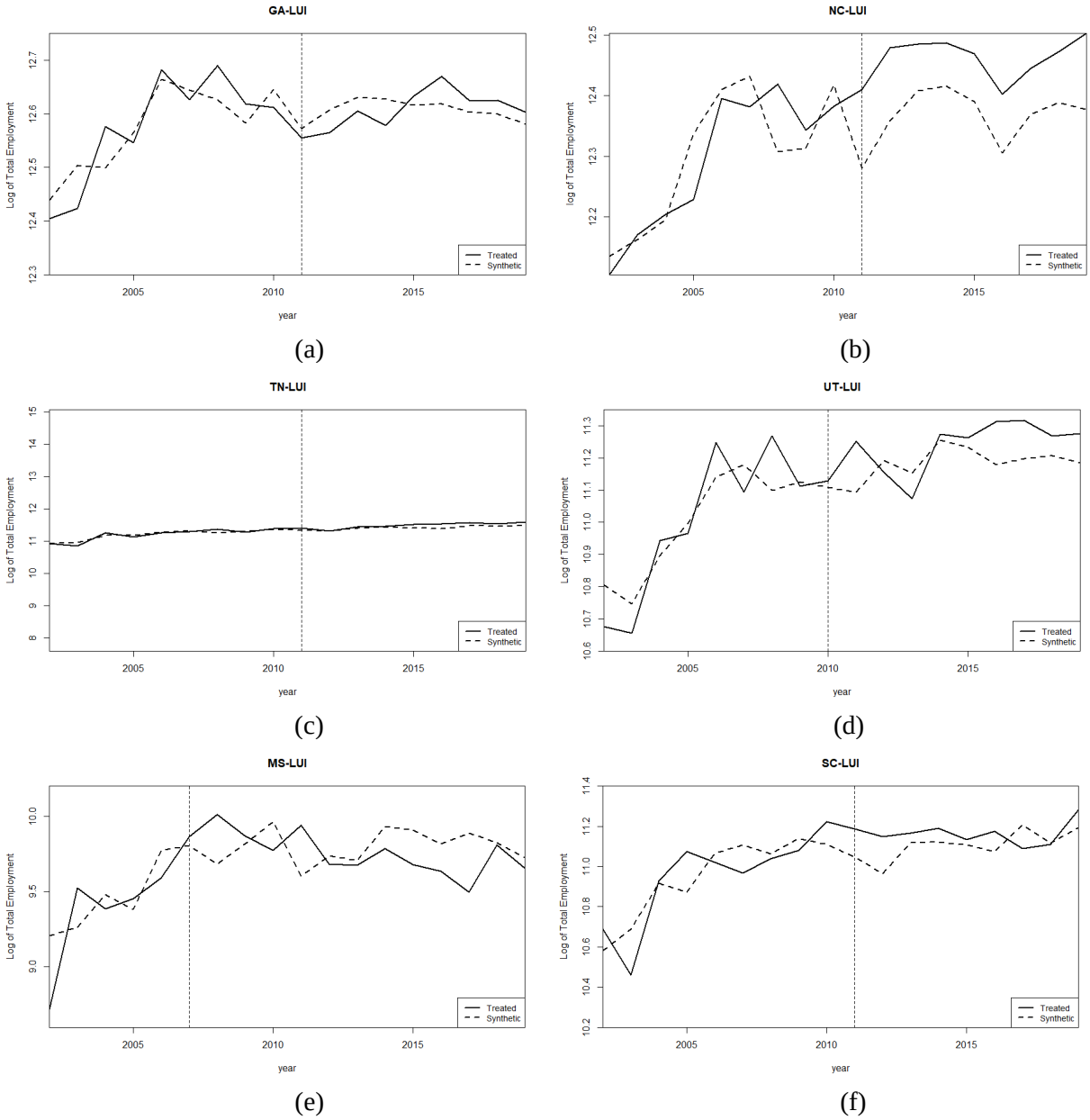


Figure 5. Total Employment (Log) of Likely Undocumented Immigrants (LUI) between Treated States with Exemptions and Synthetic States, 2002-2019. *Notes:* Synthetic Control for each E-Verify mandating state consists of the following states (with weights in parentheses): (a) Georgia: New Jersy (0.493), Illinois (0.308), Arkansas(0.136), Alaska(0.032), California (0.031); (b) North Carolina: Arkansas (0.458), California (0.432), Oregon (0.076), Alaska(0.025), Kentucky (0.009); (c) Tennessee: Indiana (0.466), Kentucky (0.278), Texas (0.107), Colorado (0.088), Idaho (0.061); (d) Utah: Oklahoma (0.392), Nebraska (0.182), New Mexico(0.129), Florida(0.180), Wyoming(0.061), Arkansas(0.056); (e) Mississippi: Alaska (0.540), Kentucky(0.460); (f) South Carolina: Kentucky (0.520), Nevada (0.280), Oregon (0.200).

7 Robustness Checks

A series of comprehensive robustness checks were conducted to ensure the reliability and consistency of the results. The findings align closely with the main results, confirming that they are not sensitive to sample weighting, neighboring effects, or industry effects.

7.1 Synthetic Difference-in-Differences

The synthetic difference-in-differences (SDID) approach, introduced by Arkhangelsky et al. (2021), integrates features of both DID and SCM. This hybrid methodology provides a robustness check for the SCM estimates from our main analysis. As shown in Table 4, the pretreatment gaps between the synthetic control and treated states vary among the treated group, reflecting a limitation of SCM: its sensitivity to the quality of pretreatment alignment and the selection of predictors. To address concerns about potential bias arising from imperfect pretreatment fit, we implement SDID for individual treated states.

The SDID approach relaxes the pretreatment alignment requirements of SCM by incorporating both unit and time weights, satisfying the parallel trend assumption. A comparison of the SCM and SDID results, presented in the Appendix Table A-1, reveals that SDID produces estimates close to those of SCM. Consistent with the main results, Figure 6 shows that E-Verify mostly do not achieve their intended goals, with significant impacts observed in Alabama and Arizona. The consistency between SCM and SDID estimates reinforces the validity of our conclusions.

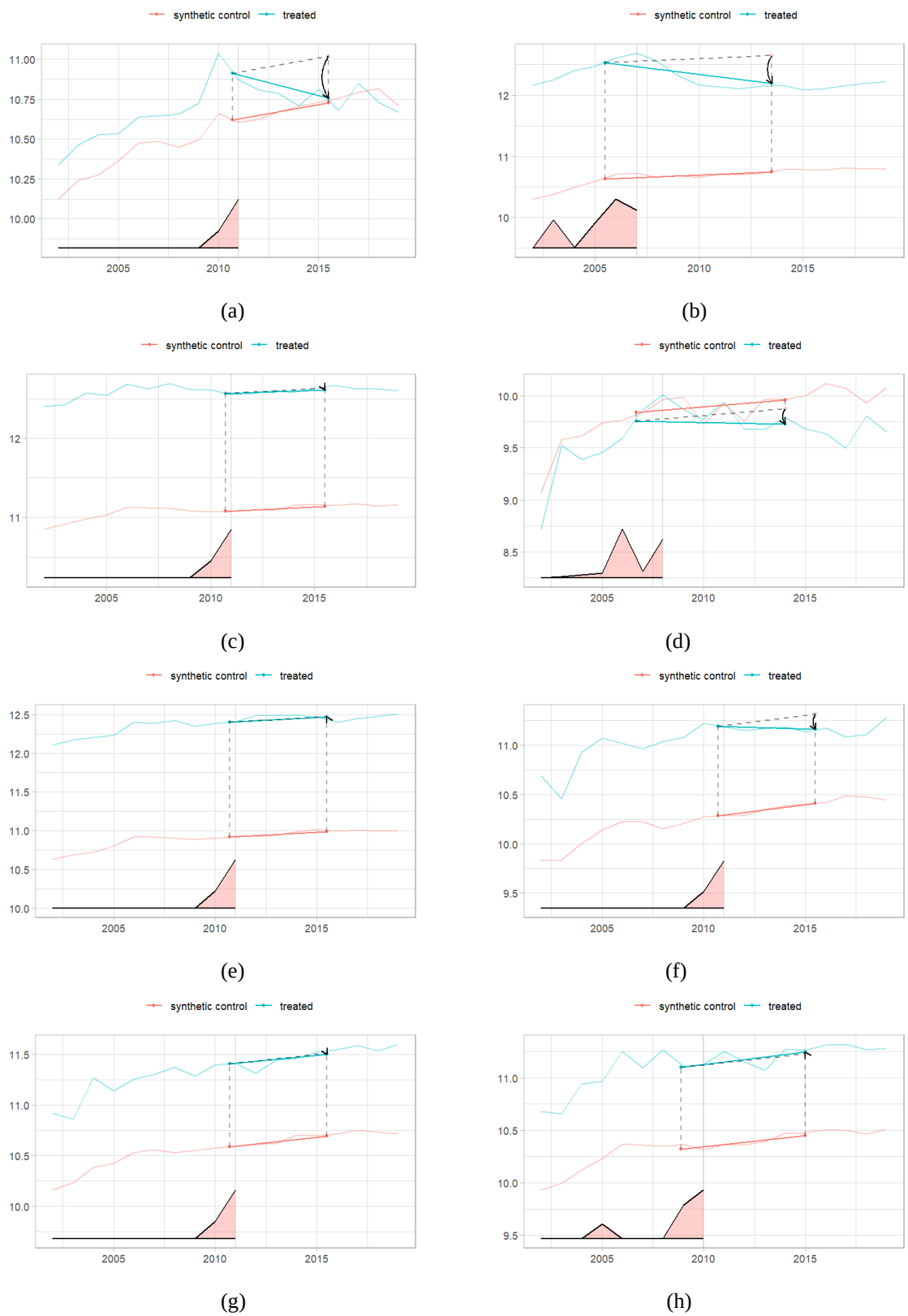


Figure 6. SDID Estimates of the Effects of E-Verify Mandates on the Total Employment (Log) of Likely Undocumented Immigrants (LUI), 2002-2019: (a) Alabama; (b) Arizona; (c) Georgia; (d) Mississippi; (e) North Carolina; (f) South Carolina; (g) Tennessee; (h) Utah.

7.2 Unweighted Sample

First, we conducted a robustness check using the unweighted sample to ensure the reliability of the analysis when identifying the likely undocumented immigrant population using Borjas (2017)'s approach. In our main analysis, we utilized the ACS sample weights, which are designed to reflect the general population rather than specifically targeting the undocumented population. This raises concerns about potential bias, as applying these weights may alter the representation of the LUI population. Since Borjas' method does not offer a reweighting strategy specifically for the undocumented, it is crucial to test the robustness of the findings using the unweighted sample. The results shown in Table 5 are consistent with the main analysis, validating Borjas's method for identifying the undocumented population.

Table 5. Estimated Impact of E-Verify Mandate on the Employment of Likely-Undocumented Immigrants, Unweighted Sample

	Pre-treatment gap	Post-treatment gap	DD estimate of treatment effect	p-value (one-tail test)
Alabama	-0.005	-0.188	-0.183***	0.000
Arizona	0.010	-0.357	-0.367**	0.023
Georgia	0.097	0.003	-0.093	0.977
Mississippi	-0.004	-0.122	-0.117	0.581
North Carolina	-0.015	0.030	0.045	0.465
South Carolina	-0.000	-0.026	-0.025	0.953
Tennessee	-0.004	0.051	0.055	0.279
Utah	-0.030	0.160	0.190	0.163

Notes: Predictors include Hispanic percentage, age, educational attainment, years of experience, log of hourly wage, state unemployment rate, log of state GDP, log of the state's total immigrant population, and log of the state's total employment. Aggregations are weighted using ACS individual sample weights. Significance levels: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$.

7.3 Alternative Treatment Timing

To account for any anticipatory effects, we adjust the treatment year to the year each state passed its E-Verify mandate, rather than the year of implementation. This approach is particularly relevant for states like Mississippi and Tennessee, where the laws were implemented in the same year they were passed, potentially influencing employer and worker behavior earlier than in other states. By assigning the treatment year to the year of passage, we aim to capture any shifts in employment outcomes triggered by the legislative process itself. The results (Table 6) are consistent with our main findings.

Table 6. Estimated Impact of E-Verify Mandate on the Employment of Likely-Undocumented Immigrants, Alternative Treatment Timing

	Pre-treatment gap	Post-treatment gap	DD estimate of treatment effect
Alabama	0.001	-0.178	-0.179***
Arizona	0.001	-0.394	-0.395**
Georgia	-0.042	-0.049	-0.008
Mississippi	0.002	-0.027	-0.029
North Carolina	0.001	0.146	0.145
South Carolina	0.064	0.075	0.011
Tennessee	0.013	0.103	0.090
Utah	-0.000	0.109	0.109

Notes: Predictors include Hispanic percentage, age, educational attainment, years of experience, log of hourly wage, state unemployment rate, log of state GDP, log of the state's total immigrant population, and log of the state's total employment. Aggregations are weighted using ACS individual sample weights. Significance levels: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$.

7.4 Phased Implementation States

For a further robustness check, we account for states that adopted a phased approach to E-Verify implementation, where compliance requirements were gradually expanded to include all employers over several years. In this analysis, we assign the treatment year to the year when full compliance for all employers was mandated: 2013 for Georgia and North Carolina, and 2011 for Mississippi. By doing so, we aim to assess whether the staggered implementation timeline influenced the

estimated employment outcomes. The results, displayed in Table 7, continue to show statistically insignificant effects, aligning with our main findings and reinforcing the conclusion that the policy had limited impact on overall employment outcomes for low-skilled unauthorized immigrants.

Table 7. Estimated Impact of E-Verify Mandate on the Employment of Likely-Undocumented Immigrants, Phased Implementation States

	Pre-treatment gap	Post-treatment gap	DD estimate of treatment effect
Georgia	-0.004	0.007	0.010
Mississippi	-0.012	-0.145	-0.133
North Carolina	0.083	0.164	0.081

Notes: Predictors include Hispanic percentage, age, educational attainment, years of experience, log of hourly wage, state unemployment rate, log of state GDP, log of the state's total immigrant population, and log of the state's total employment. Aggregations are weighted using ACS individual sample weights. Significance levels: $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$.

7.5 Neighbor Effects

Second, we exclude neighboring states from the donor pool due to concerns that migratory effects due to these mandates could bias the estimations, as individuals might cross state lines to avoid the policy's impact. For example, cross-state commuters could seek employment in neighboring states where the policy is not enforced, thereby distorting employment trends in untreated states. In the southern region, however, many states enacted the policy simultaneously, meaning that most of their neighboring states are also subject to the treatment effects. By excluding the neighboring states, we aim to ensure that our analysis reflects the policy's direct effects without confounding influences from regional spillovers or commuting patterns. As shown in Figure 5, the results of the robustness check are consistent with the main findings.

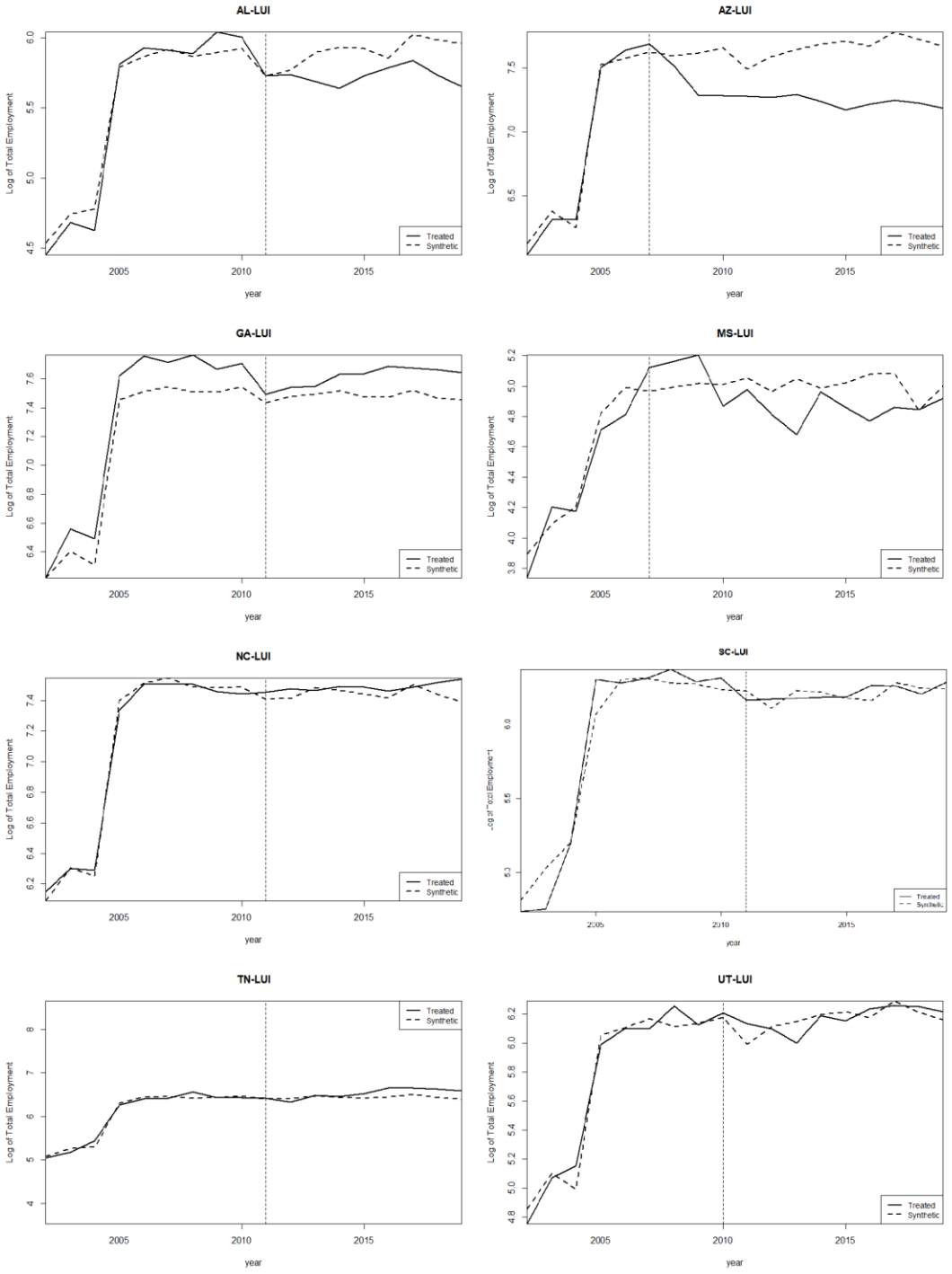


Figure 7. Total Employment (Log) of Likely Undocumented Immigrants (LUI) between Treated States and Synthetic States Excluding Neighboring States, 2002-2019.

7.6 Industry Effects

For a third robustness check, we refined our analysis to focus exclusively on four industries that heavily rely on undocumented immigrants: Construction, Restaurants and Other Food Services, Manufacturing, and Agriculture. By isolating these industries, we can capture E-Verify's direct effects on undocumented employment within sectors where such impacts are most likely to be observed. Additionally, concentrating on industries with high undocumented employment, we aim to further ensure the accuracy of the LUI identification process. As shown in Figure 6, the results are consistent with the findings in the baseline analysis.

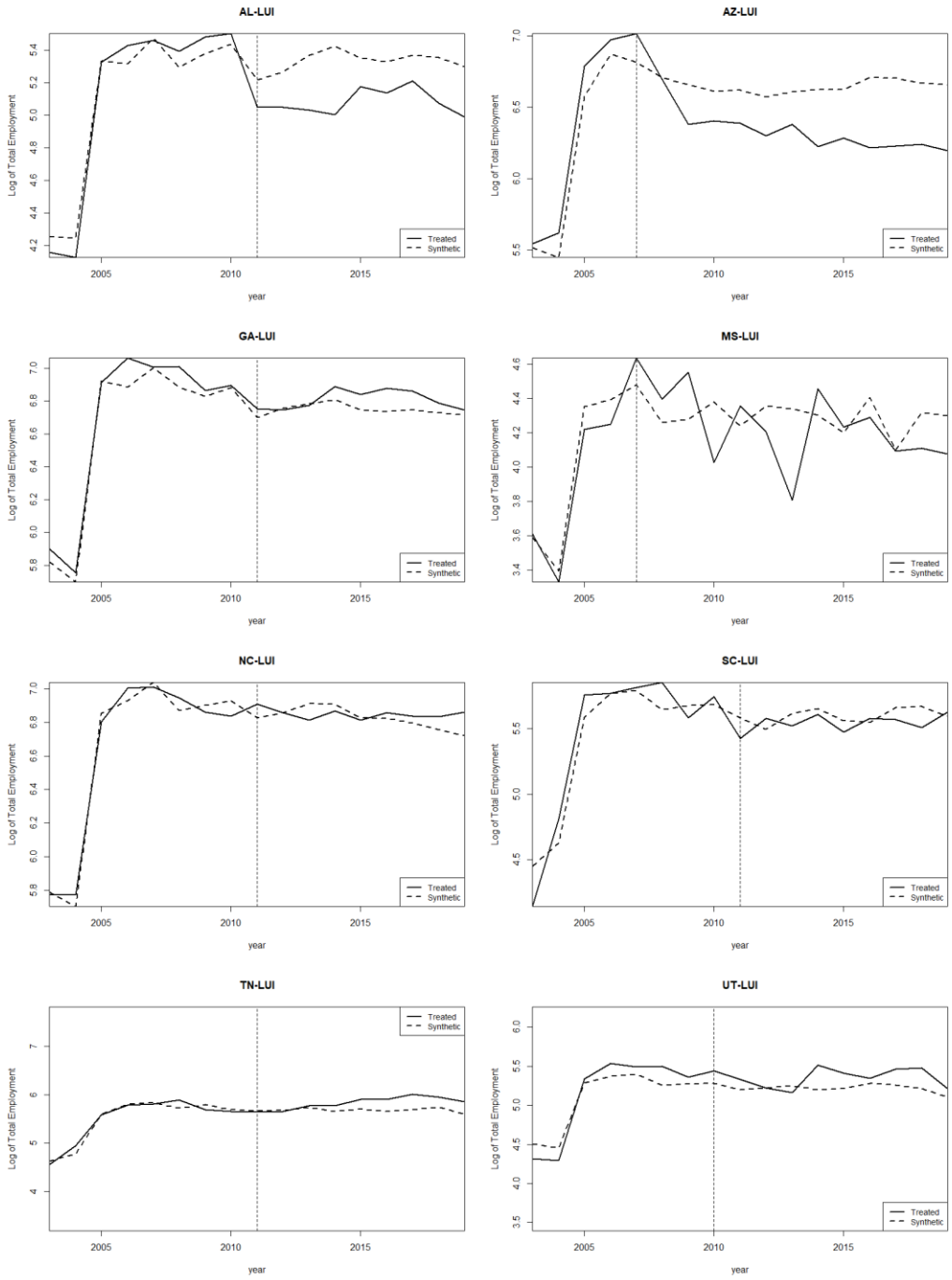


Figure 8. Total Employment (Log) of Likely Undocumented Immigrants (LUI) between Treated States and Synthetic States: Construction, Restaurants and Other Food Services, Manufacturing, and Agriculture Industries, 2002-2019.

8 Discussion

Our analysis of E-Verify mandates across eight states reveals that while some states, like Alabama and Arizona, have seen reductions in undocumented employment, the effectiveness of these policies in other states is often moderated by economic considerations and political motivations.

Among the eight states studied, Arizona demonstrated the most significant reduction in undocumented employment following the enactment of E-Verify. This effectiveness can be attributed to a combination of factors specific to Arizona's policy environment and enforcement measures. First, the state's rapid growth in undocumented immigration before the law's implementation created heightened public and political pressure, which likely contributed to strict and comprehensive enforcement of the policy. Second, Arizona's geographic position as a border state adjacent to Mexico made it a critical entry point for undocumented immigrants, intensifying state-level initiatives to control unauthorized employment. These factors not only drove the enactment of the E-Verify mandate but could also have enhanced its enforcement and efficacy.

The effectiveness of Arizona's E-Verify mandate was further reinforced by subsequent policies, particularly the 'Support Our Law Enforcement and Safe Neighborhoods Act' (SB 1070), enacted in 2010. This law enhanced the E-Verify mandate by requiring police officers to check immigration documents upon reasonable suspicion and by criminalizing undocumented workers seeking employment. Although this specific provision was blocked by federal courts, the broader policy environment created by SB 1070 amplified the deterrent effect of the E-Verify mandate, contributing to Arizona's reputation for strict immigration enforcement. This research does not isolate the specific effects of the 2010 law but instead views it as an escalation of the original E-Verify mandate. Future studies could explore the individual impacts of these restrictive measures

as part of a broader series of immigration policies. However, this constraint does not undermine the validity of the findings in other states, as the synthetic control approach allows each state's policy effect to be studied independently.

Implemented alongside other states' mandates in the early 2010s, Alabama stands out as the only Southern state to achieve a significant reduction in undocumented employment. Alabama enforces stringent penalties: upon conviction, employers may face fines up to 10 times the business expense deduction claimed for wages paid to unauthorized workers. Additionally, the Alabama Department of Homeland Security's E-Verify Employer Agent Service provides an alternative compliance mechanism for small businesses. Under Alabama law, businesses with 25 or fewer employees have the option to utilize this service instead of enrolling in E-Verify independently. This provision aims to ease the administrative burden on small employers while ensuring compliance with the state's E-Verify mandate. These distinctive provisions could contribute to the mandate's effectiveness in reducing undocumented employment.

In contrast, an examination of the legislative bills of other states reveals a softer approach. States like Georgia, North Carolina, Tennessee, and Utah implemented E-Verify mandates but included various forms of exemptions. These exemptions function as a moderating mechanism, reducing potential economic disruptions in key sectors. Agriculture, which significantly contributes to state GDP and employs a considerable portion of the undocumented workforce, is frequently excluded to maintain labor stability. North Carolina's specific exemptions for seasonal employees underscore the state's recognition of agriculture's seasonal labor demands. Additionally, concerns over potential labor shortages may have led Mississippi, Georgia, and North Carolina to adopt a phased approach, further moderating the policies' impact.

While E-Verify mandates project a tougher stance against illegal immigration, our analysis suggests that the timing, scope, and design of these laws may indicate political posturing rather than impactful immigration reform. This is evidenced by our findings, which reveal that most of these mandates have had minimal impact on the undocumented employment they claim to target. Moreover, nearly all enactments coincided with election cycles, times when public sentiment leaned toward restrictive immigration policies. This timing, combined with broad exemptions and moderations, suggests that these mandates may have been implemented more to capture electoral support than to achieve impactful reform. The recent passage of Florida's E-Verify bill ahead of the 2024 election cycle, similarly embedded with numerous exemptions, further support this hypothesis.

In conclusion, this study shows most of these employment protection bills do not significantly affect undocumented employment in most states. However, these bills may have broader implications beyond the labor market, such as psychological and behavioral impacts on undocumented immigrants. More restrictive measures may increase stress related to job security and mental health issues, and could also enable employers to exploit undocumented workers, raising important ethical concerns for future research to investigate.

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APPENDIX

Likely-Undocumented Immigrant Identification

According to Borjas (2017) ' framework, a person is likely not an undocumented immigrant (non-LUI) if they meet any of the following criteria:

a) Arrival in the U.S. before 1980;

b) Citizenship;

c) Recipients of Social Security benefits, SSI, Medicaid, Medicare, or Military Insurance;

d) Veteran or active military personnel;

e) Employment in the government sector;

f) Residency in public housing or receipt of rental subsidies (or being the spouse of such a person);

g) Birth in Cuba (as most Cuban immigrants were granted refugee status prior to 2017);

h) Engagement in licensed professions (such as physicians, registered nurses, air traffic controllers, and lawyers);

i) Spouse is a legal immigrant or citizen.

Results of Permutation Tests

Figure A-1. displays the gaps of estimations from the permutation tests. The black lines that are highlighted represent those of the eight E-Verifying mandating states, whereas gray lines represent those of the 43 placebo runs. The results notably highlight the significant effects observed in Alabama and Arizona.

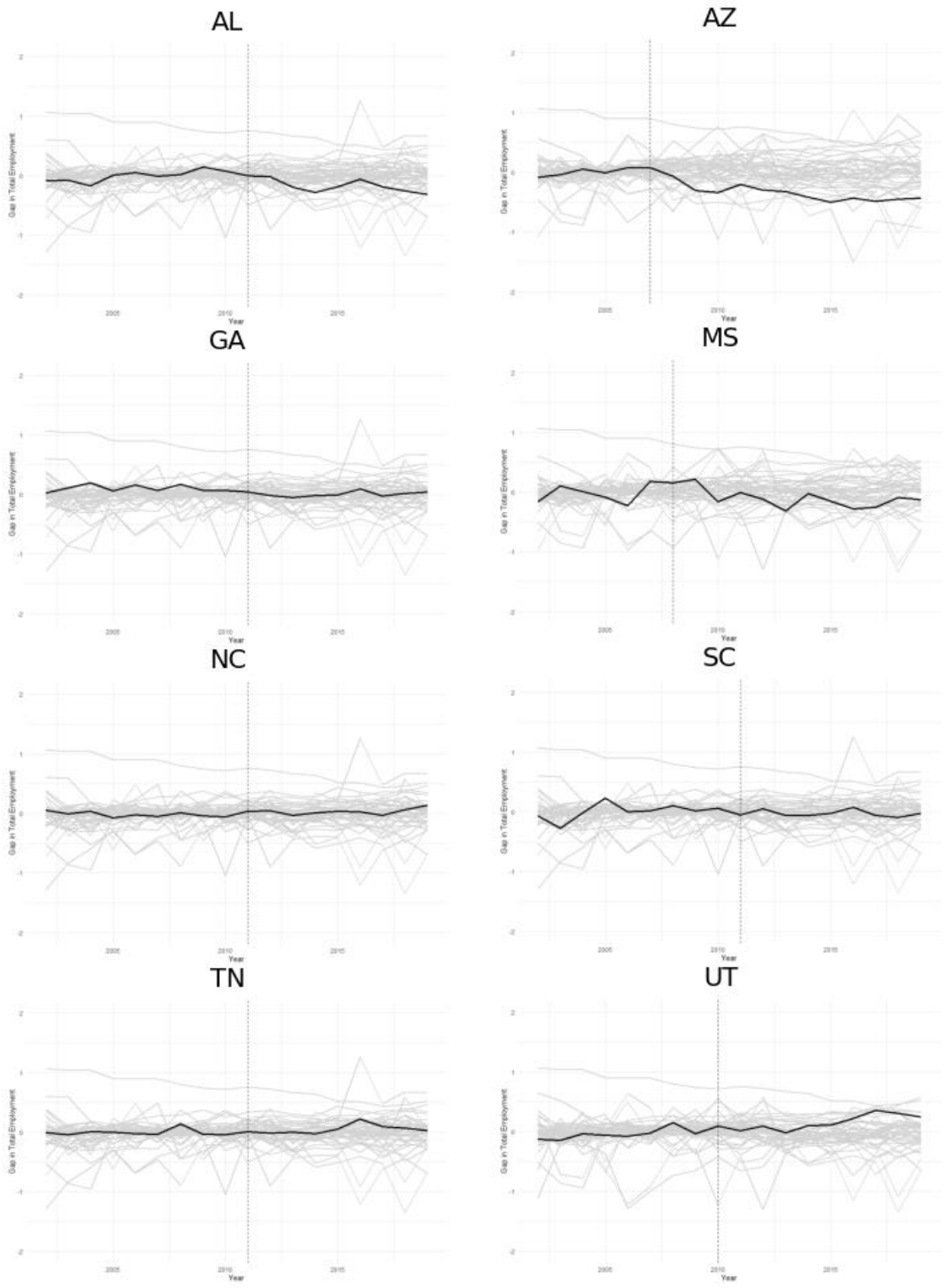


Figure A-1. Total Employment (Log) of Likely Undocumented Immigrants (LUI) Gaps between Treated States and Synthetic States, 2002-2019.

Comparison of SCM and SDID Results

Table A-1. Comparison of SCM and SDID Results: Estimated Impact of E-Verify Mandate on the Employment of Likely-Undocumented Immigrants

	SCM estimate of treatment effect	SDID estimate of treatment effect
Alabama	-0.382***	-0.265**
		(0.125)
Arizona	-0.455**	-0.451**
		(0.205)
Georgia	0.004	-0.021
		(0.138)
Mississippi	-0.078	-0.143
		(0.233)
North Carolina	0.088	0.000
		(0.139)
South Carolina	0.041	-0.155
		(0.159)
Tennessee	0.069	-0.014
		(0.131)
Utah	0.056	0.016
		(0.253)