Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion

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A replication paper by Jonathan Garson

Abstract

Clemens & al (2018) proposed the first quantitative evaluation of the exclusion of Bracero workers from farm work in the 1960s. Using a difference-in-difference approach, they found that more exposed states did not experiment with increases in wages or employment for native workers after the progressive exclusion of Mexican workers from 1961 to 1964. We only find similar results in the setup proposed by the authors. Indeed, after conducting several robustness checks we cannot accept these results without caution. It appears clear that the dynamic effects of the policy are not taken into account, the exposure to treatment varies over time, leading to instability considering the states in the treated and control. To tackle this issue we propose a complementary analysis with a more robust set of treated states and synthetic control to overcome pre-trend issues.

1 Introduction

The effect of immigrant populations on labor markets is a widely debated topic in both society and academia. Politically, immigrants are often blamed for worsening the economic prospects of local populations by increasing competition for housing and jobs, especially when employment opportunities are scarce. Immigrants are seen as providing a cheaper alternative to the native workforce, thereby weakening natives' bargaining power. These arguments have played a central role in recent debates in Europe (e.g., Brexit, the rise of far-right populism) and the U.S. (e.g., Trump's 2016 campaign). An opposing perspective emphasizes the moral obligation of wealthy nations to provide economic opportunities to all and highlights potential benefits from immigration, such as cultural diversity and increased entrepreneurship.

The academic debate has also seen its share of controversies (Card, 1990; Card and Peri, 2016; Borjas, 2017), resulting in numerous studies evaluating the effects of immigration on jobs, housing, and innovation. The literature has primarily focused on the impact of immigration on wages and employment (Kennan, 2017), generally finding small negative effects on employment or wages, though often not statistically significant, while documenting an overall positive impact from accepting immigrants. More recent studies (Monras, 2020) have explored general equilibrium effects on housing and the spatial organization of work, providing evidence of some negative impacts of immigration on low-skill native wages and location choices. Overall, the literature concludes that immigration has minor effects—frequently negative but often statistically insignificant—distributed unevenly across workers and regions.

However, if immigration entry into the local labor market and restriction to entry have been studied, there is still a gap in the effect of excluding immigrants from labor markets. Some papers try to address this question (Lee, Peri and Yasenov, 2017), which found that the exclusion of Mexican communities during the Great Depression depressed the wages and employment outcome of the most exposed cities. Nonetheless, (Clemens, Lewis and Postel, 2018) is among the first to propose a quasi-experimental set-up of worker exclusion effect on wages and employment. For this, they leverage the historical exclusion of hundreds of thousands of Mexican seasonal farm workers in the 1960s using archival data at the state level. They found that on average the exclusion of those workers had no positive effects on the native populations' wages or employment. To rationalize their findings they propose a model of directed technical change (Acemoglu, Antràs and Helpman, 2007; Acemoglu and Autor, 2011) where technology is endogenous. They found out that if technology, capital, or output can adjust, then we should not expect a change in employment or wages as farms adapt to the new economic equilibrium by diversifying their production mix or reducing it.

We replicated the authors' findings and obtained similar results under their preferred specifications. However, we also found notable pre-trends, as well as occasional divergent outcomes, such as small and temporary positive effects on native employment or wages, even within the authors' setup. Furthermore, we contend that the authors' definitions of treatment and control groups are problematic, as treatment intensity varies considerably over time. After accounting for these aspects and conducting robustness tests, we observed small and temporary positive effects on employment, though the impact on wages remained inconclusive. While we do not claim causality for our findings, they suggest the need for further research on potential heterogeneous effects of the policy and for additional work to address the pre-trend issue.

In Section 2, we briefly review the authors' setup, main findings, and robustness checks. In Section 3, we expand on our critique of Clemens, Lewis, and Postel (hereafter CLP). Finally, in Section 4, we propose complementary approaches to disentangle the repercussions of the Bracero exclusion.

2 Summary and Main Results

2.1 Context

The origins of the Bracero worker program stem from the labor shortage in U.S. agriculture during World War II. At that time, U.S. agriculture faced a scarcity of workers due to the war, leading to the signing of bilateral agreements in 1942 to issue seasonal work visas to Mexican laborers. This agreement allowed for the movement of 5 million Mexican workers between 1942 and 1964, with contracts ranging from 6 weeks to 6 months.

The first major opposition to these agreements emerged in the 1960s, when the Kennedy administration began implementing measures to mitigate the perceived negative impact of foreign competition on U.S. workers. In March 1962, the administration raised the minimum prevailing wage for Bracero workers and reduced the influx of these laborers to create a more level playing field for native workers. The Johnson administration ultimately terminated the program in December 1964.

At the time, this was considered an active labor market policy aimed at reducing the number of foreign workers to boost wages and employment for U.S. natives. As (Borjas and Katz, 2007, p.16) notes, "The main reason given for the discontinuation of the program at the time was the assertion that the Bracero Program depressed the wages of native-born Americans in the agricultural industry" (Massey and Liang 1989; Marcell 1994). This argument rested on the idea that a cheaper labor force created unfair competition for U.S. natives, as the cost of supporting a family was lower in Mexico than in the U.S., leading Mexican workers to accept more demanding and lower-paid jobs, which in turn reduced job opportunities and wage outcomes, as well as their bargaining power, for U.S. workers.

Conversely, supporters of the program argued that there was no evidence of declining working conditions for natives, nor of improvements after the program's repeal. They posited that cheap manual labor would be replaced by technology, leaving native workers unaffected. Seminal studies by (Jones and Rice, 1980) found no impact of the policy; however, most studies from that period did not control for broader wage trends across the entire industry. A significant contribution of the authors is to offer a U.S.-wide state-year panel dataset that tracks wage and employment changes in relation to the number of Bracero workers.

This debate remains both academically and historically significant in the U.S. Concerns about Mexican labor resonate with broader issues regarding competition with low-wage workers in manual industries like agriculture (Hornbeck and Naidu, 2014). More broadly, questions about how low-cost (or servile) labor influences technological adoption and structural change in the economy (Fogel *et al.*, 1976) are long-standing issues, to which the authors seek to contribute.

In the next section, we will consider the theoretical framework developed to rationalize these arguments.

2.2 Theoretical framework

2.2.1 Setup

To disentangle the different effects of labor reduction on technology adoption and production they develop a model of technology adoption and labor scarcity following (Acemoglu, 2010).

In this production model, crop producers face a trade-off between adopting a labor-saving technology that automates a part of the production and can perfectly substitute for a labor-intensive mode of production. We set, i (suppressed hereafter) as a location index that can produce a single crop. The crop can be sold to the world market for a price $p \equiv 1$ and needs to be produced to rely on a mix of capital K, labor L, land τ, and materials M. There is an initial endowment denoted $\overline{T}$ for the land; $\overline{L}$ for labor, and capital and materials are supplied elastically. Land and labor markets are competitive, and farmers rent land from landowners at rate r_T, hire workers at wage w, and purchase materials at price m. Landowners receive payments $r_T \geq 0$ per acre if they do not rent to farmers.

The production technology takes the form of a nested constant elasticity of substitution using either traditional capital K_0, elastically supplied at rental rate r_0 and used to produce a crop Y :

$$Y_0 = \left\{ K_0^{\frac{\mu-1}{\mu}} + \left[aL^{\frac{\sigma-1}{\sigma}} + (1-a)T^{\frac{\sigma-1}{\sigma}} \right]^{\left(\frac{\sigma-1}{\sigma}\right)\frac{\mu-1}{\mu}} \right\}^{\frac{\mu-1}{\mu}} \tag{1}$$

Alternatively, for some crop locations, we can use more advanced technology K_A, elastically supplied at rate r_A. This technology is less labor-intensive than the old capital K_0, therefore $b < a$.

$$Y_A = \left\{ K_A^{\frac{\mu-1}{\mu}} + \left[bL^{\frac{\sigma-1}{\sigma}} + (1-b)T^{\frac{\sigma-1}{\sigma}} \right]^{\left(\frac{\sigma-1}{\sigma}\right)\frac{\mu-1}{\mu}} \right\}^{\frac{\mu-1}{\mu}} \tag{2}$$

The outputs of both technologies are perfect substitutes, then the total crop production is the sum of both: $Y \equiv Y_0 + Y_A$.

A key aspect of this model is that more advanced capital does not dominate traditional agriculture because it would be more productive for the same level of inputs. Modern capital dominates traditional one only at a low level of labor per unit of land since it is more land intensive. Hence, farmers can use a combination of both in a competitive equilibrium.

We denote $[\phi_l, \phi_u]$ the range of $\frac{\overline{L}}{\overline{T}}$ over which farmers diversify their mode of production (diversification cone). It means that there is an allocation such that $T_0 + T_A \equiv \overline{T}$ and $L_0 + L_A \equiv \overline{L}$ have the same marginal products of land and labor in each technology. Inside the cone, the wage is given by:

$$\hat{w} = b^{\frac{\sigma}{\sigma-1}} \left(\frac{r_A^{\mu-1}}{r_A^{\mu-1} - 1} \right)^{\frac{\mu}{\mu-1}} \left[\frac{\left(\frac{a}{b}\right)^{\sigma} - \left(\frac{1-a}{1-b}\right)^{\sigma}}{\left(\frac{\frac{r_A^{\mu-1}}{r_A^{\mu-1}-1}}{\frac{r_0^{\mu-1}}{r_0^{\mu-1}-1}} \right)^{\frac{\mu}{\mu-1}(\sigma-1)} - \left(\frac{1-a}{1-b}\right)^{\sigma}} \right] \tag{3}$$

Interestingly wages in the cone are independent of factor supply because proportions are fixed within each technology. This diversification intuitively makes sense, producers do not totally shift from one mode of production to another. Tractors evolved alongside horses for a long time.

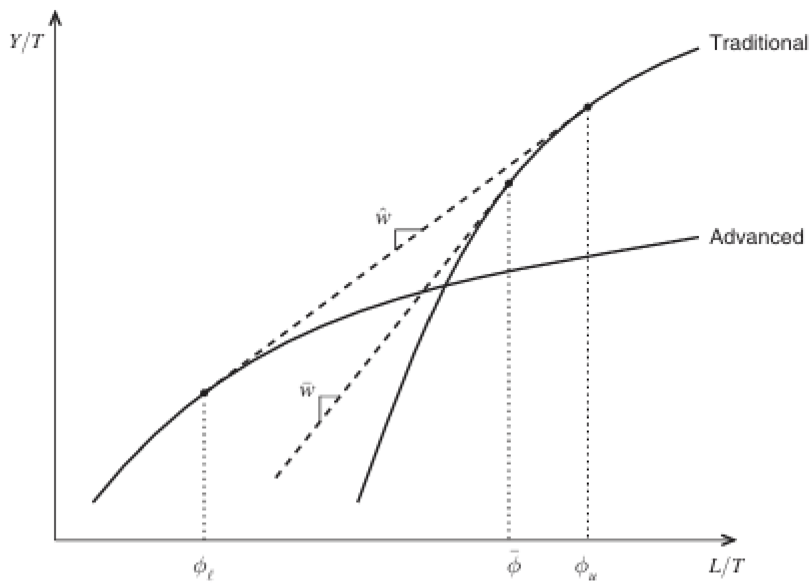


Figure 1: The Diversification Cone $[\phi_l, \phi_u]$ and shutdown margin $\overline{\phi}$

2.2.2 Effect of a workforce reduction policy

The theoretical effect of workforce reduction on wages and production largely depends on the possibility of capital, technology, and production to adjust.

Let the workforce be composed of bracero workers B and non-bracero N, such that $B + N \equiv \overline{L}$. We also assume that if the alternative technology exists, then $\frac{B+N}{T} > \phi_l$; that is, at least one farm uses the traditional technology. In this setup, a relative change in labor supply is: $\%\Delta\left(\frac{\overline{L}}{\overline{T}}\right) = \frac{\left(\frac{N}{T}\right) - \frac{B+N}{T}}{\frac{B+N}{T}} = -\frac{B}{L}$.

Using traditional technologies we obtain the following formula of wage setting:

$$w = a \left\{ \frac{\left(\frac{K}{T}\right)^{\mu-1}}{\mu} + \tilde{L}^{\frac{\sigma}{\sigma-1}\frac{\mu-1}{\mu}} \right\}^{\frac{\mu}{\mu_1}-1} \tilde{L}^{\frac{\sigma}{\sigma-1}\frac{\mu-1}{\mu}-1} \left(\frac{L}{T}\right)^{-\frac{1}{\sigma}} \tag{4}$$

with $\tilde{L} = a\left(\frac{L}{T}\right)^{\frac{\sigma-1}{\sigma}} + (1-a)$

Proposition 1: In the absence of capital, technology, and production adjustment, exclusion raises wages.

$$\frac{\partial(\ln(w))}{\partial\left(\frac{B}{L}\right)} \simeq s_K \frac{s_L}{s_L + s_T}\frac{1}{\mu} + \frac{s_T}{s_L + s_T}\frac{1}{\sigma} > 0 \tag{5}$$

with s_T, s_L, s_K the income shares of land (plus materials), labor, and capital.

Proposition 2: If we allow only capital to adjust, exclusion raises wages but less than in Proposition 1.

$$\frac{\partial(\ln(w))}{\partial\left(\frac{B}{L}\right)} \simeq \frac{s_T}{s_L + s_T}\frac{1}{\mu} > 0 \tag{6}$$

Proposition 3: If we allow total adjustment of different factors of production, then wages do not vary and the share of modern technology to produce crops increases relative to traditional technology.

$$\frac{\partial(\ln(w))}{\partial\left(\frac{B}{L}\right)} = 0 \tag{7}$$

$$\frac{\partial\left(\ln\left(\frac{Y_A}{Y}\right)\right)}{\partial\left(\frac{B}{L}\right)} > 0 \text{ and } \frac{\partial\left(\ln\left(\frac{Y_0}{Y}\right)\right)}{\partial\left(\frac{B}{L}\right)} < 0 \tag{8}$$

In this context, firms adopt the technology that emphasizes the factor whose relative supply, without any change in the price of the factor whose relative supply has fallen.

2.3 Empirical findings

2.3.1 Data

One of the important contributions of the authors is the data collection they operated for this study. They gather from different sources statistics on the population of bracero workers and the quarterly evolution of hourly and daily wages at the state level. They also combined them with the evolution of mechanization and harvest results of different crops over time.

For seasonal workers, they have monthly data at the state level from 1953[1] to 1973, combining both foreign and domestic workers. These data were collected by the Department of Labor and Department of Agriculture at the state level through a survey. The surveyed farms with more than 500 seasonal workers, any foreign workers, or with significant shortages of farm workers or surpluses available for other areas.

[1]They have data up to 1943 but they are incomplete.

A seasonal worker is defined as hired to work on a farm for less than 150 consecutive days. The data makes the distinction between Mexican workers and other legal aliens[2] and between domestic workers of different geographical origins (from the commuting zone, from the state but not the commuting zone, and from other states).

Wage data are provided quarterly and were collected from a separate sample issued by the Department of Agriculture. This data collection gathered wage information at the state level from farms employing more than 500 seasonal or migrant workers during each pay period. Respondents were asked to report the average wage rate in their locality at the time of the survey. From 1948 to 1970, the sample covered 20,000 to 25,000 farms nationwide. Two wage measures are available: the hourly wage rate (a weighted average of reported per-hour rates) and the daily wage rate. However, the daily wage measure excludes data from California[3], as well as Oregon and Washington for most of the period.

One limitation of this wage measure is that it likely does not account for differences between seasonal and non-seasonal farmworker wages. Following (Kaestner, 2020), we can also assume that seasonal and non-seasonal workers may be compensated in different ways (e.g., hourly wages, piece rates), which adds complexity to our analysis.

Statistics on the total number of hired people are collected through the Department of Agriculture survey described above, it covers 35 states between 1953 and 1973, and they include all workers doing one or more hours of farm work or chores for pay during the week. 11 states are missing[4] because there is no report at the state level but at the regional aggregation level (e.g. "New England".).

Finally, U.S. state population and harvested farmland data are retrieved from Richard Forstall (1996), *Population of the States and Counties of the United States: 1790 to 1990*, and the 1954 acreage of total harvested farmland by state from the Census of Agriculture.

2.3.2 Experimental Setup

CLP follows a quasi-experimental setup for the first regressions, they want to show that, accordingly with their model prediction when output, capital, and technology can adapt, they find no effect on employment and wages.

For that, they consider a continuous difference-in-difference approach following (Card and Krueger, 1993), where the treatment is the degree of exposure to the bracero exclusion. This exposure is the ratio of bracero workers as members of the seasonal workforce in each state for the year 1955. The authors justify their use of the year 1955 as being the maximum height of the program in the mid-1950s and long enough before the treatment. We will come back to this choice in the next section, so far we have kept the authors' approach.

$$y_{st} = \alpha' I_s + \beta' I_t + \gamma\big(I_{t\geq 1965} * \bar{l}_s^{1955}\big) + \varepsilon_{st} \tag{9}$$

where y_{st} is the outcome variable in state s at time t (month, quarter, year), I_s is a vector of state fixed effects, I_t is a vector of time fixed effects[5], $I_{t\geq 1965}$ is an indicator for the observation after bracero exclusion and $\bar{l}_s^{1955}$) is the exposure measure. The exposure measure is built as $\frac{L_{st}^{\text{mex}}}{L_{st}}$, the ratio of Mexican seasonal workers over the total number of seasonal workers. We denote ε_{st} as the error term, and α, β are vector coefficients of the fixed effects to be estimated. The standard errors are clustered at the state level. The coefficient of interest is γ, it captures, assuming parallel trends, the effect of the exclusion on the outcome variable.

[2]There is no estimation provided of illegal seasonal workers.

[3]This is a limitation, as California accounts for nearly 40% of Bracero workers.

[4]Arizona, Connecticut, Delaware, Massachusetts, Maryland, Maine, New Mexico, Nevada, Utah, Vermont, and Wyoming.

[5]The specifications varies with the regressions, year for yearly regression or quarter-by-year for quarter regressions.

Table 1: Differences-in-differences with continuous treatment, quarterly

	(1) Hourly Composite	(2) Daily w/o Board	(3) Hourly Composite (1960-1970)	(4) Daily w/o Board (1960-1970)
treatment_frac	−0.0356 (0.0426)	−0.385 (0.495)	−0.0401 (0.0315)	−0.0247 (0.309)
N	4324	5813	2024	1901
adj. R^2	0.773	0.835	0.733	0.758
N_clust	46	46	46	46

Standard errors in parentheses

Table 2: Semielasticities, DD with continuous treatment, quarterly

	(1) Hourly Wage	(2) Daily Wage rate	(3) Hourly Wage (1960-1970)	(4) Daily Wage rate (1960-1970)
treatment_frac	−0.0831 (0.0654)	−0.110 (0.0916)	−0.0750 (0.0507)	−0.0410 (0.0541)
N	4324	5813	2024	1901
adj. R^2	0.709	0.805	0.626	0.690
N_clust	46	46	46	46

Standard errors in parentheses

The first two columns use the hourly wage rate and the daily wage rate overall the period, and the other is concentrated between 1960-1970. Both return negative non-significant coefficients, in coherence with the theoretical model, with the rapid technology, capital, and output adjustment. We control for states and quarter-by-year fixed effects, to capture the state and time variations.

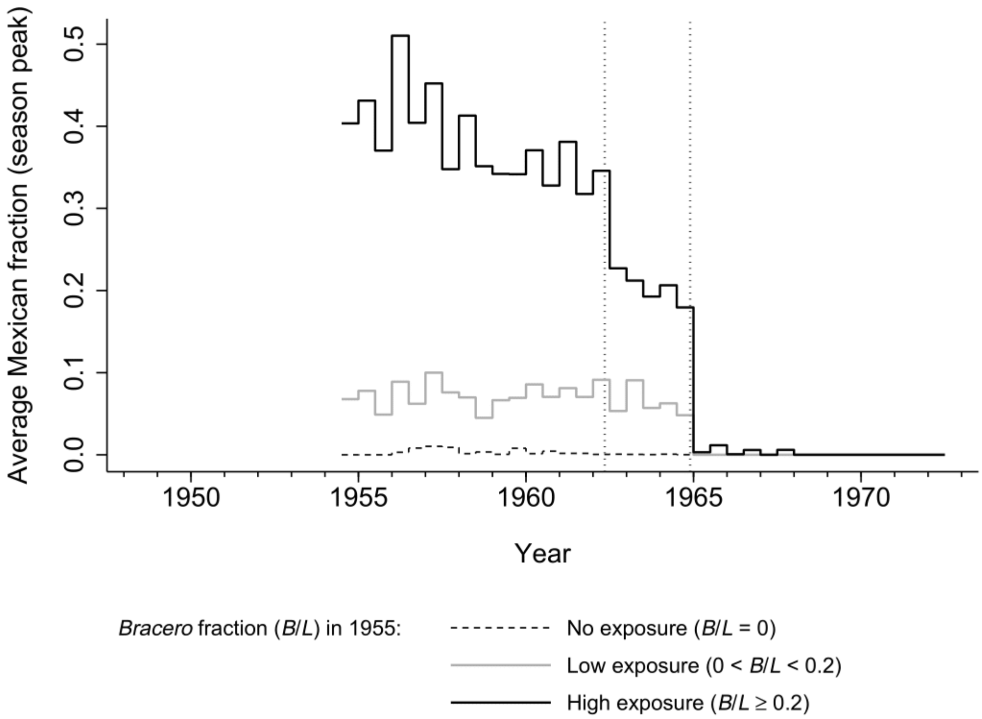


Figure 2: Illustration of the evolution of Mexican seasonal workers

The states most exposed, as defined by the 1955 criterion, experienced a significant decline in their ratio of seasonal Mexican workers. The first wage increase in March 1962 appears to have reduced this share from 30% to 20%, and the December 1964 ban brought the ratio down to 0%. In contrast, states with low exposure maintained a stable share of around 10%, which only fell to zero with the 1964 exclusion.

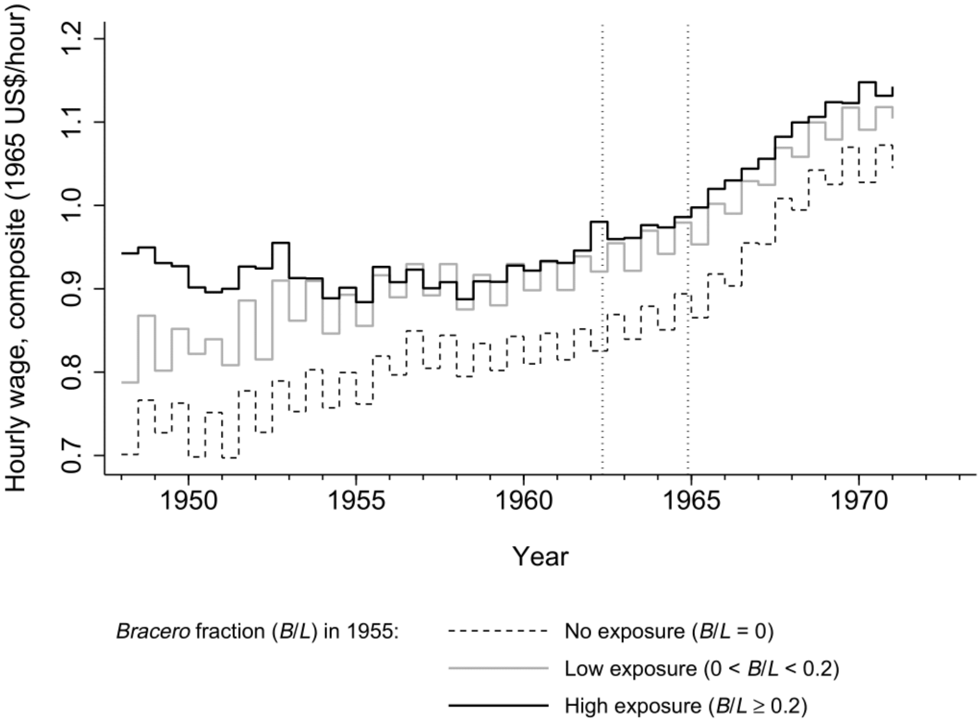


Figure 3: Evolution of wages in different exposed states

Wages appear to follow a parallel trend overall, with little direct response to the exclusion of Mexican workers. The wage increases highlighted by contemporary researchers and politicians seem to reflect a broader trend of general wage growth. Beginning in the early 1960s, wages started to rise, and by the late 1970s, wages in non-exposed states had nearly caught up.

Next, we extend our analysis to employment outcomes for domestic workers. Specifically, we examine domestic seasonal employment and distinguish among local workers (within a commuting zone), intrastate workers (outside the commuting zone but within the state), and interstate workers (from other states), as recorded in the data.

Figure 4: Number of Seasonal workers Employed, State Averages grouped by Exposure

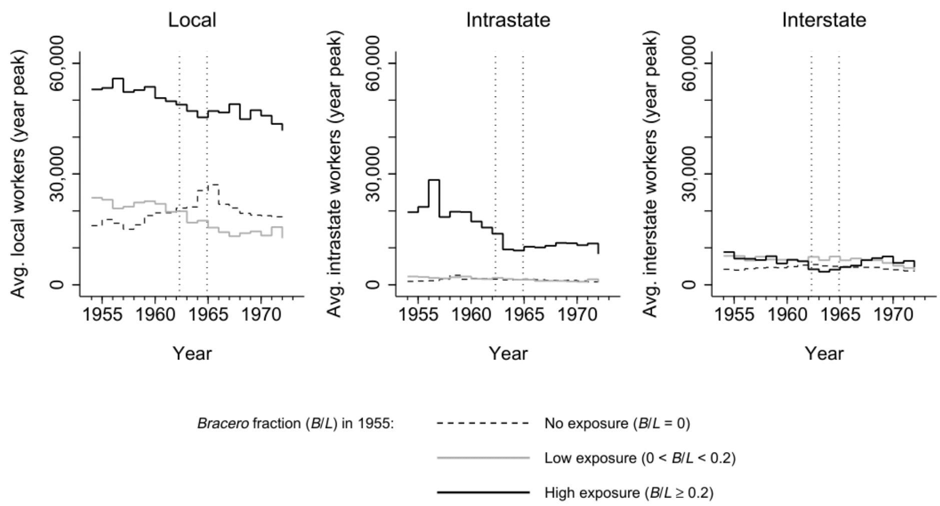


Figure 5: Number of Seasonal workers Employed by type of worker, State Averages grouped by Exposure

The descriptive evidence seems to point to no effect on employment for domestic workers. There has been a slowdown in the domestic employment decline of seasonal workers after the implementation of the policy, but the different exposed states seem to have contradictory results. The non-exposed states increased their share of domestic workers during the period, while at best it slowed down for highly exposed states and still declined for moderately exposed states. We also notice that the local, intrastate, and interstate employment of domestic workers is stable for the period in each group. Hence, despite a fall in the employment of thousands of workers, there is no substitution for domestic employment.

This null result is confirmed by the regression tables below. The linear or log outcomes are not statistically different from zero in more exposed states. We obtain similar measures when separating domestic workers into three types. This confirms our descriptive evidence that there was no move of seasonal workers in substantial numbers to alleviate the state-specific shock due to the exclusion of thousands of Mexican workers.

	(1) Linear (All States)	(2) ln (All States)	(3) Linear (1960-1970)	(4) ln (1960-1970)	(5) Linear (Exposed States)	(6) ln (Exposed States)
$I_{t>1965} * l_s^{1955}$	−6949.2	−0.311	1843.0	−0.113	312.2	−0.142
	(9093.5)	(0.509)	(6859.3)	(0.375)	(7463.0)	(0.566)
N	10329	6386	6072	3707	5168	3189
adj. R^2	0.055	0.085	0.079	0.076	0.028	0.053
N_clust	46	46	46	46	23	23

Standard errors in parentheses

	(1) Local	(2) Intrastate	(3) Interstate	(4) Local (ln)	(5) Intrastate (ln)	(6) Interstate (ln)
$I_{t>1965} * l_s^{1955}$	−2971.3	−9083.2	578.7	−0.472	−0.997	−0.574
	(4677.9)	(9777.7)	(1127.7)	(0.738)	(0.639)	(0.458)
N	10329	6370	6371	6736	4720	5773
adj. R^2	0.055	0.052	0.016	0.064	0.080	0.052
N_clust	46	46	46	46	46	46

Standard errors in parentheses

Finally, and to corroborate their results, the authors propose to control for the evolution of crop production and automatic harvesting machines in agriculture following the exclusion of Bracero workers. Figure 9 proposes the evolution of crop production between 1951 and 1972 and Figure 10 establishes that in 1964, the year before the exclusion of Mexican workers, the crops most dependent on this cheap labor force were tomatoes, lettuce, cucumbers, melons, and celery. They established an index of mechanization, being the share of harvesting done by a machine. They show that after the implementation of the policy, there is a positive and significative increase in the share of mechanized harvesting while there is a global decline in both Mexican and domestic workers employment.

	(1) Cotton mech.	(2) Sugarbeet mech.	(3) Cotton mech.	(4) Cotton mech.	(5) Sugarbeet mech	(6) Sugarbeet mech
$I_{t>1964} * l_s^{1955}$	1.205	1.363				
	(0.258)	(0.384)				
$ln(L^{mex})$			−0.113	−0.0891	−0.0764	−0.0658
			(0.0308)	(0.0230)	(0.0176)	(0.0141)
$ln(L - L^{mex})$				−0.181		−0.127
				(0.115)		(0.0468)
N	344	48	97	91	32	32
adj. R^2	0.105	0.129	0.203	0.277	0.253	0.322
N_clust	16	12	9	9	11	11

Standard errors in parentheses

Following the authors' methodology, we were able to reconstitute these results. To be shorter we compute them in the Appendix.

2.4 Robustness Checks

To ensure the robustness of their results the authors propose three main approaches : (1) semi-parametric estimation of wages and employment reaction to the bracero exclusion, (2) casting pre-trends to ensure that the parallel trend assumption, crucial to difference-in-difference, is validated, and (3) evidence that the legal Mexican workforce was not substituted for an illegal one.

2.4.1 Semi-parametric estimations

The authors adopt the semi-parametric estimation approach from (Baltagi, 2002) to analyze real wages and employment variation in the states most exposed after the Bracero exclusion. This method accounts for potential endogeneity and provides more consistent fixed effects. Their findings support the CLP claim of a null effect.

2.4.2 Pre-Trends

A common threat to difference-in-difference design is the credibility of the parallel trend assumption. Exposed states, as defined by the author, must have a common trend before treatment with the control group (non-exposed states), so that the eventual post-treatment gap is due to the policy effect only.

To test for this parallel trend assumption they recast their data as a year-by-year event study, and this reveals no significative pre-trends for wages but significative ones for employment, as shown respectively in Figure 11 and Figure 12. They acknowledge these pre-trends but argue that they find no pre-trend when the sample is restricted to states with non-zero exposure to the treatment.

2.4.3 Illegal Seasonal Worker

Another concern with the authors' results is the potential presence of former Bracero workers as undocumented laborers after the program ended. This issue is a primary point of contention raised by other researchers (Kaestner, 2020; Clemens, Lewis and Postel, 2020).

Critics argue that the authors may have underestimated the number of undocumented Mexican workers entering the U.S. after the repeal of the Bracero agreement, potentially biasing the estimates downward and explaining the zero effect observed in the difference-in-difference analysis. Even a gradual phase-out of Bracero workers after 1965 could skew the results.

To address these criticisms, the authors primarily focus on two areas: the possible substitution of Mexican workers by other immigrant laborers, and the number of undocumented migrants apprehended at the border post-exclusion.

The authors investigate the possibility of substitution effects by analyzing data on the total number of hired farm workers from 1957 to 1973. However, this dataset has three limitations: (1) it does not include 1955, the treatment year, (2) it does not differentiate between domestic and other foreign workers, and (3) it has missing data for eleven states.

To evaluate potential substitution, the authors focus on overall employment in states exposed to bracero workers. They regress the monthly total of hired farm workers on the number of bracero workers, adjusting for scale differences using three plausible scaling factors: total hired farm workers in 1957, state population in 1950, and harvested crop area in 1954. Since bracero workers are included in the total hired worker count, a null hypothesis of no substitution would be reflected in a regression coefficient of 1 (a "coefficient of unity"). This would imply that hiring braceros does not affect the employment levels of other workers.

In all models, the results do not support a coefficient of unity, indicating no significant evidence of substitution effects on employment. However, this does not fully exclude minor substitution effects, especially by unauthorized Mexican workers, as data from certain key states, like Arizona and New Mexico, are missing. Nonetheless, crucial states with significant exposure, such as Texas and California, are included in the analysis and do not show substitution effects. Overall, the findings provide no substantial evidence of a substitution effect between authorized bracero workers and unauthorized Mexican workers.

Another explanation that might explain the no-effect of bracero exclusion could be the non-departure of Mexican workers, after exclusion they would have stayed on the territory or come back illegally. Even if plausible, there is limited support for this theory. After the ban, most of the Mexican workers went back to Mexico according to the Mexican government in charge of recruiting and tracking them under the agreement. Close to 100% went back home, and if illegal Mexican workers were to replace immediately the former braceros then we should have seen a massive jump in illegal apprehension near the border, which was not the case. Additionally, these findings of limited illegal immigration flows from Mexico in the 1960s are coherent with the literature on the topic (Massey and Pren, 2012).

3 Critics

3.1 Pre-trends analysis

A key hypothesis of the difference-in-difference design is that treated and control groups follow a parallel trend before the treatment occurs, making the eventual divergence appearing after the treatment implementation (i.e. 1965) the causal change in the trends.

The authors claim to have tackled this issue in the following way :

Numerous additional robustness tests are reported in the online Appendix. First, inspection of panel A of Figure 3 suggests that pre-trends could bias the results of difference-in-differences regressions. Recasting the regressions as a year-by-year event study reveals no significant pre-trends in wages. In employment there are significant pre-trends, but not when the sample is restricted to states with non-zero exposure to the program. The results are not sensitive to this restriction, though even the restricted sample retains states with a wide range of exposure (Table 2, columns 5–6). Neither the results for wages nor employment are substantially affected by including state-specific linear time trends in the difference-in-differences regressions.

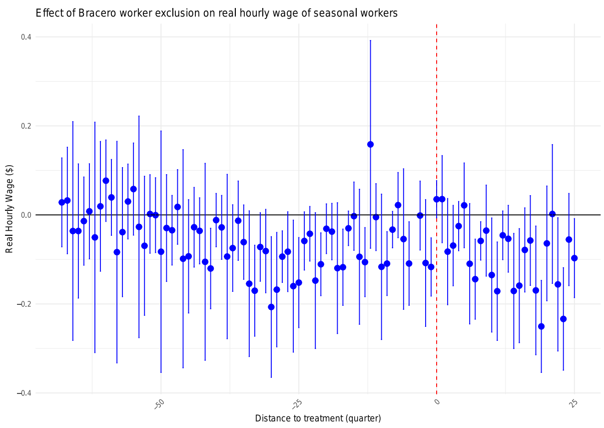
We will see that despite their claim, we still find pre-trend in most configurations. This cast doubt on the overall validity of the results.

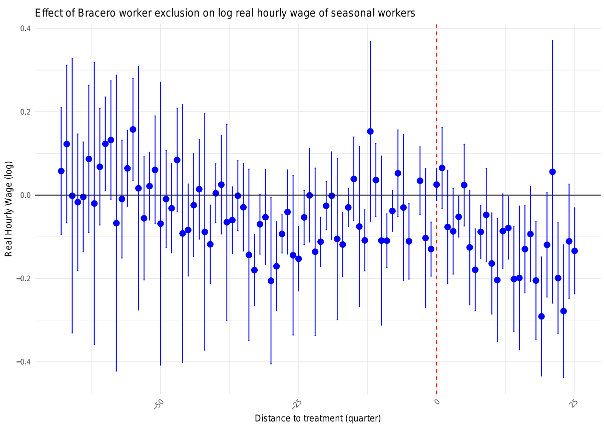
3.1.1 Quarter-by-Year

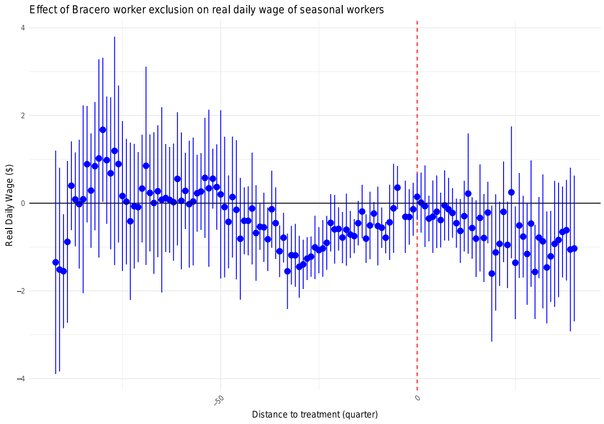
We propose to recast all the previous regressions of Section 2 as an event study to observe eventual pre-trends. A violation of the pre-trend assumption would cast doubt on the causal effect of Bracero's exclusion on workers.

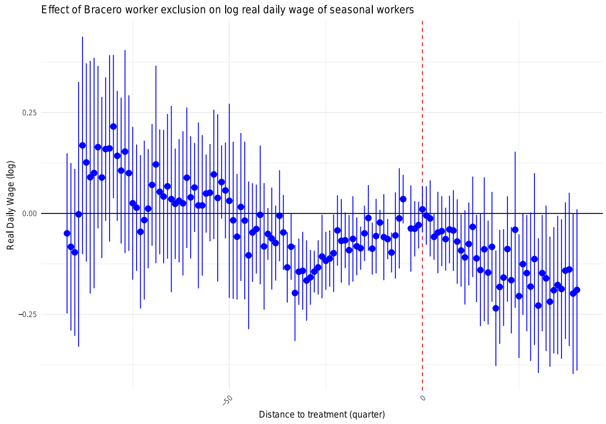
Regressions are based on equation (9). We adopt quarter-by-year fixed effects and cluster the error at the state level. The confidence intervals displayed are systematically at 5% level of confidence.

On the left axis, we have the real hourly and daily wage, and on the right axis the log of these measures.





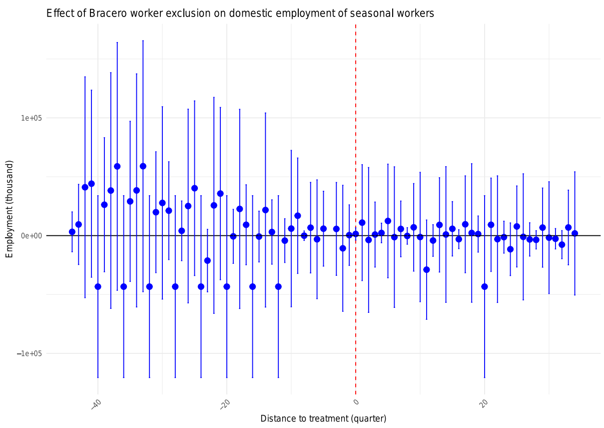


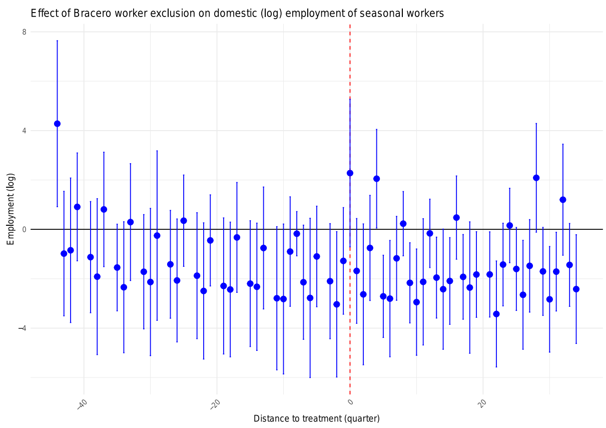


For hourly wage, even if the confidence intervals are large and point out that there are no significative values for a certain amount of quarters, we cannot avoid admitting that we can identify negative pre-trends. The most intense quarter in the use of Mexican workers are negatively impacted by the presence of Mexicans and this is constant in before and after treatment.

The results are less clear concerning the daily wage rate and would tend to support CLP claim if it were not for the trend in the quarter preceding and following the treatment. They are negative and significantly different from 0 at the 5% level and the effect is getting larger with time.

Considering the impact of domestic employment, the authors admit they found a pre-trend and their dataset offers possible explanations for the movement of domestic seasonal workers (they can be within the commuting zone (local), in the state but not in the commuting zone (intrastate), from another state (interstate)). This allows us to distinguish the potential substitution effect that would occur if domestic U.S. workers were to replace non-domestic ones.



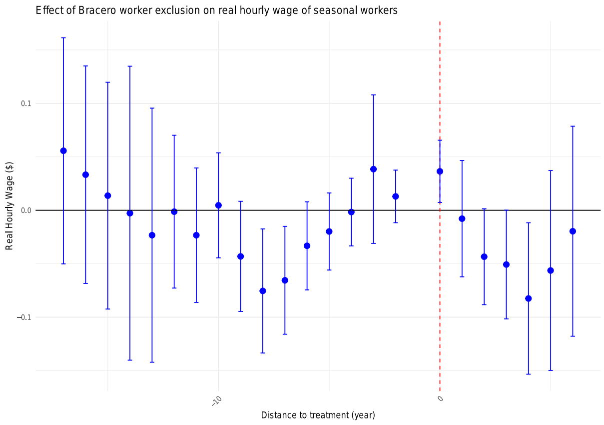


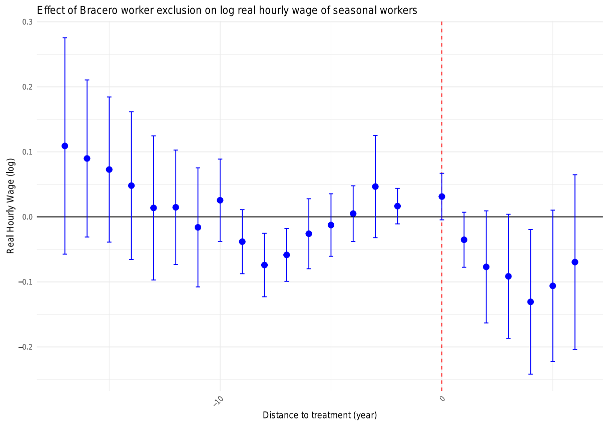
Once again we find negative pre-trends in most cases for log (right axis), leading us to reject a causal interpretation of the impact of Bracero workers on domestic workers. However, the pre-trend for non-log analysis and employment outcome of local, intra- and inter- state workers did not vary following the ban (see Appendix), which would tend to support the authors' claim. Then, for employment, the results are puzzling but still would push to accept, with caution, a causal interpretation of the effect of the bracero ban.

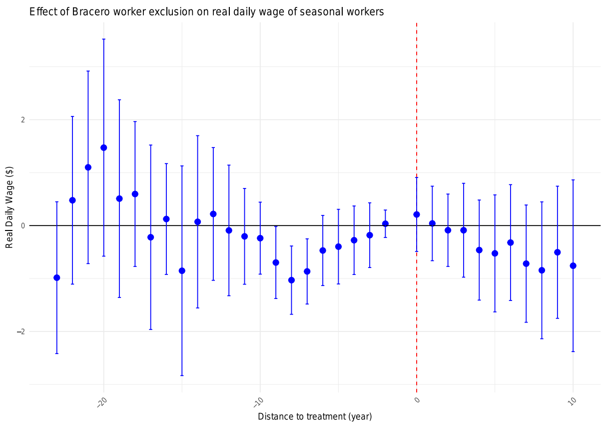
Overall, despite CLP claims their result seems to be sensible for an event study recasting, leading us to question the overall validity of the causal assumption. Following CLP, recommendation, we turn to the year-by-year analysis.

3.1.2 Year-by-Year

Shifting to a year-by-year fixed effect reduces the intra-year variations, it would smooth the strong quarterly effects observed in the previous sections. This approach, however, being more conservative on variance, would lead us to reject more categorically the parallel-trend assumptions.

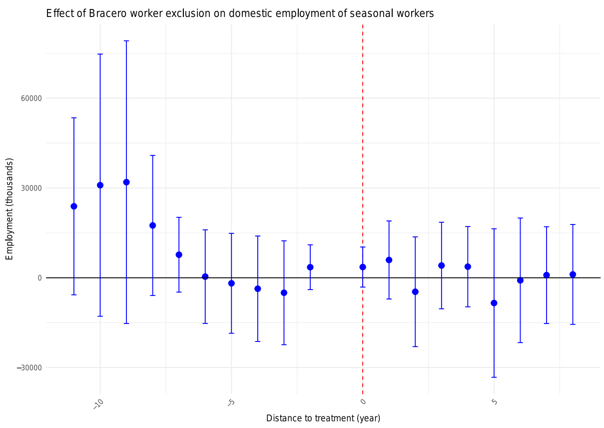


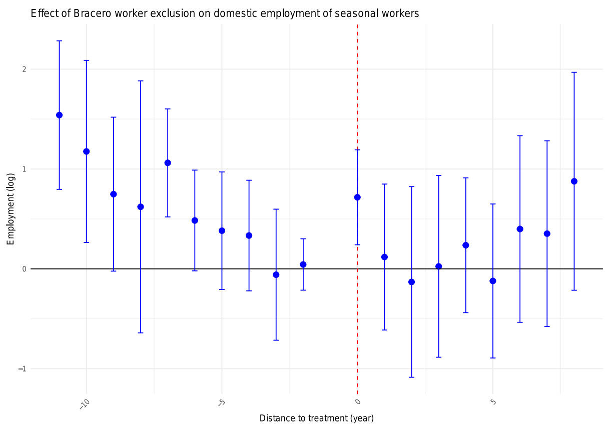




On the left axis, we observe the yearly hourly and daily wage rate in dollars, and on the right log variation. For hourly wages, we can observe small and statistically significant estimates 9 to 6 years before the treatment and a clear positive effect the year of the Bracero exclusion, followed by a statistically significant negative effect. Daily wages return more mixed results but the log estimate is also negative post-treatment even though not significant at the 5% confidence interval.

Considering the effect on domestic workers, the effect in thousands of jobs appears non-significant with no pre-trend but the log variations clearly challenge this result. We can observe consistent negative trends up to 3 years before the treatment and a positive effect the year of the treatment.





However, CLP prefers the setting with only the most exposed states. To be consistent in our robustness analysis we then computed them in the Appendix. The effects appear to be even stronger when we separate low and high exposition states. Highly exposed states have an even larger effect on wages with a clear negative trend after the exclusion.

Overall, even in CLP's preferred specification, the parallel-trend assumption is either challenged (with significative pre-trend) or we cannot admit that there is no effect of the bracero worker exclusion. The reasons that might explain these pre-trends can be of two orders: (1) confounding factors acting on the outcomes differently in exposed and less exposed states (2) a problem of definition of the treatment group which might be inconsistent over time.

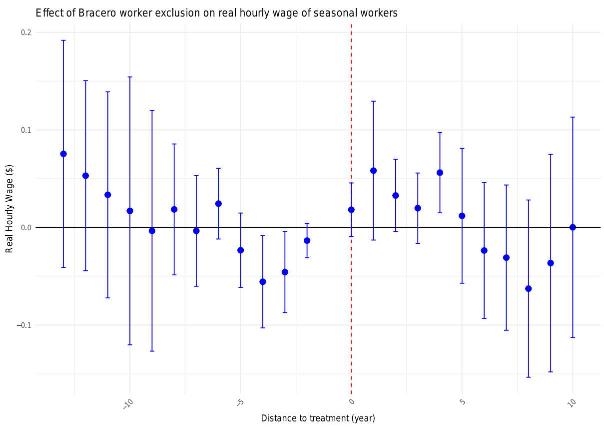
3.2 1962, a confounding year

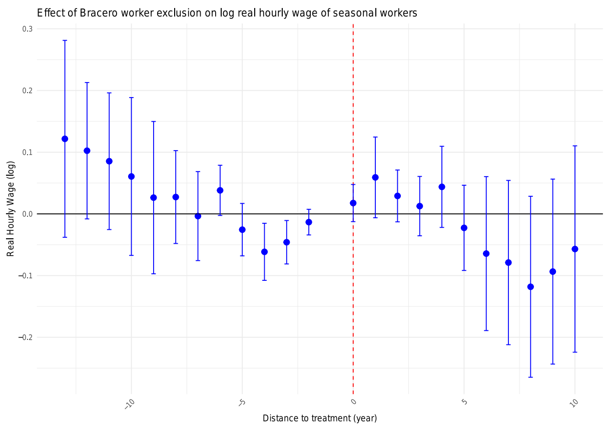
As CLP mentioned a possible confounding factor is the Kennedy reform in March 1962. At this time the administration wants to prevent domestic workers from being hurt by the concurrence with Braceros, a common belief at the time. Therefore, the Kennedy administration implemented an increase in the minimum wage at which Bracero workers could be hired and reduced the flux of workers. This resulted in a first reduction in the flux of Bracero workers in the early 1960s as shown in the Figure 4.

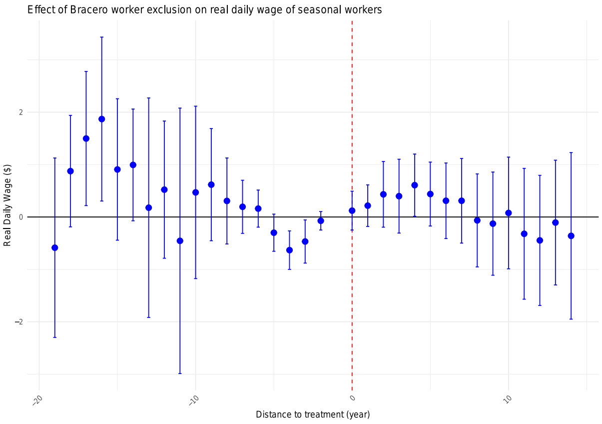
CLP evaluates the potential effect of this year as a confounding factor but they claim they found no effect.

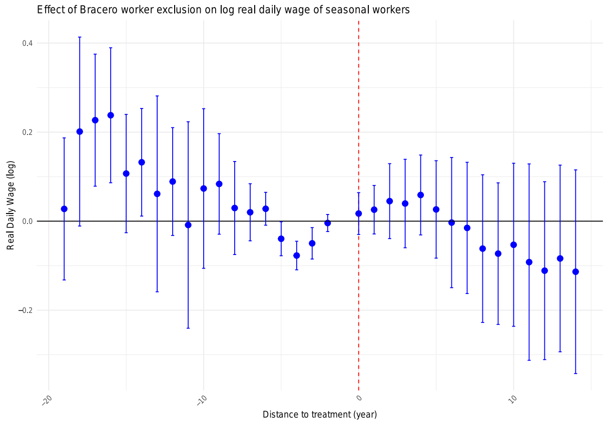
> *Here we present re-analysis of the main text Tables 1 and 2 with the new assumption that 'treatment' begins in 1962, when the first major restrictions were placed on farms 'hiring of braceros, rather than 1965 when the program was terminated. Table A7 shows the differences-in-differences analysis of wage effects under this new assumption, and Table A8 shows the analysis of employment effects. There are no substantial differences from the original results.*

For this we choose to depart from their approach and to re-analyze our data but setting the treatment year in 1961 and the reference year in 1960. The rationale is that farmers can anticipate the reversal of the agreement with the election of Kennedy in 1960 and then start reacting in 1961. This small adjustment should not have a major impact on the results but to take into account potential anticipatory effects.

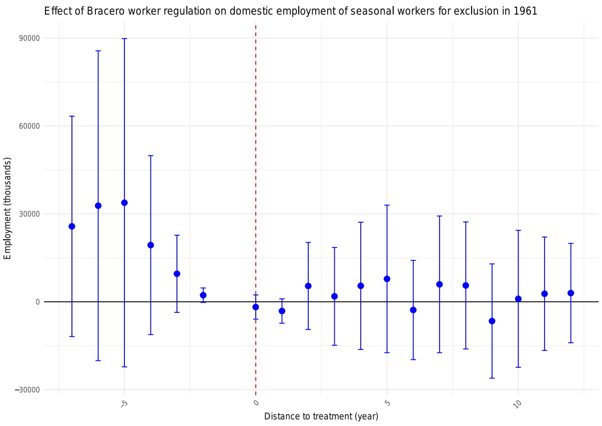


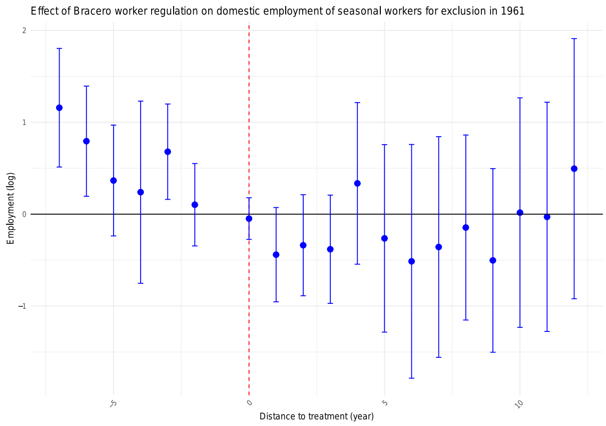






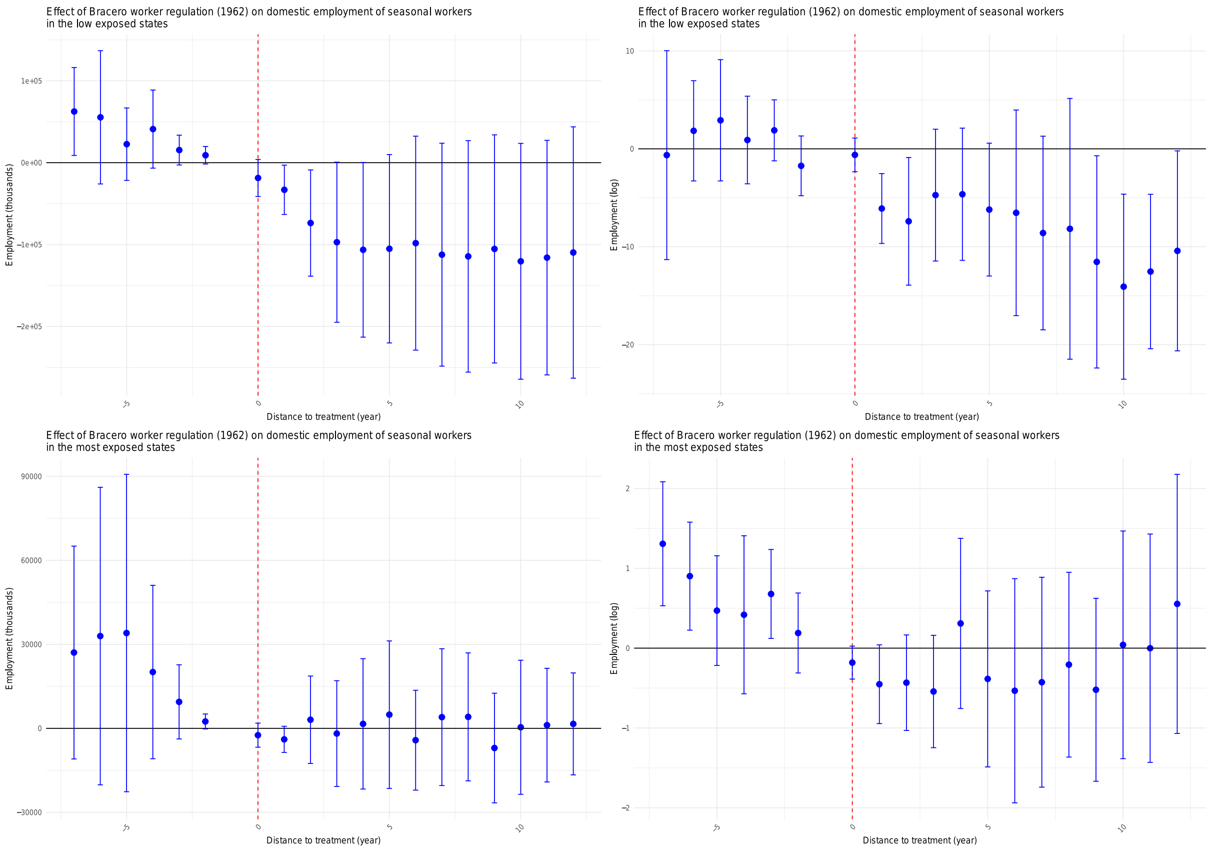
In this configuration, we can identify that in the five years preceding Kennedy's intervention, there is a slight negative pre-trend and a small but significant (10% level) positive effect on hourly wages in the year following. We cannot assess with certainty the causality of this estimation given the trends we observe, but something seems to be happening around the treatment period. This reinforces our conviction that locally, Kennedy's measure might have had an impact explaining partly the pre-trends we observe.





The figure above describes the effect of 1962 on employment in the different states in thousands of jobs and log. We observe a net declining pre-trend in the year preceding the intervention and a stabilization around 0 after.

When we distinguish the effect between low- and high- exposed states, we can observe that the states reacting more and showing the biggest trends are the low-exposed ones. They know strong declining trends before 1962 and even after. Nonetheless, log outcome tends to temper these results even though we can observe still declining estimates in the following years.



Hence, if the analysis of 1962 intervention does not bring unambiguously clear results, we can still accept cautiously a small negative effect on domestic employment and, most likely, small or no effect on wages. These results are not totally in line with our findings in the previous question, wages reacted more than employment. All in all, it seems hard to reach a clear conclusion on the effect of excluding Bracero workers from seasonal workers for domestic workers' wages or employment.

3.3 Unstable Treatment Group

An explanation for this difficulty in reaching a convincing pre-treatment parallel trend might be due to the definition of the treatment group itself. Indeed, CLP proposes to take 1955 as a treatment year, however, there is no clear justification for choosing this year. We can guess that it is one of the oldest years with all the data available and sufficiently far from 1965 (or 1962) so that we cannot suspect anticipation effects.

Nonetheless, this choice is highly arguable. 1955 appears to be an outlier in the data and choosing 1957 would have brought a different treatment group. Moreover, the treatment intensity varies considerably over the period running with some counter-intuitive results as non-exposed states like Colorado becoming treated and treated states like South Dakota and Nebraska becoming low-treated states.

Evolution of Treated, Low treated, and Control group				
Year	Not Treated	Low Treated	Treated	Total
1953	20	21	6	47
1954	24	19	3	46
1955	23	17	6	46
1956	19	22	6	47
1957	18	24	5	47
1958	23	19	5	47
1959	23	20	4	47
1960	20	22	4	46

Figure 6: Table of the evolution of the different group over the year

Some years have fewer states than others, this is mainly due to missing data for New Hampshire and Rhode Island. We can see that the number of states in the treated group largely fluctuates between 3 and 6 over the period. The groups are formed following CLP process, states with more than 20% of their seasonal workers being Braceros are considered highly treated, those at 0 are controls, and those between, low-exposed.

This fluctuation is problematic in itself, as there is no clear demarcation between the groups, and exposure intensity varies greatly, as shown in Figure 7. These variations arise from how the instrument was constructed: by using the ratio of Mexican seasonal workers to all seasonal workers, it becomes sensitive to small changes in states with only a few Mexican workers. This sensitivity explains the dramatic declines observed in South Dakota and Nebraska in the late 1950s and in New Mexico after 1962.

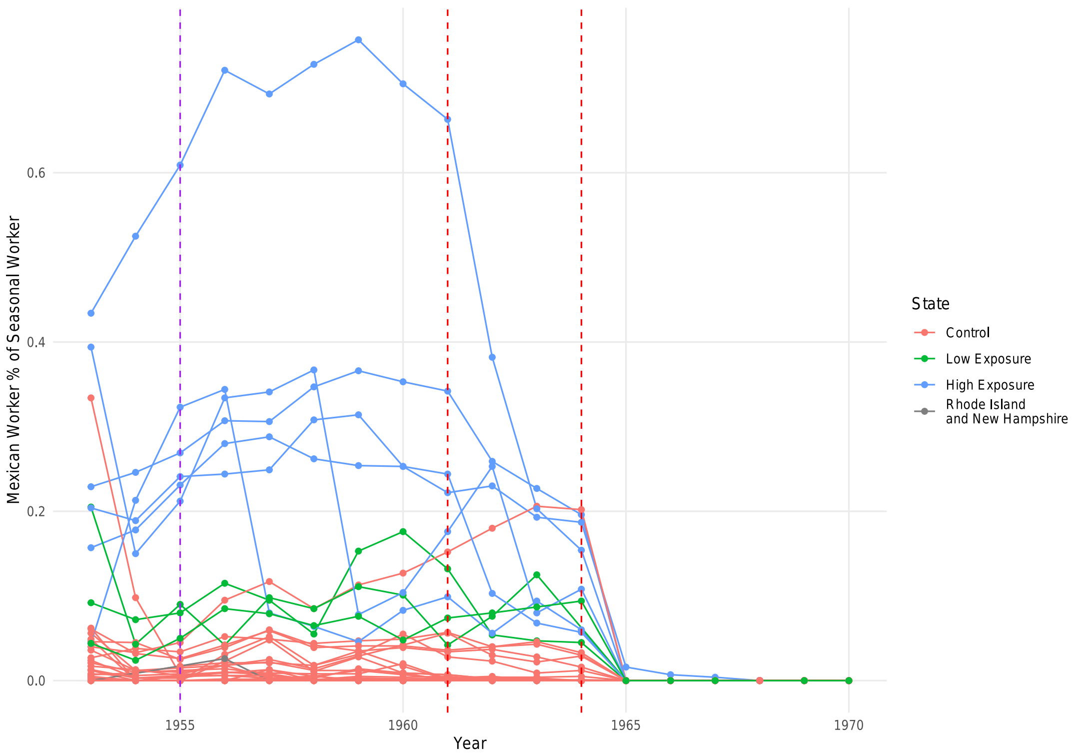


Figure 7: Variation of exposure to treatment by group over the years

When comparing states more precisely the variation intensity appears even more clearly. First, as we supposed, 1962 seems to have had a massive impact on the state exposure despite CLP claims. Second, we can observe a reduction in the Bracero exposure starting in the mid-1950s with most states but some outliers like Colorado or New Mexico, reducing their exposure to the Mexican workforce. It is hard to distinguish if it is due to the restructuration and modernization of American agriculture in the after-war period (Dimitri, Effland and Conklin, 2005) or to some anticipation of the Bracero agreement reversal coming progressively by the end of the 1950s.

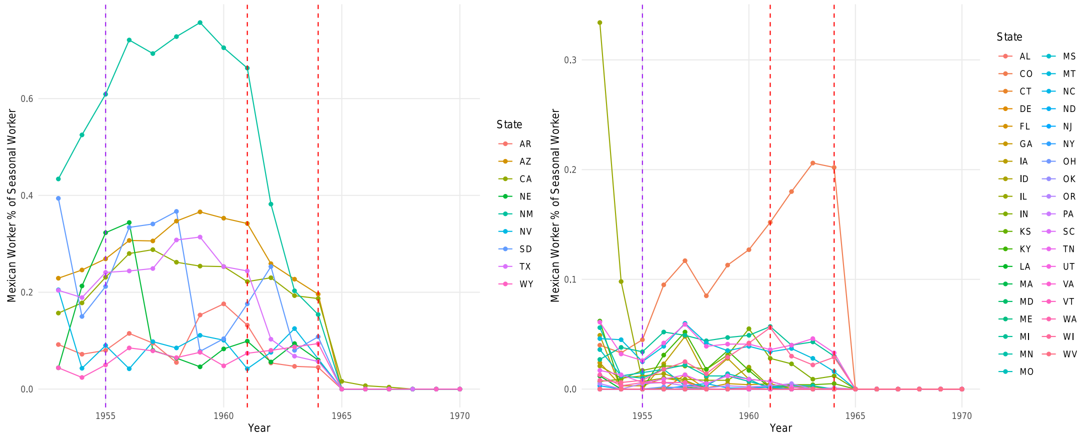


Figure 8: Variation of exposure to treatment by state over the years

In any case, the continuous treatment of the exclusion policy and the unstable exposure of the different states led us to think that there are limitations to the estimations that were provided by CLP or the author.

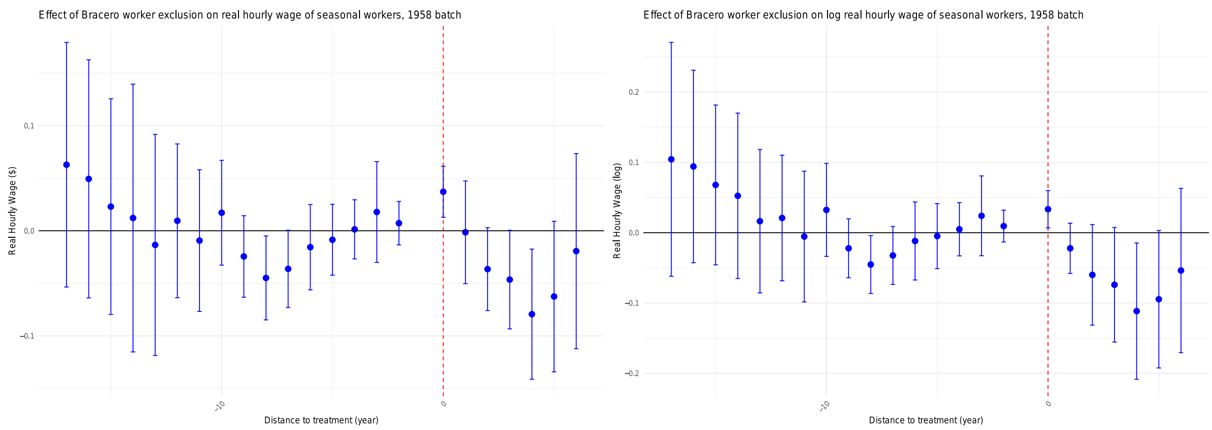
To overcome this issue, we propose two extensions: (1) preserving their analysis but changing the treatment group to one more stable, and (2) implementing synthetic control in California and Texas.

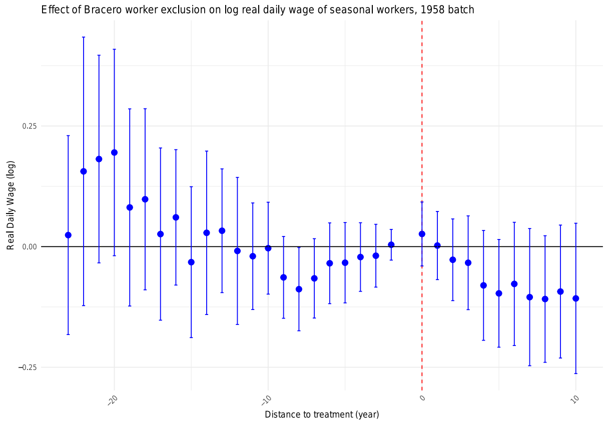
4 Extensions

4.1 New Treatment Group

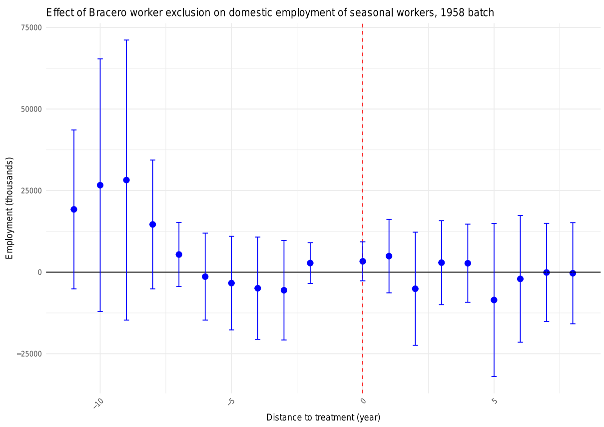
We propose to complement CLP analysis by taking the share of Bracero workers for the year 1958. This year is more stable as shown in Figure 7, and cleaned of South Dakota and Nebraska which reduced considerably their exposure between 1955 and 1958.

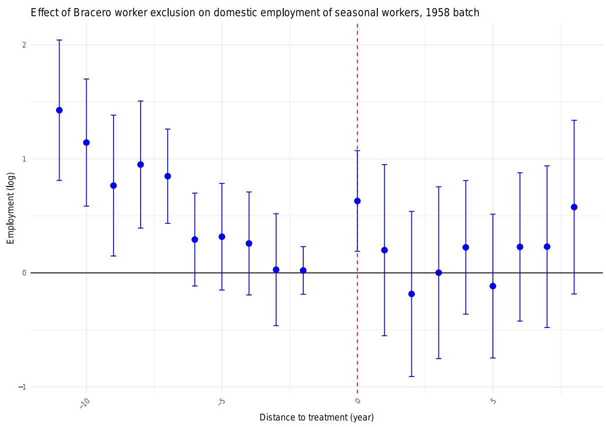
We propose the same regression as CLP and keep with the year-by-year fixed effects.





Taking 1958 as a reference year for the treatment slightly improves the pre-trends though it does not get rid of them. We have no pre-trend in a period of 6 years before the application of the 1964 ban, but we see some variations between the 7 and the 10 years. Finally, there seems to be no effect on daily wages, but hourly wages react more. We see a positive effect the year of the ban, followed by small negative effects on wages for 4 years. At maximum, it represents 10% negative variation 4 years after the bracero exclusion, in most exposed states.





Domestic employment is still having consequent pre-trend though it stabilizes 6 years before the treatment. We also see a positive jump in domestic employment (about 8%) the year of the ban, but this goes back to 0 the year after.

Using a new treatment group has slightly improved our previous results and added nuance to our findings. It appears that the employment and hourly wage effects of the policy were positive during the year of the ban. This outcome aligns with Proposition 2 of the CLP model: if only capital adjusts, and not production or technology, we might expect a modest increase of approximately 0.1 in both wages and employment. This effect, however, is short-lived; farmers appear to have adapted quickly, substituting domestic workers with other labor sources or harvesting machinery.

In the medium term, hourly wages continue to decline, making it difficult to interpret the underlying causes. Is this due to an underestimated level of undocumented migration, which would increase competition for domestic workers? Or does the adoption of harvesting machinery reduce labor demand to the point that farmers are unwilling to pay above the minimum wage? Despite these possibilities, we must delve deeper into our analysis, as the presence of pre-trends still restricts the causal interpretation of our findings.

4.2 Synthetic Control

A complementary approach could be the Synthetic Control (SC) method (Abadie, 2021), which enables a case study of individual states like California and Texas. The SC approach has advantages over traditional difference-in-differences: it assigns positive weights to each unit that sum to 1, avoiding the issues of negative weights and extrapolation. Additionally, by constructing combinations of untreated units, SC creates a "tailored" control group that closely matches the treated unit, relaxing the parallel trends assumption required in difference-in-differences.

To assess the effects across all treated states, we could have used the Synthetic Difference-in-Differences approach (Arkhangelsky *et al.*, 2021). However, given the ambiguity in defining a treatment group, it is clearer in our case to focus on individual states. Examining states independently allows for more heterogeneity in the results, which is particularly relevant in agriculture, where endogenous factors like crop type can constrain the choice of capital and technology.

In our extension, we include only California and Texas as treated units, while the "pool of donors" (control units) consists of consistently less exposed states.

We exclude Arizona and New Mexico from the sample since they cannot serve as clean control units due to their exposure to treatment. However, they are also not considered treated states due to their small size; they could be reintegrated as treated in a more detailed analysis.

The donor pool is composed of non-exposed states, except Colorado, which displays a distinct trend and thus does not qualify as a suitable donor. Including Colorado could distort the results, as it might receive significant weight due to its climate and crop similarities with California.

Treated	**Donor Pool**	**Excluded**
California	Other States[6]	Arizona
Texas		New Mexico
		South Dakota
		Nebraska

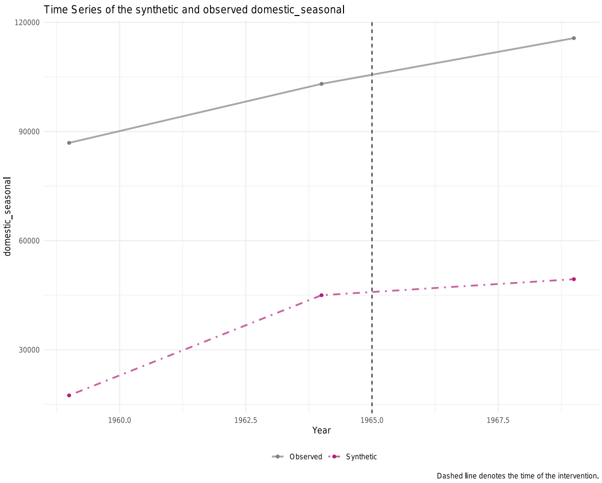
The SC method calculates weights for states and covariates over time, and then applies these weights to reweight the control group estimation. After treatment occurs, we use the pre-treatment weights to estimate expected values for the outcome variable and observe the gap between the observed and synthetic data. For our analysis, we used variables such as crop types (in tons) averaged by year and state when available, as well as tractor counts, real hourly wages, and real daily wages.

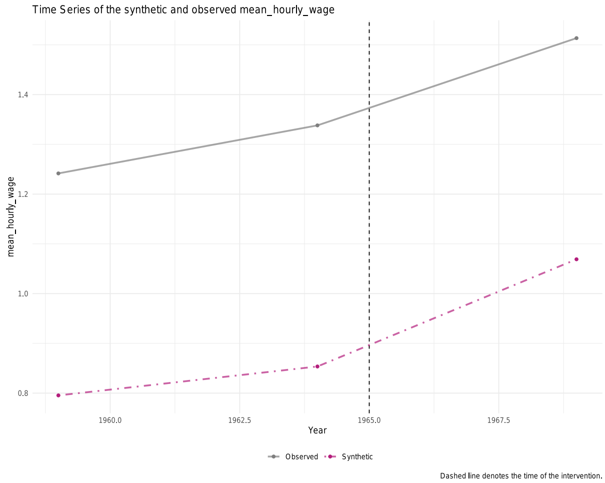
California

At first glance, we observe a small positive effect on domestic employment in California, with almost no effect on wages. This result is surprising, as previous findings indicated either no effect or a slight negative effect on domestic employment. This difference could stem from trend adjustments or from the nature of crops grown in the area (primarily tomatoes and strawberries), which require intensive labor[7]. This labor intensity may make short- and medium-term adjustments more challenging leading us to accept the second proposition of CLP's model.

[6] AL,AR,CT,DE,FL,GA,IA,ID,IL,IN,KS,KY,LA,MA,MD,ME,MI,MN,MO,MS,MT,NC,ND,NH,NJ,NV,NY,OH,OK,OR, PA,RI,SC,SD,TN,UT,VA,VT,WA,WI,WV,WY

[7] as noted by CLP in their paper, p.15



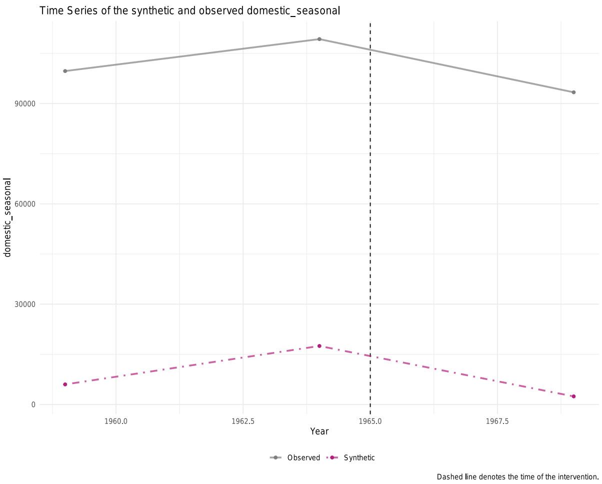


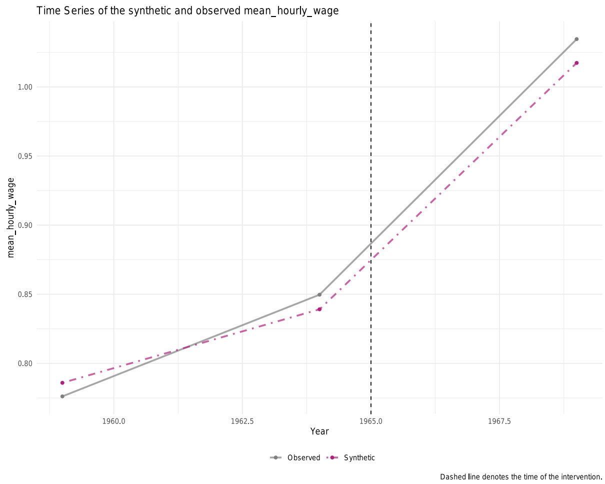
In constructing the synthetic control for California, we observe in Figure 13 that Florida and Illinois receive the highest weights, particularly when focusing on mean wage comparisons. The primary variable influencing this outcome is the availability of tractors. When examining employment, Florida once again serves as the main control state, reflecting its labor-intensive production of tomatoes and strawberries. These crops, along with similar climates, make Florida and California comparable; additionally, Caribbean immigration may affect wages and employment in Florida in ways similar to the influence of Bracero workers in California and Texas.

While we cannot make a definitive causal claim—further robustness testing would be needed—we suggest there may be a heterogeneous effect of the Bracero exclusion, varying according to crop type and labor demands.

Texas

There appears to be no distinguishable effect of the Bracero exclusion on wages or domestic employment in Texas. As shown in Figure 15, strawberries are the primary variable influencing wages, while a mix of crops—mainly cotton, tomatoes, and strawberries—drives domestic employment comparisons. While tomatoes and strawberries are particularly labor-intensive and challenging to automate, cotton has seen significant mechanization advances over this period, making it more adaptable to labor shocks. In terms of comparability for these variables, the closest states were Montana, Illinois, and Missouri.





At this stage, it remains impossible to conclude any causal relationship from the results provided by the SC method. To strengthen the credibility of our estimates, we propose the following robustness checks:

- Compare states with similar types of agriculture and climate. For instance, while tomatoes may be grown in New York, the agricultural practices there are likely quite different from those in Texas.
- Control for the presence of other foreign minorities (e.g., Caribbean populations in Florida) or other minority groups (e.g., Black populations).

In sum, the SC method appears to be a promising approach for evaluating the effects of this policy, which seem to be heterogeneous and, in any case, modest.

5 Conclusion

CLP has provided a valuable first quantitative evaluation of the Bracero policy and developed an important dataset on U.S. agriculture from the 1950s to the 1970s. However, this replication has exposed significant limitations to their claim of no effect on wages and employment from the Bracero exclusion. Pre-trends are evident in most configurations, challenging the parallel trend assumption crucial to difference-in-differences analysis.

Some of the extensions we proposed slightly improve the results and suggest a small, short-lived positive effect on employment and wages in the year of the exclusion. However, this effect quickly returns to zero or even becomes negative in certain hourly wage configurations. These findings should be interpreted cautiously, as they also suffer from pre-trend issues similar to those in CLP's analysis.

While the Synthetic Control method reduced our pre-trend concerns and provided insight into potential heterogeneous effects between states, the results are not definitive. Further investigation and robustness checks on the selection of control states are needed.

Overall, we cannot decisively confirm or refute CLP's thesis. Some findings align with theirs, and their model shows promise for explaining employment variation by crop type. A valuable direction for future research would be to examine the heterogeneous effects of the policy depending on the type of agriculture.

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6 Appendix

6.1 Authors Appendix

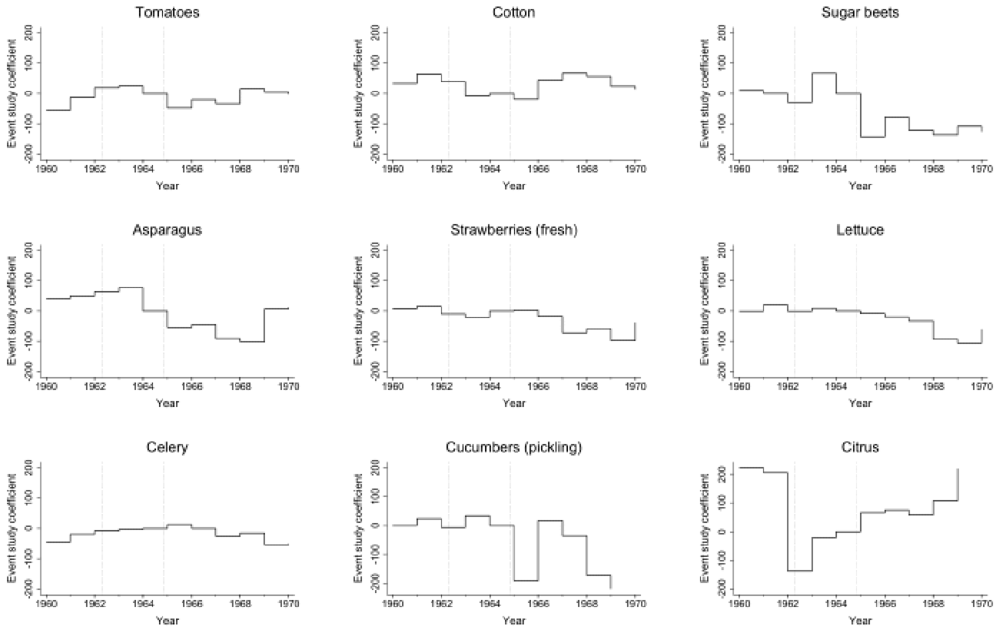
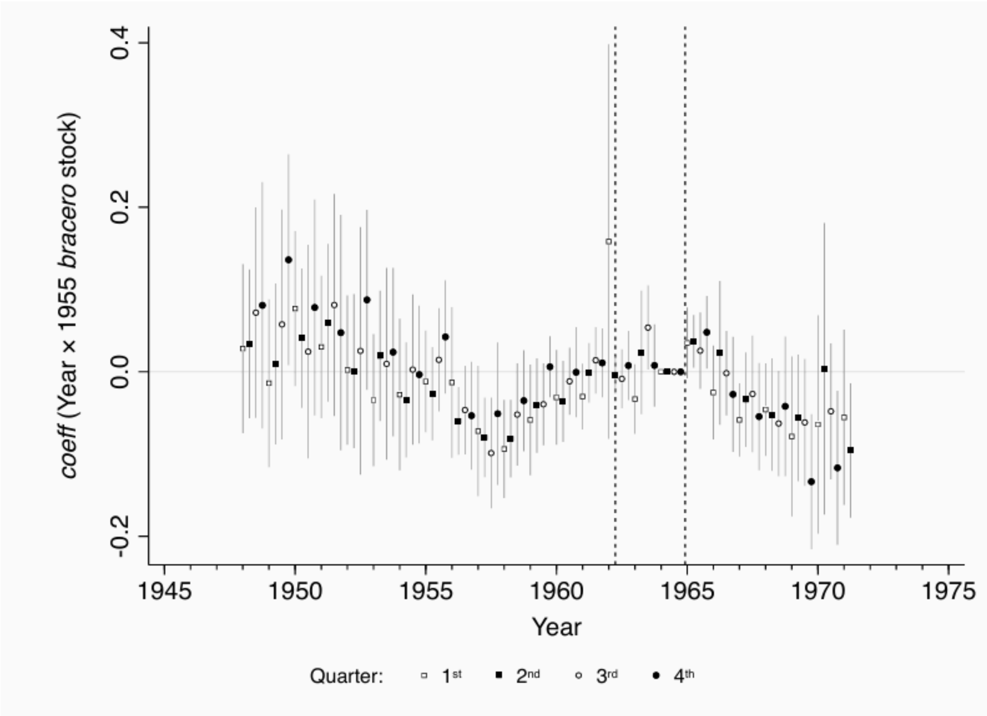


Figure 9: Event Study Regression Coefficients: Crop Physical Production Index

Crop	Thousand man-months Total labor	Thousand man-months Foreign labor	Foreign/ total, %	% of all foreign labor
Tomatoes	345.1	90.5	26.2	14.3
Citrus	319.8	69.1	21.6	10.9
Lettuce	122.5	67.8	55.3	10.7
Cotton	1769.4	65.2	3.7	10.3
Strawberries	308.5	42.5	13.8	6.7
Sugar beets	160.6	31.9	19.9	5.0
Cucumbers	105.5	28.9	27.4	4.6
Melons	64.7	18.4	28.4	2.9
Celery	44.4	14.4	32.4	2.3
Asparagus	60.5	11.5	19.0	1.8

From Hirsch (1966, 6). For these crops the 'foreign labor' employed was almost entirely Mexican labor. Two other crops had a comparable intensity of foreign labor—tobacco and sugarcane harvesting—but these employed primarily non-Mexican hired seasonal workers.

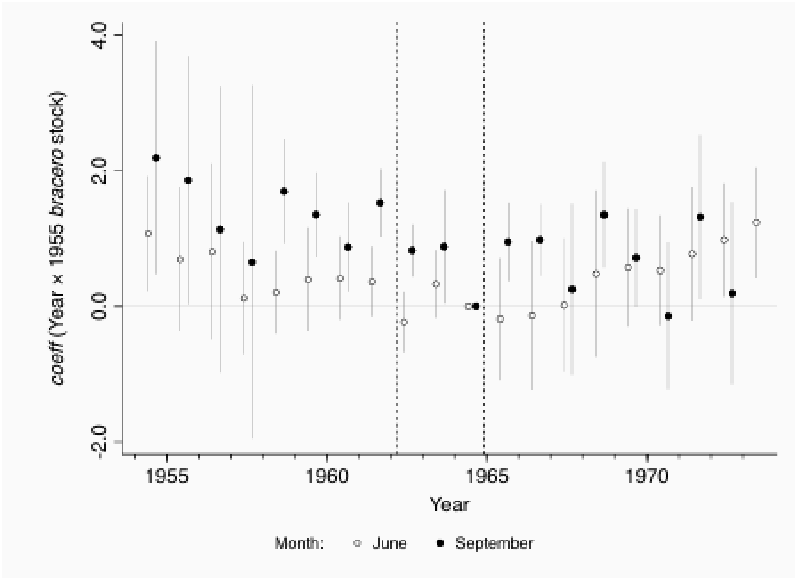
Figure 10: U.S. employment of Mexican hired seasonal labor by crop, 1964



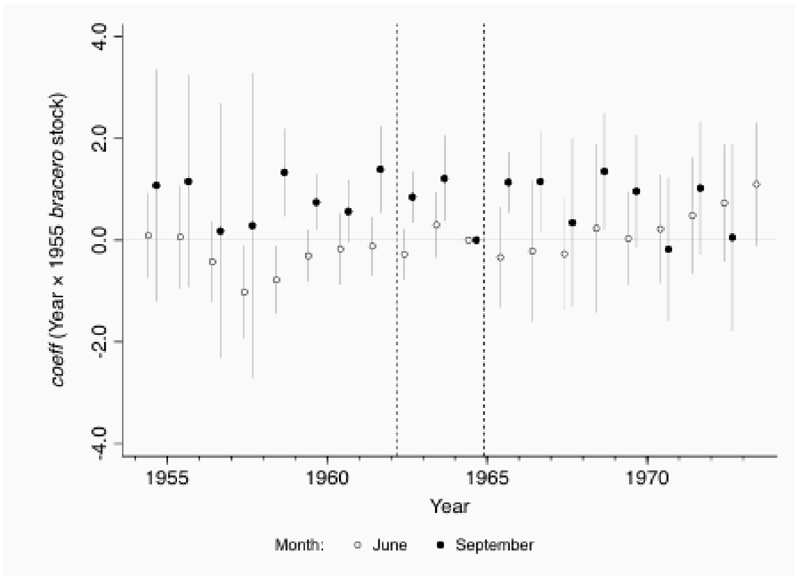
Observations are state-quarters. Omitted year is 1964, in an event-study regression for each quarter separately. Solid gray vertical lines show 95% confidence interval around the coefficient on the interaction of the year dummy and the 1955 *bracero* fraction $\left(I_t \cdot \bar{\ell}_s^{1955}\right)$. Vertical dotted lines show the beginning of major government efforts toward *bracero* exclusion (March 1962) and near-complete exclusion at the termination of the program (December 1964).

Figure 11: Event Study for hourly wage, composite

(a) *All states*



(b) *Only states exposed to exclusion (1955 bracero stock > 0)*



For clarity, superimposed event study graphs are shown for two selected months of the year: June is chosen to represent the early season, September to represent the late season. Observations are state-months. Omitted year is 1964, in an event-study regression for each month separately. Solid gray vertical lines show 95% confidence interval around the coefficient on the interaction of the year dummy and the 1955 *bracero* fraction $(I_t \cdot \overline{\ell}_s^{1955})$. Vertical dotted lines show the beginning of major government efforts toward *bracero* exclusion (March 1962) and near-complete exclusion at the termination of the program (December 1964).

Figure 12: Event study for ln domestic hired seasonal workers, selected months

Appendix Table A7: Alternative 'treatment' year 1962: Effects of *bracero* exclusion on real wages: Differences-in-differences with continuous treatment, quarterly

	Wage, all years		Wage, 1960–1970	
Dep. var.	Hourly composite	Daily w/o board	Hourly composite	Daily w/o board
$I_{t \geqslant 1962} \cdot \overline{\ell}_s^{1955}$	−0.0167 (0.0367)	−0.323 (0.454)	−0.00626 (0.0248)	0.240 (0.263)
N	4324	5813	2024	1901
adj. R^2	0.773	0.835	0.732	0.758
Clusters	46	46	46	46
Semielasticity $\frac{\partial \ln w}{\partial (B/L)}$	−0.0189 (0.0414)	−0.0373 (0.0549)	−0.00655 (0.0260)	0.0264 (0.0290)
p-val. of χ^2 test: $\frac{\partial \ln w}{\partial (B/L)} = 0.1$	[0.0041]	[0.0123]	[< 0.001]	[0.0113]

'Treatment' is the degree of exposure to exclusion. Observations are state-quarters. All regressions include state and quarter-by-year fixed effects. Standard errors clustered by state in parentheses. $\overline{\ell}_{1955}$ is average fraction of Mexicans among the state's total hired seasonal workers across the months of 1955. Wages in constant 1965 US$ deflated by CPI.

Appendix Table A8: Alternative 'treatment' year 1962: Effects of *bracero* exclusion on domestic seasonal agricultural employment: Differences-in-differences with continuous treatment, monthly

Dep. var.: Domestic seasonal workers	All states, all years		All states, years 1960–1970		Exposed states only, all years	
Specification:	linear	ln	linear	ln	linear	ln
$I_{t \geqslant 1962} \cdot \overline{\ell}_s^{1955}$	−10770.9 (9155.2)	−0.536 (0.458)	3814.2 (8297.2)	−0.243 (0.284)	−565.3 (6735.3)	−0.285 (0.535)
N	10329	6386	6072	3707	5168	3189
adj. R^2	0.056	0.086	0.079	0.076	0.028	0.053
Clusters	46	46	46	46	23	23

'Treatment' is the degree of exposure to exclusion. Observations are state-months. All regressions include state and quarter-by-year fixed effects. Standard errors clustered by state in parentheses. $\overline{\ell}_{1955}$ is average fraction of Mexicans among the state's total hired seasonal workers across the months of 1955. Covers only January 1954 to July 1973, as in original sources. Farm worker stocks missing in original sources for 1955 in Rhode Island and New Hampshire. If no workers reported for state-month in a month when source report was issued, assume zero. 'Exposed states' means states with nonzero *bracero* stocks in 1955 (i.e., only the 'high' and 'low' groups in the figures).

6.2 Comment Appendix

The two tables below present summary statistics for Bracero workers in the different U.S. states in 1955 and 1960.

Summary table of Mexican workers present in the U.S.A farms in 1955

State	Prop. Seasonal Mexican Workers	Total Mexican Seasonal mexican workers	Total Seasonal workers	Total Workers on farm
NM	0.609	6 634	11 300	131 500
NE	0.323	96	1 890	194 000
AZ	0.269	6 271	25 071	131 500
TX	0.241	52 578	230 878	291 250
CA	0.231	42 956	206 125	302 750
SD	0.212	25	527	194 000
NV	0.090	5	810	131 500
AR	0.080	6 069	47 240	291 250
WY	0.050	125	1 983	131 500
CO	0.045	533	17 049	131 500
MI	0.034	1 878	40 017	217 000
UT	0.026	145	7 800	131 500
MT	0.025	209	6 993	131 500
IN	0.017	74	6 797	217 000
MO	0.015	302	21 236	194 000
ID	0.012	100	13 470	131 500
MN	0.010	69	8 419	194 000
WI	0.008	140	14 522	217 000
IL	0.007	35	8 441	217 000
TN	0.006	183	27 890	235 500
WA	0.006	181	37 262	302 750
OR	0.005	131	33 498	302 750
GA	0.003	81	15 388	369 750
AL	0.000	0	25 458	235 500
CT	0.000	0	7 800	60 000
DE	0.000	0	2 839	369 750
FL	0.000	0	43 179	369 750
IA	0.000	0	3 093	194 000
KS	0.000	0	11 446	194 000
KY	0.000	0	10 000	235 500
LA	0.000	0	15 498	291 250
MA	0.000	0	11 745	60 000
MD	0.000	0	11 943	369 750
ME	0.000	0	13 763	60 000
MS	0.000	0	9 693	235 500
NC	0.000	0	17 568	369 750
ND	0.000	0	8 775	194 000
NJ	0.000	0	14 096	144 250
NY	0.000	0	30 238	144 250
OH	0.000	0	16 319	217 000
OK	0.000	0	11 105	291 250
PA	0.000	0	16 961	144 250
SC	0.000	0	15 118	369 750
VA	0.000	0	11 523	369 750
VT	0.000	0	2 291	60 000
WV	0.000	0	1 866	369 750
Sum	2.324	118 820	1 096 923	10 141 000

Summary table of Mexican workers present in the U.S.A farms in 1960				
State	Prop. Seasonal Mexican Workers	Total Mexican Seasonal mexican workers	Total Seasonal workers	Total Workers on farm
NM	0.705	3 548	8 497	130 500
AZ	0.353	5 319	24 760	130 500
CA	0.253	29 624	198 157	302 250
TX	0.253	35 294	231 233	364 750
AR	0.176	6 419	50 740	364 750
CO	0.127	1 302	14 759	130 500
SD	0.104	19	439	167 500
NV	0.101	36	644	130 500
NE	0.083	203	5 384	167 500
IN	0.055	109	4 546	183 000
MI	0.049	1 774	42 459	183 000
WY	0.048	117	2 790	130 500
WI	0.042	128	7 168	183 000
UT	0.041	151	6 273	130 500
MT	0.039	250	6 813	130 500
IL	0.020	62	6 678	183 000
KY	0.017	31	11 198	207 250
IA	0.009	18	3 642	167 500
MO	0.009	65	14 624	167 500
TN	0.009	160	24 731	207 250
MN	0.007	20	4 670	167 500
GA	0.004	107	35 688	342 500
OR	0.002	29	31 026	302 250
KS	0.001	7	19 915	167 500
ND	0.001	4	9 794	167 500
WA	0.001	10	29 031	302 250
AL	0.000	0	13 387	207 250
CT	0.000	0	8 150	62 000
DE	0.000	0	2 276	342 500
FL	0.000	0	35 494	342 500
ID	0.000	0	10 529	130 500
LA	0.000	0	17 486	364 750
MA	0.000	0	9 624	62 000
MD	0.000	0	6 421	342 500
ME	0.000	0	11 624	62 000
MS	0.000	0	26 406	207 250
NC	0.000	0	58 345	342 500
NH	0.000	0	1 630	62 000
NJ	0.000	0	14 623	112 750
NY	0.000	0	20 573	112 750
OH	0.000	0	20 712	183 000
OK	0.000	0	21 248	364 750
PA	0.000	0	13 612	112 750
SC	0.000	0	16 368	342 500
VA	0.000	0	10 160	342 500
VT	0.000	0	825	62 000
Sum	2.509	84 806	1 115 152	9 372 000

6.2.1 Reproduction of the main output

This reproduces the results of Table 1 of CLP.

	Hourly Composite (Full)	Daily w/o Board (Full)	Hourly Composite (1960-1970)	Daily w/o Board (1960-1970)
BraceroExclusion1965 * ExposureToExclusion	-0.036	-0.385	-0.040	-0.025
	(0.043)	(0.495)	(0.031)	(0.309)
Num.Obs.	4324	5813	2024	1901
R2	0.936	0.943	0.936	0.964
R2 Adj.	0.934	0.941	0.933	0.963
FE: State_FIPS	X	X	X	X
FE: time_q	X	X	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 1: Differences-in-differences with continuous treatment, quarterly

	Log Hourly Composite (Full)	Log Daily w/o Board (Full)	Log Hourly Composite (1960-1970)	Log Daily w/o Board (1960-1970)
BraceroExclusion1965 * ExposureToExclusion	-0.083	-0.110	-0.075	-0.041
	(0.065)	(0.092)	(0.051)	(0.054)
Num.Obs.	4324	5813	2024	1901
R2	0.917	0.934	0.900	0.954
R2 Adj.	0.915	0.932	0.895	0.952
FE: State_FIPS	X	X	X	X
FE: time_q	X	X	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 1: Differences-in-differences with continuous treatment, quarterly (semi elasticities)

This reproduces the results of Table 2 of CLP.

	All States, all year	All States, all year (ln)	All States, 1960-1970	All States, 1960-1970 (ln)	Exposed States, all years	Exposed States, all years (ln)	Highly Exposed States, all years	Highly Exposed States, all years (ln)
BraceroExclusion1965 * ExposureToExclusion	-7909.760	-0.406	2101.152	-0.034	-312.662	-0.161	-312.662	-0.161
	(9152.532)	(0.557)	(7394.778)	(0.495)	(7304.322)	(0.637)	(7304.322)	(0.637)
Num.Obs.	10329	6386	6072	3707	5168	3189	5168	3189
R2	0.669	0.686	0.681	0.727	0.726	0.759	0.726	0.759
R2 Adj.	0.665	0.680	0.677	0.721	0.721	0.751	0.721	0.751
FE: State_FIPS	X	X	X	X	X	X	X	X
FE: time_q	X	X	X	X	X	X	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 2: Effects of Bracero Exclusion on Domestic Seasonal Agricultural Employment: Difference-in-Differences with Continuous Treatment, Monthly

This reproduces the results of Table 3 of CLP.

	Local	Instrate	Instrate	Local (ln)	Instrate (ln)	Instrate (ln)
BraceroExclusion1965 * ExposureToExclusion	-3494.353	-4881.133	176.356	-0.632	-1.087	-0.571
	(5050.951)	(5072.902)	(1025.097)	(0.804)	(0.677)	(0.525)
Num.Obs.	10007	9955	9957	6736	4720	5773
R2	0.694	0.490	0.463	0.767	0.673	0.591
R2 Adj.	0.686	0.476	0.448	0.756	0.652	0.570
FE: State_FIPS	X	X	X	X	X	X
FE: time_m	X	X	X	X	X	X

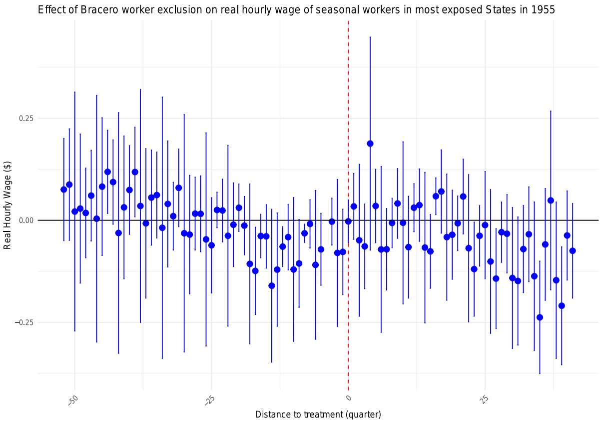
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

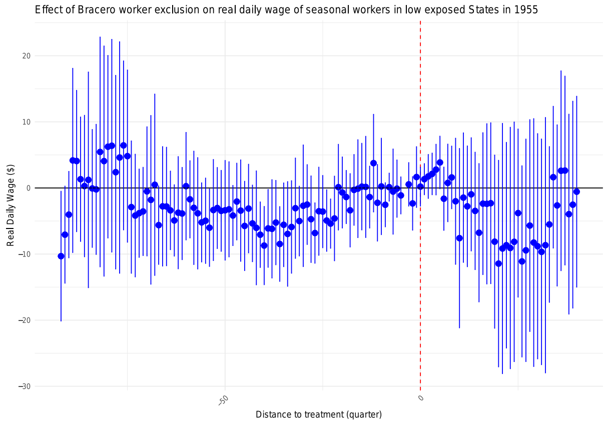
TABLE 3: Effects of Bracero Exclusion on the Three Types of Domestic Seasonal Agricultural Employment: Difference-in-Differences with Continuous Treatment, Monthly

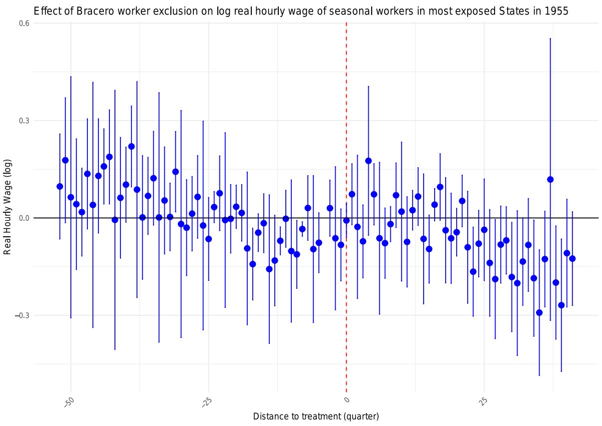
6.2.2 DiD Quarter-by-Year

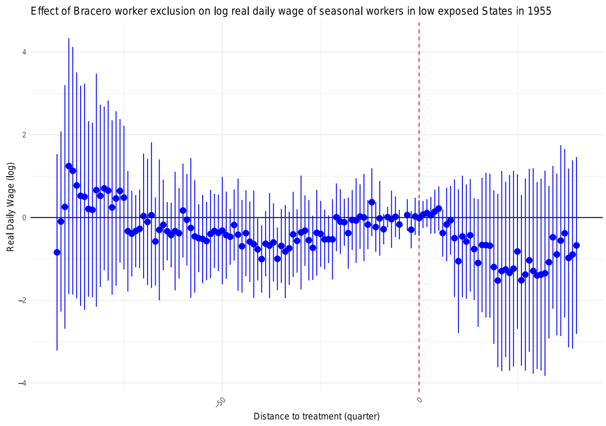
CLP argues that controlling for state exposition, differentiating between highly exposed states (more than 20% of Mexican seasonal workers) and low exposed states could reduce the pre-trends.

We argue that pre-trends are still present even when considering only non-treated states and highly (low) exposed states.

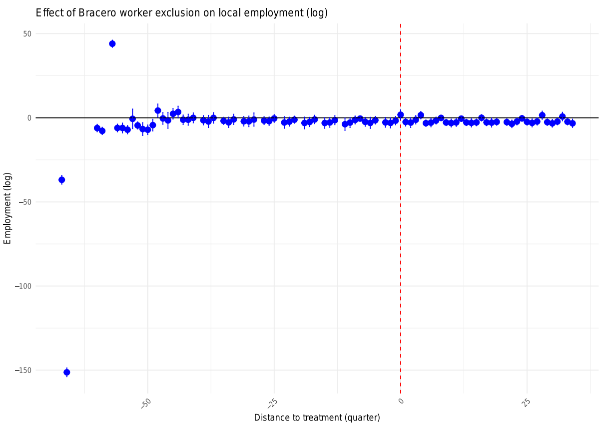


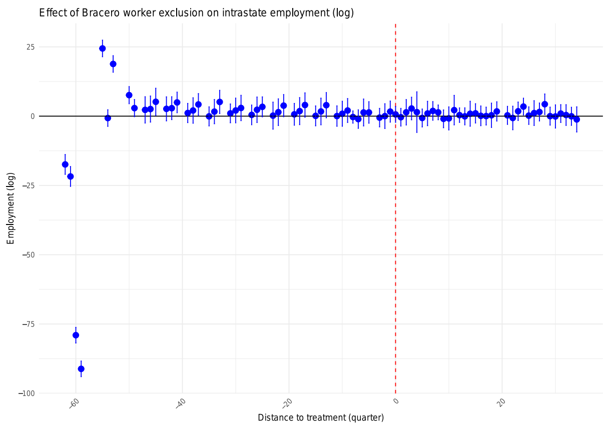


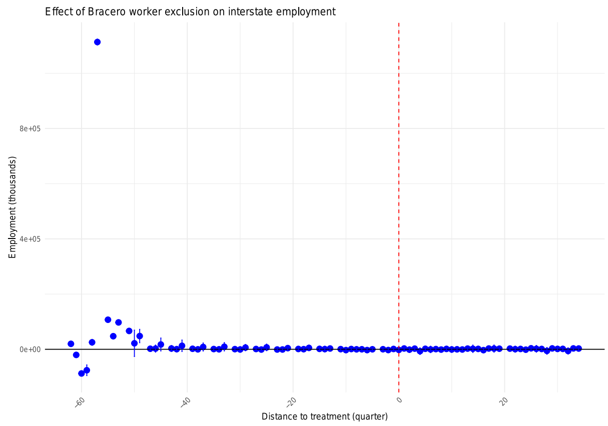




For employment issue we here provide the log outcome of employment by origin of domestic seasonal workers (local, intra- or inter- state) :



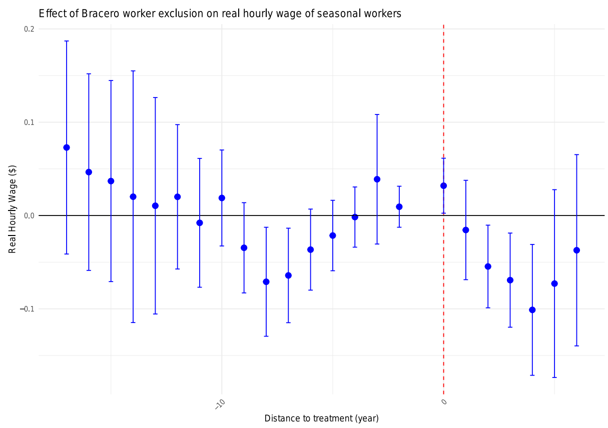


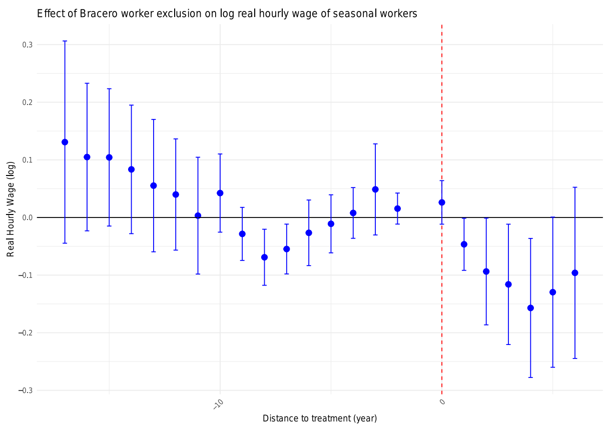


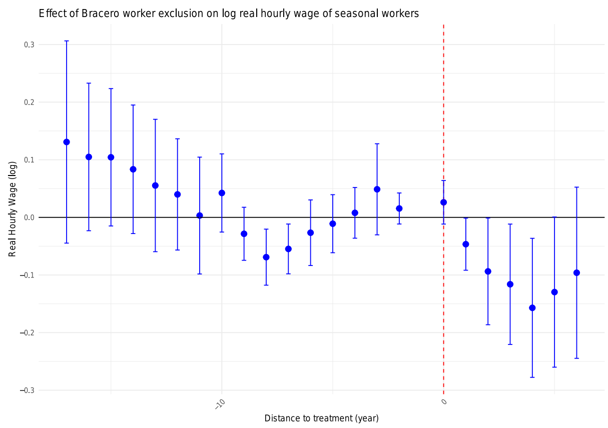
6.2.3 DiD Year-by-Year

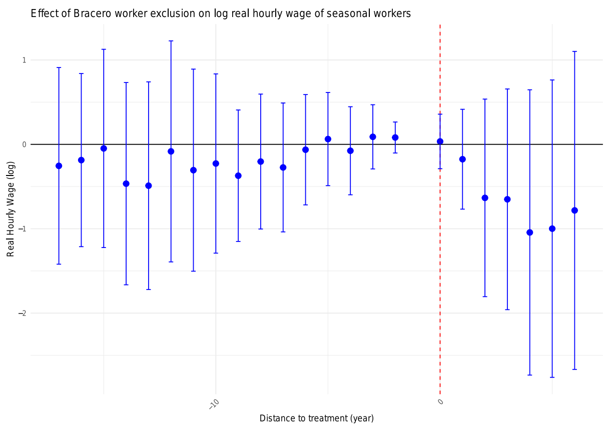
Adopting a year-by-year analysis does not erase the pre-trends despite CLP's claim. We propose here to consider only the most exposed states and low exposed states to see if the overall results is not biased by some heterogeneity in the treatment effect.

The four figures below present the effect of the bracero exclusion on real hourly wage and log hourly wages in highly exposed and low exposed states (the last graph). If we can admit a causal null effect in for low exposed states, it is much harder for exposed ones. Either, we accept the parallel trend assumptions, even though it definitely show some trends, but we reject the null effect on wages (a negative impact), or we reject the entire finding.

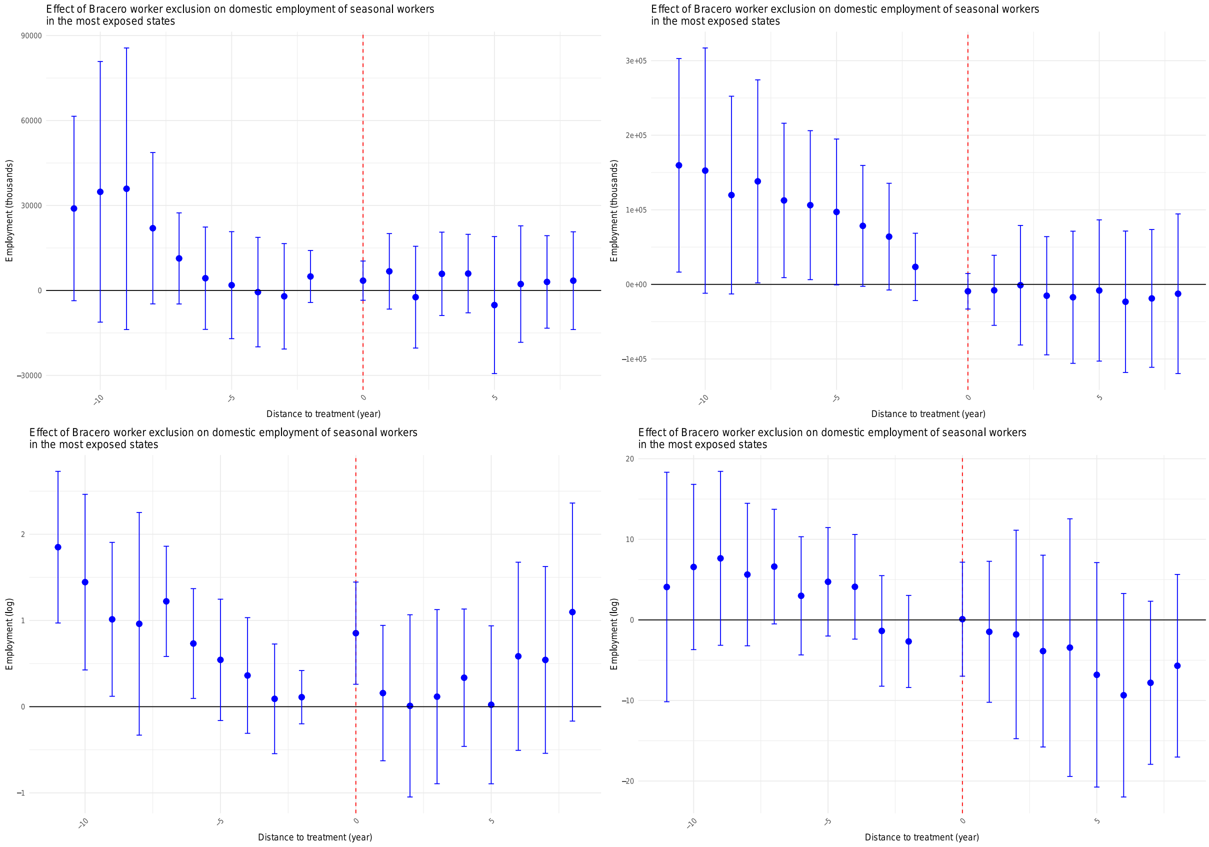








The graph below display the impact of domestic seasonal workers in high and low exposed states. Here the evidence are mixed, when we consider the high exposed state (left column), we see that taking log variation or variation in real number makes important difference. The pretrend that were not significative, but existant when accounting in thousands of jobs, are now significative in highly exposed states. Conversely, in the low treated states (left column), we can observe clean and strong negative trend before the application of the exclusion in 1965, however log results tend to mitigate this results. Overall, we find mix of evidence of both CLP and the author's claim. Nonetheless, being conservative, we can only partially accept CLP results and suggests further work to reduce the trends.



6.3 Synthetic Control

This part display the weights of the states and covariates used to calculate the synthetic control group of California and Texas.

6.3.1 California

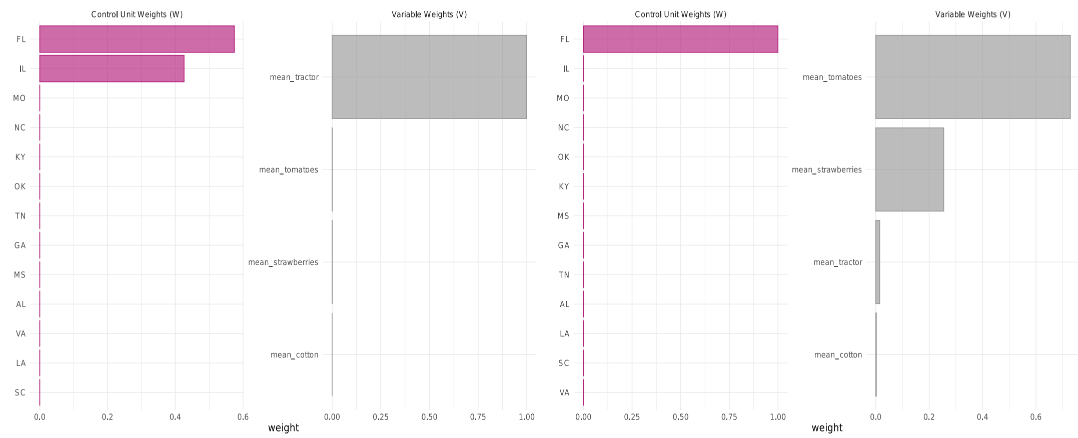


Figure 13: Weights for the Synthetic Control of California, for mean hourly wage and domestic employment

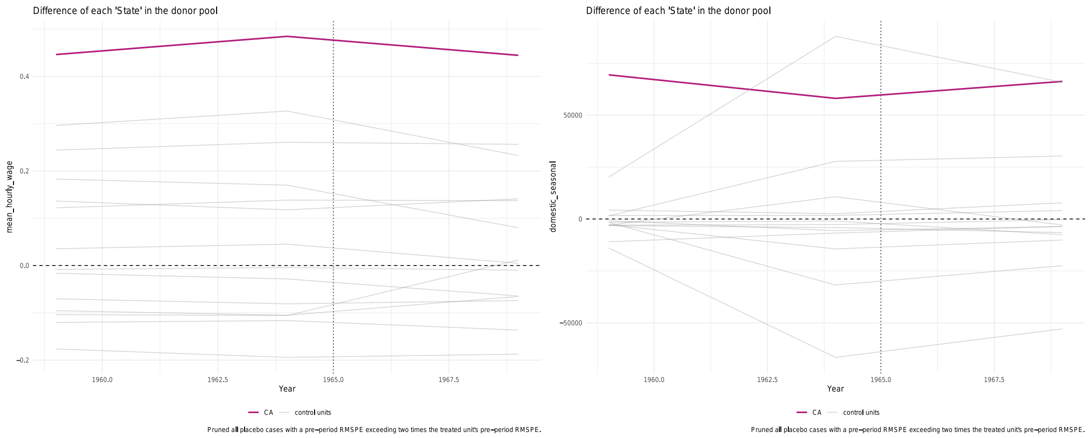


Figure 14: Placebo for the Synthetic Control of California, for mean hourly wage and domestic employment

6.3.2 Texas

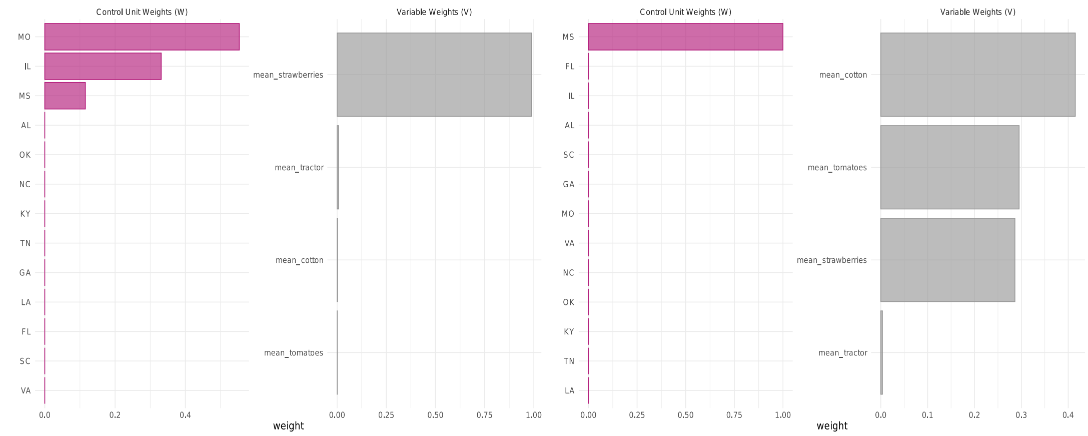


Figure 15: Weights for the Synthetic Control of Texas, for mean hourly wage and domestic employment

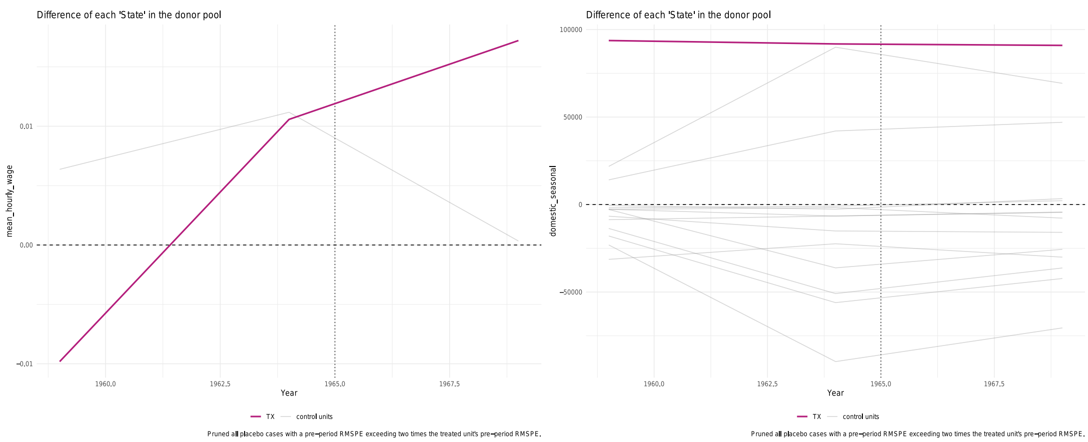


Figure 16: Placebo for the Synthetic Control of Texas, for mean hourly wage and domestic employment

6.4 Code

The code is in R and has been entirely transposed here. For more complete information please refer to the GitHub replication package.

6.4.1 Data Cleaning

6.4.1.1 Converting Data Type

```
# This code converts to parquet formats all .dta dataset

clear_rm()
gc()

library(arrow)
library(haven)
library(glue)

for (file in list.files("original_data/", pattern = ".dta")){
  data = read_dta(glue("original_data/{file}"))
  data_name = gsub(".dta", "", x = file)
  write_parquet(data, glue("data/raw/{data_name}.parquet"))
}
```

6.4.1.2 Generating the Dataset

```
# This code generates the data used by Clemens & al (2018)
# It reproduces the data tables producede by the code : "bracero_aer_code.do" from line 54 to 138

clear_rm()
invisible(gc)

library(arrow)
library(data.table)
library(glue)
library(ggplot2)
library(lubridate)
library(haven)
library(tictoc)
library(tinytable)
library(zoo)

tic()
# Data Path ---------------------------------------------------------------

raw_path = "data/raw"
final_path = "data/final"

# Data Cleaning -----------------------------------------------------------

bracero = as.data.table(read_parquet(glue("{raw_path}/bracero_aer_dataset.parquet")))
cpi_data = as.data.table(read_parquet(glue("{raw_path}/cpi_data.parquet")))

## Cotton machine ---------------------------------------------------------

bracero[, Cotton_machine := ifelse(Cotton_machine == 0 & State == "FL" & Year > 1969, NA,
Cotton_machine)]
bracero[, Cotton_machine := ifelse(Cotton_machine == 0 & State == "VA" & Year > 1965, NA,
```

```
Cotton_machine)]

## Generate Flag ----------------------------------------------------------
bracero[, Month := as.numeric(as_factor(Month))]
bracero[, := (january = ifelse(Month == 1, 1, 0),
                april = ifelse(Month == 4, 1, 0),
                july = ifelse(Month == 7, 1, 0),
                october = ifelse(Month == 10, 1, 0))]
bracero[, quarterly_flag := fcase(
  Month %in% 1:3, 1,
  Month %in% 4:6, 2,
  Month %in% 7:9, 3,
  Month %in% 10:12, 4,
  default = NA
)]

## Generate time variables ------------------------------------------------

bracero[, :=(
  time_m = make_date(year = Year, month = Month, day = 1),
  time_m_formatted = format(make_date(year = Year, month = Month, day = 1), "%Ym%m")
)]

bracero[, :=(
  time_q_formatted = factor(paste0(Year,"q",quarterly_flag))
)]

## Merge different Mexican Series ---------------------------------------------------

bracero[, := (Mexican = Mexican_final,
                ln_Mexican = log(Mexican_final))]


## Set panel --------------------------------------------------------------

bracero = na.omit(bracero,cols = c("time_m", "State_FIPS"))
# CHECK FOR THE YEAR BEFORE
bracero[, fulldata := ((Year >= 1954 & Month >= 7)|(Year >= 1955)) & (Year <= 1972)]
# // Few states are covered in the employment data outside of this window
bracero[is.na(Mexican) & fulldata != 0, Mexican := 0]

## Non-Mexican workers ----------------------------------------------------

bracero[, TotalHiredSeasonal := TotalHiredSeasonal_final,]
bracero[, := (NonMexican = TotalHiredSeasonal - Mexican),]
bracero[, := (ln_NonMexican = log(NonMexican),
                ln_HiredWorkersonFarms = log(HiredWorkersonFarms_final),
                mex_frac = Mexican/TotalHiredSeasonal)]
bracero[, mex_frac_tot := Mexican/(Farmworkers_Hired*1000)]

## Merging datasets -------------------------------------------------------

setorderv(bracero, cols = c("State_FIPS","time_m"))
```

```
bracero = merge(bracero, cpi_data, by = c("State_FIPS", "time_m"), all.x = TRUE)

## Setting real wages ------------------------------------------------------

bracero[, priceadjust := cpi/0.1966401] #Divide by value of index in January 1965 TRY TO NORMALIZE
BY OTHER YEARS
bracero[, := (realwage_daily = DailywoBoard_final/priceadjust,
                realwage_hourly = HourlyComposite_final/priceadjust)]
bracero[, cpi := NULL]

## Generate employment data ------------------------------------------------

setorderv(bracero, cols = c("State_FIPS", "time_m"))
bracero[, domestic_seasonal := rowSums(.SD, na.rm = TRUE), .SDcols = c("Local_final",
"Intrastate_final", "Interstate_final")]
bracero[, := (ln_domestic_seasonal = log(domestic_seasonal),
                ln_foreign = log(TotalForeign_final),
                dom_frac = domestic_seasonal/TotalHiredSeasonal_final,
                for_frac = TotalForeign_final/TotalHiredSeasonal_final,
                ln_local = log(Local_final),
                ln_instrastate = log(Intrastate_final),
                ln_interstate = log(Interstate_final))]

bracero[Year<1954 | Year>1973 | (Year == 1973 & Month>7), domestic_seasonal := NA] # No coverage
in original sources outside Jan 1954 to Jul 1973
bracero[Year<1954 | Year>1973 | (Year == 1973 & Month>7), ln_domestic_seasonal := NA] # No
coverage in original sources outside Jan 1954 to Jul 1973

# Normalize by, respectively, data from the latest Census of Agriculture before 1955 and latest
Census of Population before 1955:
bracero[, := (mex_area = Mexican/(cropland_1954/1000), # Mexican seasonal workers per 1000 acres
of (predetermined 1954) harvested cropland
                 dom_area = domestic_seasonal/(cropland_1954/1000), # Domestic hired seasonal
workers per 1000 acres of (predetermined 1954) harvested cropland
               mex_pop = Mexican/(pop1950/1000), # Mexican seasonal workers per 1000 population
                dom_pop = domestic_seasonal/(pop1950/1000), # Domestic hired seasonal workers
per 1000 population
                Farmworkers_Hired_pop = (Farmworkers_Hired*1000)/(pop1950/1000),
                Farmworkers_Hired_area = (Farmworkers_Hired*1000)/(cropland_1954/1000))]

# For Appendix graph comparing Mexican to non-Mexican foreign
bracero[, Mexican_zeros := Mexican]
bracero[Year >= 1967 & is.na(Mexican_zeros), Mexican_zeros := 0]
bracero[, ForNonMexican := rowSums(.SD, na.rm = TRUE), .SDcols = c("Jamaican_final",
"Bahamian_final", "BWIOthers_final",
                                                                     "Canadian_final",
"PuertoRican_final", "OtherForeign_final")]
bracero[, mextot := sum(Mexican_zeros, na.rm = TRUE), by = time_m]
bracero[, fornonmextot := sum(ForNonMexican, na.rm = TRUE), by = time_m]

# Creating the treatment and control groups ------------------------------
# Create the treatment exposure var
bracero_exposure_treatment = bracero[, .(mex_frac_year = mean(mex_frac, na.rm = TRUE),
```

```
                                 mexican_mean = mean(Mexican, na.rm = TRUE),
                                      TotalHiredSeasonal_mean = mean(TotalHiredSeasonal, na.rm
= TRUE),
                                    HiredWorkersonFarms_mean = mean(HiredWorkersonFarms_final,
na.rm = TRUE)),
                             by = .(State, Year)]
bracero_exposure_treatment = na.omit(unique(bracero_exposure_treatment))
# Round the relevant columns
bracero_exposure_treatment[, mex_frac_year := round(mex_frac_year, 3)]
bracero_exposure_treatment[, mexican_mean := round(mexican_mean, 0)]
bracero_exposure_treatment[, HiredWorkersonFarms_mean := round(HiredWorkersonFarms_mean, 0)]
bracero_exposure_treatment[, TotalHiredSeasonal_mean := round(TotalHiredSeasonal_mean, 0)]
mex_frac_1955_value = bracero_exposure_treatment[Year == 1955, .(State,mex_frac_year)]
setnames(mex_frac_1955_value, "mex_frac_year", "mex_frac_1955")
bracero_exposure_treatment  =  merge(bracero_exposure_treatment,  mex_frac_1955_value,  by  =
c("State"), all.x = T)
# Create the three groups based on the year 1955
# Check that all states are treated
bracero_exposure_treatment[Year == 1955, group := fcase(
  mex_frac_year >= 0.20, 2,
  mex_frac_year < 0.20 & mex_frac_year > 0.2, 1,
  mex_frac_year == 0, 0
)]
bracero_exposure_treatment[,  post  :=  (Year  >=  1965)*1]  #the  authors  propose  to  period  of
treatment, the final exclusion
bracero_exposure_treatment[, post_2 := (Year >= 1962)*1] # the alternative is 1962 when the
wages were mandatory increased
bracero_exposure_treatment[, post_3 := (Year >= 1960)*1] # I add this one to account for eventual
anticipatory effect
bracero_exposure_treatment[, treatment_frac := post * mex_frac_1955]
bracero_exposure_treatment[, treatment_frac_2 := post_2 * mex_frac_1955]

# We merge the dataset
bracero = merge(bracero, bracero_exposure_treatment, by = c("State", "Year"), all.x = T)

write_parquet(bracero, glue("{final_path}/bracero_final.parquet"))
toc()
```

6.4.2 Generating Descriptive Graph

```
# This code is mainly exploratory. It produces descriptive statistics about the different states.

rm(list = ls())
gc()

library(arrow)
library(data.table)
library(ggplot2)
library(flextable)
library(magick)
library(glue)
source("./paths.R")

# Import Data ------------------------------------------------------------
```

```
# bracero = read_parquet("data/final/bracero_final.parquet")
bracero = as.data.table(fread(glue("{final_data}/final_data_aer.csv")))

# Tables and figures setting ---------------------------------------------

use_df_printer()
set_flextable_defaults(
  theme_fun = theme_booktabs,
  big.mark = " ",
  font.color = "black",
  border.color = "black",
  padding = 3,
)

# Appendix ----------------------------------------------------------------

## Table A2 -----------------------------------------------------------------

# We want to reproduce the fraction of total seasonal farm workers, average across months
bracero55  =  bracero[Year  ==  1955,  .(State,  Year,  mex_frac,  Mexican,  TotalHiredSeasonal,
HiredWorkersonFarms_final)] # I do not use mex_frac_tot since no data are reported for this year
bracero55 = na.omit(unique(bracero55[, .(mex_frac_year = mean(mex_frac, na.rm = T),
                                         mexican_mean = mean(Mexican, na.rm =T),
                                            TotalHiredSeasonal_mean = mean(TotalHiredSeasonal,
na.rm = T),
                                    HiredWorkersonFarms_mean = mean(HiredWorkersonFarms_final,
na.rm =T)),
                                     by = c("State")]))
bracero55[, mex_frac_year := round(mex_frac_year, 3)]
bracero55[, mexican_mean := round(mexican_mean, )]
bracero55[, HiredWorkersonFarms_mean := round(HiredWorkersonFarms_mean, )]
bracero55[, TotalHiredSeasonal_mean := round(TotalHiredSeasonal_mean, )]
setorderv(bracero55, cols = "mex_frac_year", order = -1)
bracero55 = rbind(bracero55, bracero55[, lapply(.SD, function(x) if(is.numeric(x)) sum(x, na.rm
= TRUE) else NA)], use.names = FALSE)
bracero55[.N, State := "Sum" ]

# We isolate the most exposed states
bracero55_highexposed = list(bracero55[mex_frac_year >= 0.2 & mex_frac_year <= 1,.(State)])

bracero55 |>
  flextable() |>
  autofit() %>%
  add_header_lines("Summary table of Mexican workers present in the U.S.A farms in 1955") %>%
  set_header_labels(mex_frac_year = "Prop. Seasonal Mexican Workers",
                    mexican_mean = "Total Mexican Seasonal mexican workers",
                    TotalHiredSeasonal_mean = "Total Seasonal workers",
                    HiredWorkersonFarms_mean = "Total Workers on farm") %>%
  save_as_image("output/tables/appendix/mexican_usfarms_1955.png")

bracero55 %>%
  select(State, mex_frac_year) %>%
```

```
  filter(mex_frac_year >0) %>%
  flextable() %>%
  autofit() %>%
   add_header_lines("Proportion of Mexican seasonal workers among seasonal workers in U.S.A. 
farms in 1955") %>%
  set_header_labels(mex_frac_year = "Prop. Seasonal Mexican Workers") %>%
  save_as_image("output/tables/main/mexicain_usfarms_1955_short.png")

# Interesting points :
# - some of the most affected states count a very low total number of Mexican workers in 
their workforce.
# In fact, TX an CA represents 80% of the concerned work force.
# - considering know more qualitative aspect : the states seems to have a high number of total 
hired workers, mexican are mostly seasonal
# and then probably entitled with more manual task. More in depth analysis of farm size, arable 
land, type of culture is necessary

# Robustness ------------------------------------------------------------
bracero60 = bracero[Year == 1960, .(State, Year, mex_frac, Mexican, TotalHiredSeasonal, 
HiredWorkersonFarms_final)] # I do not use mex_frac_tot since no data are reported for this year
bracero60 = na.omit(unique(bracero60[, .(mex_frac_year = mean(mex_frac, na.rm = T),
                                         mexican_mean = mean(Mexican, na.rm =T),
                                            TotalHiredSeasonal_mean = mean(TotalHiredSeasonal, 
na.rm = T),
                                    HiredWorkersonFarms_mean = mean(HiredWorkersonFarms_final, 
na.rm =T)),
                                     by = c("State")]))
bracero60[, mex_frac_year := round(mex_frac_year, 3)]
bracero60[, mexican_mean := round(mexican_mean, )]
bracero60[, HiredWorkersonFarms_mean := round(HiredWorkersonFarms_mean, )]
bracero60[, TotalHiredSeasonal_mean := round(TotalHiredSeasonal_mean, )]
setorderv(bracero60, cols = "mex_frac_year", order = -1)
bracero60 = rbind(bracero60, bracero60[, lapply(.SD, function(x) if(is.numeric(x)) sum(x, na.rm 
= TRUE) else NA)], use.names = FALSE)
bracero60[.N, State := "Sum" ]

# We select the most affected state in 1960
bracero60_highexposed = (list(bracero60[mex_frac_year >= 0.2 & mex_frac_year <= 1,.(State)]))
bracero_fallen = setdiff(unlist(bracero55_highexposed), unlist(bracero60_highexposed)) # 
collecting the state who are less exposed in 1960
bracero55_highexposed = setdiff(unlist(bracero55_highexposed), bracero_fallen)

bracero60 |>
  flextable() |>
  autofit() %>%
  add_header_lines("Summary table of Mexican workers present in the U.S.A farms in 1960") %>%
  set_header_labels(mex_frac_year = "Prop. Seasonal Mexican Workers",
                    mexican_mean = "Total Mexican Seasonal mexican workers",
                    TotalHiredSeasonal_mean = "Total Seasonal workers",
                    HiredWorkersonFarms_mean = "Total Workers on farm") %>%
  style(i = ~State %in%  unlist(bracero55_highexposed),
        pr_t = fp_text_default(
          italic = TRUE,
```

```
          color = "red")) %>%
  style(i = ~State %in%  unlist(bracero_fallen),
        pr_t = fp_text_default(
          italic = TRUE,
          color = "blue")) %>%
  save_as_image("output/tables/appendix/mexican_usfarms_1960.png")

bracero60 %>%
  select(State, mex_frac_year) %>%
  filter(mex_frac_year >0) %>%
  flextable() %>%
  autofit() %>%
   add_header_lines("Proportion of Mexican seasonal workers among seasonal workers in U.S.A.
farms in 1960") %>%
  set_header_labels(mex_frac_year = "Prop. Seasonal Mexican Workers") %>%
  save_as_image("output/tables/main/mexicain_usfarms_1960_short.png")


## Evolution of the mexican force (exposure treatment) ---------------------
bracero_all_years = bracero[,.(State, Year, mex_frac, Mexican, TotalHiredSeasonal,
HiredWorkersonFarms_final)]
bracero_all_years = na.omit(unique(bracero_all_years[, .(mex_frac_year = mean(mex_frac, na.rm
= T),
                             mexican_mean = mean(Mexican, na.rm =T),
                             TotalHiredSeasonal_mean = mean(TotalHiredSeasonal, na.rm = T),
                         HiredWorkersonFarms_mean = mean(HiredWorkersonFarms_final, na.rm =T)),
                         by = c("State", "Year")]))
bracero_all_years[, mex_frac_year := round(mex_frac_year, 3)]
bracero_all_years[, mexican_mean := round(mexican_mean, )]
bracero_all_years[, HiredWorkersonFarms_mean := round(HiredWorkersonFarms_mean, )]
bracero_all_years[, TotalHiredSeasonal_mean := round(TotalHiredSeasonal_mean, )]

# A table to know them all
# Generate the table with unique state counts by Year and treatment_status
bracero_all_years[Year %in% 1950:1960, treatment_status := fcase(
  mex_frac_year >= 0.2, "Treated",
  mex_frac_year > 0 & mex_frac_year < 0.2, "Low_Treated",
  mex_frac_year == 0, "Non_Treated"
)]
# Check stability: flag as switcher if group_cm changes over years 1955-1960
bracero_all_years[Year %in% 1950:1960, stability_check := uniqueN(treatment_status, na.rm =
TRUE), by = State]
bracero_all_years[stability_check > 1, switcher_status := "Switcher"]
bracero_all_years[stability_check == 1, switcher_status := "Stayer"]
bracero_summary = bracero_all_years[Year %in% 1950:1960, .(unique_states = uniqueN(State)), by
= .(Year, treatment_status)]
bracero_summary = dcast(bracero_summary, Year ~ treatment_status, value.var = "unique_states",
fill = 0)
setnames(bracero_summary, c("Non_Treated", "Low_Treated", "Treated"), c("Not Treated", "Low
Treated", "Treated"))
bracero_summary[, Total := rowSums(.SD), .SDcols = c("Not Treated", "Low Treated", "Treated")]

bracero_summary %>%
```

```
  flextable(col_keys = c("Year","Not Treated", "Low Treated", "Treated", "Total")) %>%
  autofit() %>%
  add_header_lines("Evolution of Treated, Low treated, and Control group") %>%
  colformat_num(big.mark = "") %>%
  save_as_image(path = glue("{output_tables}/main/evolution_group_bracero.png"))

# We set the groups to distinguish them
bracero_all_years[, group_treatment := fcase(
  Year == 1955 & mex_frac_year >= 0.20, 2,
  Year == 1955 & mex_frac_year < 0.20 & mex_frac_year >= 0.05, 1,
  default = 0
)]
group_1955 = bracero_all_years[Year == 1955, .(State, group_treatment)]
bracero_all_years = merge(bracero_all_years, group_1955, by = "State", all.x = TRUE, suffixes =
c("", "_1955"))

ggplot(bracero_all_years[Year %in% 1953:1970], aes(x = Year, y = mex_frac_year, color =
factor(group_treatment_1955), group = State)) +
  geom_line() +
  geom_point() +
  geom_vline(xintercept = 1955, linetype = "dashed", color = "purple")+
  geom_vline(xintercept = 1961, linetype = "dashed", color = "red")+
  geom_vline(xintercept = 1964, linetype = "dashed", color = "red")+
  theme_minimal() +
  labs(
    # title = "Evolution of the Ratio of Seasonal Mexican Worker State (1954 - 1970)",
       x = "Year",
       y = "Mexican Worker % of Seasonal Worker") +
  theme(panel.grid.major = element_line(size = 0.5),
        panel.grid.minor = element_blank(),
        legend.position = "right") +
  scale_color_discrete(name = "State", labels = c("Control", "Low Exposure", "High Exposure",
"Rhode Island \nand New Hampshire"))
ggsave("output/figures/ratio_mexican_all_states.pdf", width = 10, height = 7)

ggplot(bracero_all_years[Year %in% 1953:1970 & group_treatment_1955 %in% 1:2], aes(x = Year, y
= mex_frac_year, color = State, group = State)) +
  geom_line() +
  geom_point() +
  geom_vline(xintercept = 1955, linetype = "dashed", color = "purple")+
  geom_vline(xintercept = 1961, linetype = "dashed", color = "red")+
  geom_vline(xintercept = 1964, linetype = "dashed", color = "red")+
  theme_minimal() +
  labs(
      # title = "Evolution of the Ratio of Seasonal Mexican Worker State \nin the moderatly and
highly exposed states (1954 - 1970)",
       x = "Year",
       y = "Mexican Worker % of Seasonal Worker") +
  theme(panel.grid.major = element_line(size = 0.5),
        panel.grid.minor = element_blank(),
        legend.position = "right") +
  scale_color_discrete(name = "State")
ggsave("output/figures/ratio_mexican_moderatly_exposed_states.pdf")
```

```
ggplot(bracero_all_years[Year %in% 1953:1970 & group_treatment_1955 == 0], aes(x = Year, y =
mex_frac_year, color = State, group = State)) +
  geom_line() +
  geom_point() +
  geom_vline(xintercept = 1955, linetype = "dashed", color = "purple")+
  geom_vline(xintercept = 1961, linetype = "dashed", color = "red")+
  geom_vline(xintercept = 1964, linetype = "dashed", color = "red")+
  theme_minimal() +
  labs(
        # title = "Evolution of the Ratio of Seasonal Mexican Worker State in the non Exposed
States (1954 - 1970)",
       x = "Year",
       y = "Mexican Worker % of Seasonal Worker") +
  theme(panel.grid.major = element_line(size = 0.5),
        panel.grid.minor = element_blank(),
        legend.position = "right") +
  scale_color_discrete(name = "State")
ggsave("output/figures/ratio_mexican_non_exposed_states.pdf")

# Show the proportion of Mexican worker out of all Mexican per states in a stacked line figures

## Work force composition in farms ----------------------------------------
farmsworkers = bracero[Year == 1955, .(State, Year, Mexican,TotalHiredSeasonal,
HiredWorkersonFarms_final)]
farmsworkers = na.omit(unique(farmsworkers[, .(mean_seasonal = mean(TotalHiredSeasonal, na.rm
= T),
                                               mexican_mean = mean(Mexican, na.rm =T),
                                          mean_workersonfarm = mean(HiredWorkersonFarms_final,
na.rm = T)), by = "State"]))
farmsworkers[, :=(seasonal_frac = mean_seasonal/mean_workersonfarm,
                    seasonal_frac_mex = mexican_mean/mean_seasonal), by = "State"]
farmsworkers[, mean_workersonfarm := round(mean_workersonfarm, )]
farmsworkers[, mean_seasonal := round(mean_seasonal, )]
farmsworkers[, mexican_mean := round(mexican_mean, )]
setorderv(farmsworkers, cols = "mexican_mean", order = -1)
```

6.4.3 Regressions

6.4.3.1 Reproducing CLP

```
# This code replicate the main results found by Clemens & al (2018)

rm(list = ls())
gc()

source("./paths.R")
source("./code/functions/output_functions.R")
library(arrow)
library(data.table)
library(fixest)
library(modelsummary)
library(dplyr)
library(tinytex)
library(webshot2)
```

```
library(gt)
library(glue)
library(kableExtra)
library(ggplot2)

# Import Data -------------------------------------------------------------

data_final = as.data.table(fread(glue("{final_data}/final_data_aer.csv")))
# data_final = as.data.table(read_parquet(glue("{final_data}/bracero_final.parquet")))

# Table 1 -----------------------------------------------------------------
tab1 = copy(data_final)
tab1[, := (ln_realwage_hourly = log(realwage_hourly),
             ln_realwage_daily = log(realwage_daily))]

## Regressions -------------------------------------------------------------

full_year = list(
   "Hourly Composite (Full)" = feols(realwage_hourly ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1),
  "Daily w/o Board (Full)" = feols(realwage_daily ~ treatment_frac | State_FIPS + time_q, cluster
= ~State_FIPS, data = tab1),
  "Hourly Composite (1960-1970)" = feols(realwage_hourly ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1[Year %in% 1960:1970]),
  "Daily w/o Board (1960-1970)" = feols(realwage_daily ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1[Year %in% 1960:1970])
)

table_1 = modelsummary(
  full_year,
  output = glue("{output_tables}/table_1_reg.png"),  # Specify output as kableExtra
  title = "TABLE 1: Differences-in-differences with continuous treatment, quarterly",
  stars = TRUE,
  coef_rename = c("treatment_frac" = "BraceroExclusion1965 * ExposureToExclusion"),
  gof_omit = 'R2 Within|R2 Within Adj.|AIC|BIC|RMSE|Std.Errors'
)

## Semi Elasticities ------------------------------------------------------
semi_elasticities = list(
   "Log Hourly Composite (Full)" = feols(ln_realwage_hourly ~ treatment_frac | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab1),
  "Log Daily w/o Board (Full)" = feols(ln_realwage_daily ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1),
  "Log Hourly Composite (1960-1970)" = feols(ln_realwage_hourly ~ treatment_frac | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab1[Year %in% 1960:1970]),
  "Log Daily w/o Board (1960-1970)" = feols(ln_realwage_daily ~ treatment_frac | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab1[Year %in% 1960:1970])
)

modelsummary(
  semi_elasticities,
  output = glue("{output_tables}/table1_semi_elasticities.png"),
   title = "TABLE 1: Differences-in-differences with continuous treatment, quarterly (semi
```

```
elasticities)",
  stars = TRUE,
  coef_rename = c("treatment_frac" = "BraceroExclusion1965 * ExposureToExclusion"),
  gof_omit = 'R2 Within|R2 Within Adj.|AIC|BIC|RMSE|Std.Errors'
)

# Table 2 ----------------------------------------------------------------
# Effect of the bracero exclusion on domestic seasonal agricultural employment
domestic_season_worker = list(
 "All States, all year" = feols(domestic_seasonal ~ treatment_frac | State_FIPS + time_q, cluster
= ~State_FIPS, data = tab1),
 "All States, all year (ln)" = feols(ln_domestic_seasonal ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1),
 "All States, 1960-1970" = feols(domestic_seasonal ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1[Year %in% 1960:1970,]),
 "All States, 1960-1970 (ln)" = feols(ln_domestic_seasonal ~ treatment_frac | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab1[Year %in% 1960:1970,]),
 "Exposed States, all years" = feols(domestic_seasonal ~ treatment_frac | State_FIPS + time_q,
cluster = ~State_FIPS, data = tab1[none == 0,]),
 "Exposed States, all years (ln)" = feols(ln_domestic_seasonal ~ treatment_frac | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab1[none == 0]),
 "Highly Exposed States, all years" = feols(domestic_seasonal ~ treatment_frac | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab1[exposure > 0.15,]),
 "Highly Exposed States, all years (ln)" = feols(ln_domestic_seasonal ~ treatment_frac |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab1[exposure > 0.15])
)

modelsummary(
  domestic_season_worker,
  output = glue("{output_tables}/table2_domestic_seasonal_worker_employment.png"),
   title = "TABLE 1: Differences-in-differences with continuous treatment, quarterly (semi
elasticities)",
  stars = TRUE,
  coef_rename = c("treatment_frac" = "BraceroExclusion1965 * ExposureToExclusion"),
  gof_omit = 'R2 Within|R2 Within Adj.|AIC|BIC|RMSE|Std.Errors'
)

# Table 3 ----------------------------------------------------------------
# Effects of Bracero Exclusion on the three types of domestic seasonal agricultural employment

tab3 = copy(data_final)
tab3[is.na(Local_final), :=(Local_final = 0,
                            Intrastate_final = 0,
                            Interstate_final = 0)]
tab3[(Year < 1954 | Year > 1973 | (Year == 1973 & Month > 7)), :=(Local_final = NA_real_,
                                                                   Intrastate_final = NA_real_,
                                                                  Interstate_final = NA_real_)]

type_employment = list(
 "Local" = feols(Local_final ~ treatment_frac | State_FIPS + time_m, data = tab3),
 "Instrate" = feols(Intrastate_final ~ treatment_frac | State_FIPS + time_m, data = tab3),
 "Instrate" = feols(Interstate_final ~ treatment_frac | State_FIPS + time_m, data = tab3),
 "Local (ln)" = feols(ln_local ~ treatment_frac | State_FIPS + time_m, data = tab3),
```

```
 "Instrate (ln)" = feols(ln_intrastate ~ treatment_frac | State_FIPS + time_m, data = tab3),
 "Instrate (ln)" = feols(ln_interstate ~ treatment_frac | State_FIPS + time_m, data = tab3)
)

modelsummary(
  type_employment,
  output = glue("{output_tables}/table3_type_employment.png"),
   title = "TABLE 1: Differences-in-differences with continuous treatment, quarterly (semi
elasticities)",
  stars = TRUE,
  coef_rename = c("treatment_frac" = "BraceroExclusion1965 * ExposureToExclusion"),
  gof_omit = 'R2 Within|R2 Within Adj.|AIC|BIC|RMSE|Std.Errors'
)
```

6.4.3.2 Robustness Checks of CLP & Extensions for wages

```
# This code check the robustness findings for the 1955 original group of treated states on the
wage component

rm(list = ls())
gc()

source("./paths.R")
source("./code/functions/output_functions.R")
library(arrow)
library(data.table)
library(DIDmultiplegtDYN)
library(did)
library(dplyr)
library(fixest)
library(glue)
library(ggplot2)
library(MatchIt)
library(modelsummary)
library(synthdid)
library(tinytex)
library(tidyverse)
library(webshot2)

# Import Data -----------------------------------------------------------

data_final = as.data.table(fread(glue("{final_data}/final_data_aer.csv")))

# Settings --------------------------------------------------------------
tab = copy(data_final)
# We take the log of the quartly data
tab[, := (ln_realwage_hourly = log(realwage_hourly),
             ln_realwage_daily = log(realwage_daily))]

# We average wages over the year to have yearly effects and limit seasonal variations
tab[, := (realwage_hourly_year = mean(realwage_hourly, na.rm = T),
             realwage_daily_year = mean(realwage_daily, na.rm = T)), by = c("Year", "State")]
tab[, := (realwage_hourly_year_ln = log(realwage_hourly_year),
             realwage_daily_year_ln = log(realwage_daily_year))]
```

```
# We set a date has being the reference treatment point, here 1965q1. We will test for 1961 and took it to yearly effect
tab[, distance_treat_1965_q := (Year - 1965)*4 + (quarter - 1)] # treatment in 1965 with full ban
tab[, distance_treat_1961_q := (Year - 1961)*4 + (quarter - 1)] # treatment in 1961 with first regulation
# Similarly but for years
tab[, distance_treat_1965_year := (Year - 1965)]
tab[, distance_treat_1961_year := (Year - 1961)]

# Generate a year wage
tab[, annual_hourly_wage := mean(realwage_hourly, na.rm = TRUE), by = .(Year, State)]
tab[, annual_daily_wage := mean(realwage_daily, na.rm = TRUE), by = .(Year, State)]

# We generate fraction of seasonal Mexican worker for each year
tab = tab[, mex_frac_year := mean(mex_frac, na.rm = T),by = c("State", "Year")]
tab[, mex_frac_year := round(mex_frac_year, 3)]
mex_frac_year_1958 = unique(tab[Year == 1958, .(mex_frac_year, State)])
setnames(mex_frac_year_1958, "mex_frac_year", 'mex_frac_58')
tab = merge(tab, mex_frac_year_1958, by = c("State"), all.x = T)

# Highly treated are above 20% exposure, low treated are between 0% and 20%, and  the rest is control (following Clemens & al)
tab[, group := fcase(
  mex_frac_55 >= 0.2, 2,
  mex_frac_55 > 0 & mex_frac_55 < 0.2, 1,
  default = 0
)]

tab[, group_58 := fcase(
  mex_frac_58 >= 0.2, 2,
  mex_frac_58 > 0 & mex_frac_58 < 0.2, 1,
  default = 0
)]

tab_high = tab[group %in% c(0,2),]
tab_low = tab[group %in% c(0,1)]

tab_high = tab[group_58 %in% c(0,2),]
tab_low = tab[group_58 %in% c(0,1)]

# Pretrend analysis -------------------------------------------------------
# Full sample, quaterly rate

# full ban
hourly_full = feols(realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_full = feols(realwage_daily ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
hourly_ln = feols(ln_realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_ln = feols(ln_realwage_daily ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
```

```
# regulation
hourly_full_61 = feols(realwage_hourly ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_full_61 = feols(realwage_daily ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
hourly_ln_61 = feols(ln_realwage_hourly ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_ln_61 = feols(ln_realwage_daily ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)

# full ban
result_hourly_full = retrieve_result(hourly_full)
result_daily_full = retrieve_result(daily_full)
result_hourly_ln = retrieve_result(hourly_ln)
result_daily_ln = retrieve_result(daily_ln)

# regulation
result_hourly_full_61 = retrieve_result(hourly_full_61)
result_daily_full_61 = retrieve_result(daily_full_61)
result_hourly_ln_61 = retrieve_result(hourly_ln_61)
result_daily_ln_61 = retrieve_result(daily_ln_61)

# ban
event_study_plot(result_hourly_full, title = "Effect of Bracero worker exclusion on real hourly
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/
real_hourly_bracero55_et.pdf")
event_study_plot(result_daily_full, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/
real_daily_bracero55_et.pdf")
event_study_plot(result_hourly_ln, title = "Effect of Bracero worker exclusion on log real hourly
wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_hourly_bracero55_et.pdf")
event_study_plot(result_daily_ln, title = "Effect of Bracero worker exclusion on log real daily
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
            save = T, output_path = "output/figures/regression/1965/log_daily_bracero55_et.pdf")

# regulation
event_study_plot(result_hourly_full_61, title = "Effect of Bracero worker exclusion on real
hourly wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/
real_hourly_bracero55_1961_et.pdf")
event_study_plot(result_daily_full_61, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/
```

```
real_daily_bracero55_1961_et.pdf")
event_study_plot(result_hourly_ln_61, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                 save  =  T,  output_path  =  "output/figures/regression/1961/
log_hourly_bracero55_1961_et.pdf")
event_study_plot(result_daily_ln_61, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
                                 save  =  T,  output_path  =  "output/figures/regression/1961/
log_daily_bracero55_1961_et.pdf")

# Look for distinction between treatment exposure ------------------------------------

## High --------------------------------------------------------------------

#ban
hourly_full_high = feols(realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
daily_full_high  =  feols(realwage_daily  ~  i(distance_treat_1965_q,  mex_frac_55,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
hourly_ln_high = feols(ln_realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
daily_ln_high  =  feols(ln_realwage_daily  ~  i(distance_treat_1965_q,  mex_frac_55,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)

#regulation
hourly_full_high_61 = feols(realwage_hourly ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
daily_full_high_61 = feols(realwage_daily ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
hourly_ln_high_61 = feols(ln_realwage_hourly ~ i(distance_treat_1961_q, mex_frac_55, ref = -4)
| State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
daily_ln_high_61 = feols(ln_realwage_daily ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)

#ban
result_hourly_full_high = retrieve_result(hourly_full_high)
result_daily_full_high = retrieve_result(daily_full_high)
result_hourly_ln_high = retrieve_result(hourly_ln_high)
result_daily_ln_high = retrieve_result(daily_ln_high)
#regulation
result_hourly_full_high_61 = retrieve_result(hourly_full_high_61)
result_daily_full_high_61 = retrieve_result(daily_full_high_61)
result_hourly_ln_high_61 = retrieve_result(hourly_ln_high_61)
result_daily_ln_high_61 = retrieve_result(daily_ln_high_61)


event_study_plot(result_hourly_full_high, title = "Effect of Bracero worker exclusion on real
hourly wage of seasonal workers in most exposed States in 1955",
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
real_hourly_bracero55_high_et.pdf")
```

```
event_study_plot(result_daily_full_high, title = "Effect of Bracero worker exclusion on real daily wage of seasonal workers in most exposed States in 1955",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                save = T, output_path = "output/figures/regression/1965/real_daily_bracero55_high_et.pdf")
event_study_plot(result_hourly_ln_high, title = "Effect of Bracero worker exclusion on log real hourly wage of seasonal workers in most exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                save = T, output_path = "output/figures/regression/1965/log_hourly_bracero55_high_et.pdf")
event_study_plot(result_daily_ln_high, title = "Effect of Bracero worker exclusion on log real daily wage of seasonal workers in most exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
                                save = T, output_path = "output/figures/regression/1965/log_daily_bracero55_high_et.pdf")

event_study_plot(result_hourly_full_high_61, title = "Effect of Bracero worker exclusion on real hourly wage of seasonal workers in most exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                save = T, output_path = "output/figures/regression/1961/real_hourly_bracero55_high_1961_et.pdf")
event_study_plot(result_daily_full_high_61, title = "Effect of Bracero worker exclusion on real daily wage of seasonal workers in most exposed States in 1955",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                save = T, output_path = "output/figures/regression/1961/real_daily_bracero55_high_1961_et.pdf")
event_study_plot(result_hourly_ln_high_61, title = "Effect of Bracero worker exclusion on log real hourly wage of seasonal workers in most exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                save = T, output_path = "output/figures/regression/1961/log_hourly_bracero55_high_1961_et.pdf")
event_study_plot(result_daily_ln_high_61, title = "Effect of Bracero worker exclusion on log real daily wage of seasonal workers in most exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
                                save = T, output_path = "output/figures/regression/1961/log_daily_bracero55_high_1961_et.pdf")

## Low -------------------------------------------------------------------

hourly_full_low = feols(realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)
daily_full_low = feols(realwage_daily ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)
hourly_ln_low = feols(ln_realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)
daily_ln_low = feols(ln_realwage_daily ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)

result_hourly_full_low = retrieve_result(hourly_full_low)
result_daily_full_low = retrieve_result(daily_full_low)
result_hourly_ln_low = retrieve_result(hourly_ln_low)
result_daily_ln_low = retrieve_result(daily_ln_low)
```

```
event_study_plot(result_hourly_full_low, title = "Effect of Bracero worker exclusion on real
hourly wage of seasonal workers in low exposed States in 1955",
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
real_hourly_bracero55_low_et.pdf")
event_study_plot(result_daily_full_low, title = "Effect of Bracero worker exclusion on real
daily wage of seasonal workers in low exposed States in 1955",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
real_daily_bracero55_low_et.pdf")
event_study_plot(result_hourly_ln_low, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers in low exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
log_hourly_bracero55_low_et.pdf")
event_study_plot(result_daily_ln_low, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers in low exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
log_daily_bracero55_low_et.pdf")

# Year frequency -----------------------------------------------------


## All --------------------------------------------------------------------

#ban
hourly_year = feols(realwage_hourly_year ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
daily_year = feols(realwage_daily_year ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
hourly_year_ln = feols(realwage_hourly_year_ln ~ i(distance_treat_1965_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)
daily_year_ln = feols(realwage_daily_year_ln ~ i(distance_treat_1965_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)

#regulation
hourly_year_61 = feols(realwage_hourly_year ~ i(distance_treat_1961_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)
daily_year_61 = feols(realwage_daily_year ~ i(distance_treat_1961_year, mex_frac_55, ref = -1)
| State_FIPS + Year, cluster = ~State_FIPS, data = tab)
hourly_year_ln_61 = feols(realwage_hourly_year_ln ~ i(distance_treat_1961_year, mex_frac_55,
ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)
daily_year_ln_61 = feols(realwage_daily_year_ln ~ i(distance_treat_1961_year, mex_frac_55, ref
= -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)

#ban
result_hourly_year = retrieve_result(hourly_year)
result_daily_year = retrieve_result(daily_year)
result_hourly_year_ln = retrieve_result(hourly_year_ln)
result_daily_year_ln = retrieve_result(daily_year_ln)

#regulation
```

```
result_hourly_year_61 = retrieve_result(hourly_year_61)
result_daily_year_61 = retrieve_result(daily_year_61)
result_hourly_year_ln_61 = retrieve_result(hourly_year_ln_61)
result_daily_year_ln_61 = retrieve_result(daily_year_ln_61)

#ban
event_study_plot(result_hourly_year, title = "Effect of Bracero worker exclusion on real hourly
wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage ($)",
                                 save = F, output_path = "output/figures/regression/1965/
real_hourly_bracero55_year_et.pdf")
event_study_plot(result_daily_year, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage ($)",
                                 save = F, output_path = "output/figures/regression/1965/
real_daily_bracero55_year_et.pdf")
event_study_plot(result_hourly_year_ln, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers",
                x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_hourly_bracero55_year_et.pdf")
event_study_plot(result_daily_year_ln, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_daily_bracero55_year_et.pdf")

#regulation
event_study_plot(result_hourly_year_61, title = "Effect of Bracero worker exclusion on real
hourly wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/
real_hourly_bracero55_year_1961_et.pdf")
event_study_plot(result_daily_year_61, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/
real_daily_bracero55_year_1961_et.pdf")
event_study_plot(result_hourly_year_ln_61, title = "Effect of Bracero worker exclusion on log
real hourly wage of seasonal workers",
                x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1961/
log_hourly_bracero55_year_1961_et.pdf")
event_study_plot(result_daily_year_ln_61, title = "Effect of Bracero worker exclusion on log
real daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage (log)",
                                 save = T, output_path = "output/figures/regression/1961/
log_daily_bracero55_year_1961_et.pdf")

## High --------------------------------------------------------------------

# High exposed group
#ban
```

```
hourly_year = feols(realwage_hourly_year ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
daily_year = feols(realwage_daily_year ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
hourly_year_ln = feols(realwage_hourly_year_ln ~ i(distance_treat_1965_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
daily_year_ln = feols(realwage_daily_year_ln ~ i(distance_treat_1965_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)

#regulation
hourly_year_61 = feols(realwage_hourly_year ~ i(distance_treat_1961_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
daily_year_61 = feols(realwage_daily_year ~ i(distance_treat_1961_year, mex_frac_55, ref = -1)
| State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
hourly_year_ln_61 = feols(realwage_hourly_year_ln ~ i(distance_treat_1961_year, mex_frac_55,
ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
daily_year_ln_61 = feols(realwage_daily_year_ln ~ i(distance_treat_1961_year, mex_frac_55, ref
= -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)

#ban
result_hourly_year = retrieve_result(hourly_year)
result_daily_year = retrieve_result(daily_year)
result_hourly_year_ln = retrieve_result(hourly_year_ln)
result_daily_year_ln = retrieve_result(daily_year_ln)

#regulation
result_hourly_year_61 = retrieve_result(hourly_year_61)
result_daily_year_61 = retrieve_result(daily_year_61)
result_hourly_year_ln_61 = retrieve_result(hourly_year_ln_61)
result_daily_year_ln_61 = retrieve_result(daily_year_ln_61)

#ban
event_study_plot(result_hourly_year, title = "Effect of Bracero worker exclusion on real hourly
wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/
real_hourly_bracero55_year_high_et.pdf")
event_study_plot(result_daily_year, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/
real_daily_bracero55_year_high_et.pdf")
event_study_plot(result_hourly_year_ln, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers",
                x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_hourly_bracero55_year_high_et.pdf")
event_study_plot(result_daily_year_ln, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_daily_bracero55_year_high_et.pdf")
```

```
#regulation
event_study_plot(result_hourly_year_61, title = "Effect of Bracero worker exclusion on real hourly wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/real_hourly_bracero55_year_high_1961_et.pdf")
event_study_plot(result_daily_year_61, title = "Effect of Bracero worker exclusion on real daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/real_daily_bracero55_year_high_1961_et.pdf")
event_study_plot(result_hourly_year_ln_61, title = "Effect of Bracero worker exclusion on log real hourly wage of seasonal workers",
                x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1961/log_hourly_bracero55_year_high_1961_et.pdf")
event_study_plot(result_daily_year_ln_61, title = "Effect of Bracero worker exclusion on log real daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage (log)",
                                 save = T, output_path = "output/figures/regression/1961/log_daily_bracero55_year_high_1961_et.pdf")

## Low --------------------------------------------------------------------

hourly_year = feols(realwage_hourly_year ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)
daily_year = feols(realwage_daily_year ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)
hourly_year_ln = feols(realwage_hourly_year_ln ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)
daily_year_ln = feols(realwage_daily_year_ln ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)

#ban
result_hourly_year = retrieve_result(hourly_year)
result_daily_year = retrieve_result(daily_year)
result_hourly_year_ln = retrieve_result(hourly_year_ln)
result_daily_year_ln = retrieve_result(daily_year_ln)

#ban
event_study_plot(result_hourly_year, title = "Effect of Bracero worker exclusion on real hourly wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/real_hourly_bracero55_year_low_et.pdf")
event_study_plot(result_daily_year, title = "Effect of Bracero worker exclusion on real daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/real_daily_bracero55_year_low_et.pdf")
event_study_plot(result_hourly_year_ln, title = "Effect of Bracero worker exclusion on log real hourly wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage (log)",
```

```
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
log_hourly_bracero55_year_low_et.pdf")
event_study_plot(result_daily_year_ln, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage (log)",
                                 save  =  T,  output_path  =  "output/figures/regression/1965/
log_daily_bracero55_year_low_et.pdf")

#                         Alternative                        method                        of
estimations ------------------------------------------------------------

## 1958 batch ----------------------------------------------------
### Quarterly ------------------------------------------------------------
# Full sample, quaterly rate

# full ban
hourly_full  =  feols(realwage_hourly  ~  i(distance_treat_1965_q,  mex_frac_58,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_full = feols(realwage_daily ~ i(distance_treat_1965_q, mex_frac_58, ref = -4) | State_FIPS
+ time_q, cluster = ~State_FIPS, data = tab)
hourly_ln  =  feols(ln_realwage_hourly  ~  i(distance_treat_1965_q,  mex_frac_58,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_ln = feols(ln_realwage_daily ~ i(distance_treat_1965_q, mex_frac_58, ref = -4) | State_FIPS
+ time_q, cluster = ~State_FIPS, data = tab)
# regulation
hourly_full_61  =  feols(realwage_hourly  ~  i(distance_treat_1961_q,  mex_frac_58,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_full_61  =  feols(realwage_daily  ~  i(distance_treat_1961_q,  mex_frac_58,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
hourly_ln_61  =  feols(ln_realwage_hourly  ~  i(distance_treat_1961_q,  mex_frac_58,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_ln_61  =  feols(ln_realwage_daily  ~  i(distance_treat_1961_q,  mex_frac_58,  ref  =  -4)  |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)

# full ban
result_hourly_full = retrieve_result(hourly_full)
result_daily_full = retrieve_result(daily_full)
result_hourly_ln = retrieve_result(hourly_ln)
result_daily_ln = retrieve_result(daily_ln)

# regulation
result_hourly_full_61 = retrieve_result(hourly_full_61)
result_daily_full_61 = retrieve_result(daily_full_61)
result_hourly_ln_61 = retrieve_result(hourly_ln_61)
result_daily_ln_61 = retrieve_result(daily_ln_61)

# ban
event_study_plot(result_hourly_full, title = "Effect of Bracero worker exclusion on real hourly
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save  =  F,  output_path  =  "output/figures/regression/1965/
real_hourly_bracero55_et.pdf")
event_study_plot(result_daily_full, title = "Effect of Bracero worker exclusion on real daily
```

```
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                save = F, output_path = "output/figures/regression/1965/
real_daily_bracero55_et.pdf")
event_study_plot(result_hourly_ln, title = "Effect of Bracero worker exclusion on log real hourly
wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                save = F, output_path = "output/figures/regression/1965/
log_hourly_bracero55_et.pdf")
event_study_plot(result_daily_ln, title = "Effect of Bracero worker exclusion on log real daily
wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
            save = F, output_path = "output/figures/regression/1965/log_daily_bracero55_et.pdf")

# regulation
event_study_plot(result_hourly_full_61, title = "Effect of Bracero worker exclusion on real
hourly wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                save = T, output_path = "output/figures/regression/1961/
real_hourly_bracero55_1961_et.pdf")
event_study_plot(result_daily_full_61, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                save = T, output_path = "output/figures/regression/1961/
real_daily_bracero55_1961_et.pdf")
event_study_plot(result_hourly_ln_61, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                save = T, output_path = "output/figures/regression/1961/
log_hourly_bracero55_1961_et.pdf")
# event_study_plot(result_daily_ln_61, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers",
#               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",


### Yearly ---------------------------------------------------------------

#ban
hourly_year = feols(realwage_hourly_year ~ i(distance_treat_1965_year, mex_frac_58, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
daily_year = feols(realwage_daily_year ~ i(distance_treat_1965_year, mex_frac_58, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
hourly_year_ln = feols(realwage_hourly_year_ln ~ i(distance_treat_1965_year, mex_frac_58, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)
daily_year_ln = feols(realwage_daily_year_ln ~ i(distance_treat_1965_year, mex_frac_58, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)

#ban
result_hourly_year = retrieve_result(hourly_year)
result_daily_year = retrieve_result(daily_year)
result_hourly_year_ln = retrieve_result(hourly_year_ln)
result_daily_year_ln = retrieve_result(daily_year_ln)
```

```
#ban
event_study_plot(result_hourly_year, title = "Effect of Bracero worker exclusion on real hourly
wage of seasonal workers, 1958 batch",
                 x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage ($)",
                          save = T, output_path = "output/figures/regression/1965/58_batch/
real_hourly_bracero58_year_et.pdf")
event_study_plot(result_daily_year, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers, 1958 batch",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage ($)",
                          save = T, output_path = "output/figures/regression/1965/58_batch/
real_daily_bracero58_year_et.pdf")
event_study_plot(result_hourly_year_ln, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers, 1958 batch",
                x_label = "Distance to treatment (year)", y_label = "Real Hourly Wage (log)",
                          save = T, output_path = "output/figures/regression/1965/58_batch/
log_hourly_bracero58_year_et.pdf")
event_study_plot(result_daily_year_ln, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers, 1958 batch",
                 x_label = "Distance to treatment (year)", y_label = "Real Daily Wage (log)",
                          save = T, output_path = "output/figures/regression/1965/58_batch/
log_daily_bracero58_year_et.pdf")

## Synthetic Control --------------------------------------------------------------------

### California --------------------------------------------------------------
tab_sc <- tab %>%
  select(all_of(cols)) %>%
  group_by(State, Year) %>%
  summarise(mean_hourly_wage = mean(realwage_hourly, na.rm = TRUE),
            # domestic_seasonal = ln_domestic_seasonal,
            realwage_hourly = mean(realwage_hourly, na.rm = TRUE),
            realwage_daily = mean(realwage_daily, na.rm = TRUE),
            Cotton_machine = mean(Cotton_machine, na.rm = TRUE),
            Sugarbeet_machine = mean(Sugarbeet_machine, na.rm = TRUE),
            Tractors = mean(Tractors, na.rm = TRUE),
            Cotton = mean(Cotton, na.rm = TRUE),
            Tomatoes_total = mean(Tomatoes_total, na.rm = TRUE),
            Lettuce = mean(Lettuce, na.rm = TRUE),
            Strawberries_total = mean(Strawberries_total, na.rm = TRUE),
            Citrus = mean(Citrus, na.rm = TRUE),
            Cantaloupes = mean(Cantaloupes, na.rm = TRUE),
            BrusselsSprouts = mean(BrusselsSprouts, na.rm = TRUE),
            Asparagus_total = mean(Asparagus_total, na.rm = TRUE),
            Celery = mean(Celery, na.rm = TRUE),
            Cucumbers_pickle = mean(Cucumbers_pickle, na.rm = TRUE),
            .groups = 'drop')

# Filter data to retain only complete rows for all relevant columns
tab_sc_clean <- tab_sc %>%
 filter(complete.cases(mean_hourly_wage, Cotton, Tomatoes_total, Strawberries_total, Tractors))

# Drop treated States
tab_sc_clean = tab_sc_clean %>%
```

```
  filter(!State %in% c("TX", "AR", "AZ", "COL", "NM", "NV"))

# Synthetic control setup
synth_output <- tab_sc_clean %>%
  synthetic_control(outcome = mean_hourly_wage,
                    unit = State,
                    time = Year,
                    i_unit = "CA",
                    i_time = 1965,
                    generate_placebos = TRUE) %>%
  generate_predictor(time_window = 1955:1964,
                     mean_cotton = mean(Cotton, na.rm = TRUE),
                     mean_tomatoes = mean(Tomatoes_total, na.rm = TRUE),
                     mean_strawberries = mean(Strawberries_total, na.rm = TRUE),
                     mean_tractor = mean(Tractors, na.rm = TRUE)) %>%
  generate_weights(optimization_window = 1955:1964,
                   margin_ipop = .02, sigf_ipop = 7, bound_ipop = 6) %>%
  generate_control()

# Plot trends
synth_plot <- synth_output %>% plot_trends()
ggsave(glue("output/sc/sc_plot_mean_hourly_wage_CA.pdf"), plot = synth_plot, width = 10, height
= 8, dpi = 300)
synth_diff = synth_output %>% plot_differences()
ggsave(glue("output/sc/sc_diff_mean_hourly_wage_CA.pdf"), plot = synth_diff, width = 10, height
= 8, dpi = 300)
synth_weights = synth_output %>% plot_weights()
ggsave(glue("output/sc/sc_wieghts_mean_hourly_wage_CA.pdf"), plot = synth_weights, width = 10,
height = 8, dpi = 300)
synth_placebo = synth_output %>% plot_placebos(prune = TRUE)
ggsave(glue("output/sc/sc_placebo_mean_hourly_wage_CA.pdf"), plot = synth_placebo, width = 10,
height = 8, dpi = 300)

### Texas -------------------------------------------------------------
tab_sc <- tab %>%
  select(all_of(cols)) %>%
  group_by(State, Year) %>%
  summarise(mean_hourly_wage = mean(realwage_hourly, na.rm = TRUE),
            # domestic_seasonal = ln_domestic_seasonal,
            realwage_hourly = mean(realwage_hourly, na.rm = TRUE),
            realwage_daily = mean(realwage_daily, na.rm = TRUE),
            Cotton_machine = mean(Cotton_machine, na.rm = TRUE),
            Sugarbeet_machine = mean(Sugarbeet_machine, na.rm = TRUE),
            Tractors = mean(Tractors, na.rm = TRUE),
            Cotton = mean(Cotton, na.rm = TRUE),
            Tomatoes_total = mean(Tomatoes_total, na.rm = TRUE),
            Lettuce = mean(Lettuce, na.rm = TRUE),
            Strawberries_total = mean(Strawberries_total, na.rm = TRUE),
            Citrus = mean(Citrus, na.rm = TRUE),
            Cantaloupes = mean(Cantaloupes, na.rm = TRUE),
            BrusselsSprouts = mean(BrusselsSprouts, na.rm = TRUE),
            Asparagus_total = mean(Asparagus_total, na.rm = TRUE),
            Celery = mean(Celery, na.rm = TRUE),
```

```
            Cucumbers_pickle = mean(Cucumbers_pickle, na.rm = TRUE),
            .groups = 'drop')

# Filter data to retain only complete rows for all relevant columns
tab_sc_clean <- tab_sc %>%
 filter(complete.cases(mean_hourly_wage, Cotton, Tomatoes_total, Strawberries_total, Tractors))

# Drop treated States
tab_sc_clean = tab_sc_clean %>%
  filter(!State %in% c("CA", "AR", "AZ", "COL", "NM", "NV"))

# Synthetic control setup
synth_output <- tab_sc_clean %>%
  synthetic_control(outcome = mean_hourly_wage,
                    unit = State,
                    time = Year,
                    i_unit = "TX",
                    i_time = 1965,
                    generate_placebos = TRUE) %>%
  generate_predictor(time_window = 1955:1964,
                     mean_cotton = mean(Cotton, na.rm = TRUE),
                     mean_tomatoes = mean(Tomatoes_total, na.rm = TRUE),
                     mean_strawberries = mean(Strawberries_total, na.rm = TRUE),
                     mean_tractor = mean(Tractors, na.rm = TRUE)) %>%
  generate_weights(optimization_window = 1955:1964,
                   margin_ipop = .02, sigf_ipop = 7, bound_ipop = 6) %>%
  generate_control()

# Plot trends
synth_plot <- synth_output %>% plot_trends()
ggsave(glue("output/sc/sc_plot_mean_hourly_wage_TX.pdf"), plot = synth_plot, width = 10, height
= 8, dpi = 300)
synth_diff = synth_output %>% plot_differences()
ggsave(glue("output/sc/sc_diff_mean_hourly_wage_TX.pdf"), plot = synth_diff, width = 10, height
= 8, dpi = 300)
synth_weights = synth_output %>% plot_weights()
ggsave(glue("output/sc/sc_wieghts_mean_hourly_wage_TX.pdf"), plot = synth_weights, width = 10,
height = 8, dpi = 300)
synth_placebo = synth_output %>% plot_placebos(prune = TRUE)
ggsave(glue("output/sc/sc_placebo_mean_hourly_wage_TX.pdf"), plot = synth_placebo, width = 10,
height = 8, dpi = 300)
```

6.4.3.3 Robustness Checks of CLP & Extensions for employment

```
# This code check the robustness findings for the 1955 original group of treated states on the
employment component

rm(list = ls())
gc()

source("./paths.R")
source("./code/functions/output_functions.R")
library(arrow)
library(data.table)
library(DIDmultiplegtDYN)
```

```
library(did)
library(dplyr)
library(fixest)
library(glue)
library(ggplot2)
library(MatchIt)
library(modelsummary)
library(tidysynth)
library(tinytex)
library(tidyverse)
library(webshot2)

# Import Data -------------------------------------------------------------

data_final = as.data.table(fread(glue("{final_data}/final_data_aer.csv")))

# Settings ----------------------------------------------------------------
tab = copy(data_final)
# We take the log of the quartly data
tab[, := (ln_realwage_hourly = log(realwage_hourly),
            ln_realwage_daily = log(realwage_daily))]

# Ln of employment variables
tab[, := (ln_local = log(Local_final),
            ln_interstate = log(Interstate_final),
            ln_intrastate = log(Intrastate_final))]

# We average wages over the year to have yearly effects and limit seasonal variations
tab[, := (realwage_hourly_year = mean(realwage_hourly, na.rm = T),
            realwage_daily_year = mean(realwage_daily, na.rm = T)), by = c("Year", "State")]
tab[, := (realwage_hourly_year_ln = log(realwage_hourly_year),
            realwage_daily_year_ln = log(realwage_daily_year))]

# We set a date has being the reference treatment point, here 1965q1. We will test for 1961 and
took it to yearly effect
tab[, distance_treat_1965_q := (Year - 1965)*4 + (quarter - 1)] # treatment in 1965 with full ban
tab[, distance_treat_1961_q := (Year - 1961)*4 + (quarter - 1)] # treatment in 1961 with
first regulation
# Similarly but for years
tab[, distance_treat_1965_year := (Year - 1965)]
tab[, distance_treat_1961_year := (Year - 1961)]

# We generate fraction of seasonal Mexican worker for each year
tab = tab[, mex_frac_year := mean(mex_frac, na.rm = T),by = c("State", "Year")]
tab[, mex_frac_year := round(mex_frac_year, 3)]
mex_frac_year_1958 = unique(tab[Year == 1958, .(mex_frac_year, State)])
tab = merge(tab, mex_frac_year_1958, by = c("State"))

# Highly treated are above 20% exposure, low treated are between 0% and 20%, and  the rest is
control (following Clemens & al)
tab[, group := fcase(
  mex_frac_55 >= 0.2, 2,
  mex_frac_55 > 0 & mex_frac_55 < 0.2, 1,
```

```
  default = 0
)]

# conservative group
tab[, conservative_group := fcase(
  State %in% c("CA", "TX"), 2,
  State %in% c("AR", "AZ", "NM"), 1,
  default = 0
)]

tab_high = tab[group %in% c(0,2),]
tab_low = tab[group %in% c(0,1)]

tab_conservative = tab[conservative_group %in% c(0,2)]

# Pretrend analysis --------------------------------------------------------
# Full sample, quaterly rate

# full ban
domestic = feols(domestic_seasonal ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS
+ time_q, cluster = ~State_FIPS, data = tab)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
local = feols(Local_final ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab)
intrastate = feols(Intrastate_final ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
interstate = feols(Interstate_final ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
local_ln = feols(ln_local ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab)
intrastate_ln = feols(ln_intrastate ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
interstate_ln = feols(ln_interstate ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)

# regulation
hourly_full_61 = feols(realwage_hourly ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_full_61 = feols(realwage_daily ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
hourly_ln_61 = feols(ln_realwage_hourly ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)
daily_ln_61 = feols(ln_realwage_daily ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab)

# full ban
domestic_ban = retrieve_result(domestic)
domestic_ln_ban = retrieve_result(domestic_ln)
local_ban = retrieve_result(local)
intrastate_ban = retrieve_result(intrastate)
interstate_ban = retrieve_result(interstate)
local_ban_ln = retrieve_result(local_ln)
```

```
intrastate_ban_ln = retrieve_result(intrastate_ln)
interstate_ban_ln = retrieve_result(interstate_ln)

# regulation
result_hourly_full_61 = retrieve_result(hourly_full_61)
result_daily_full_61 = retrieve_result(daily_full_61)
result_hourly_ln_61 = retrieve_result(hourly_ln_61)
result_daily_ln_61 = retrieve_result(daily_ln_61)

# ban
event_study_plot(domestic_ban, title = "Effect of Bracero worker exclusion on domestic employment of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Employment (thousand)",
                                 save = T, output_path = "output/figures/regression/1965/domestic_employment_bracero55_et.pdf")
event_study_plot(domestic_ln_ban, title = "Effect of Bracero worker exclusion on domestic (log) employment of seasonal workers",
                 x_label = "Distance to treatment (quarter)", y_label =  "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/domestic_employment_ln_bracero55_et.pdf")
event_study_plot(local_ban, title = "Effect of Bracero worker exclusion on local employment",
              x_label = "Distance to treatment (quarter)", y_label = "Employment (thousands)",
                                 save = T, output_path = "output/figures/regression/1965/local_employment_bracero55_et.pdf")
event_study_plot(intrastate_ban, title = "Effect of Bracero worker exclusion on intrastate employment",
              x_label = "Distance to treatment (quarter)", y_label = "Employment (thousands)",
                                 save = T, output_path = "output/figures/regression/1965/intrastate_employment_bracero55_et.pdf")
event_study_plot(interstate_ban, title = "Effect of Bracero worker exclusion on interstate employment",
              x_label = "Distance to treatment (quarter)", y_label = "Employment (thousands)",
                                 save = T, output_path = "output/figures/regression/1965/interstate_employment_bracero55_et.pdf")
event_study_plot(local_ban_ln, title = "Effect of Bracero worker exclusion on local employment (log)",
                 x_label = "Distance to treatment (quarter)", y_label = "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/local_employment_ln_bracero55_et.pdf")
event_study_plot(intrastate_ban_ln, title = "Effect of Bracero worker exclusion on intrastate employment (log)",
                 x_label = "Distance to treatment (quarter)", y_label = "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/intrastate_employment_ln_bracero55_et.pdf")
event_study_plot(interstate_ban_ln, title = "Effect of Bracero worker exclusion on interstate employment (log)",
                 x_label = "Distance to treatment (quarter)", y_label = "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/interstate_employment_ln_bracero55_et.pdf")

# regulation
event_study_plot(result_hourly_full_61, title = "Effect of Bracero worker exclusion on real hourly wage of seasonal workers",
```

```
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/
real_hourly_bracero55_1961_et.pdf")
event_study_plot(result_daily_full_61, title = "Effect of Bracero worker exclusion on real daily
wage of seasonal workers",
                x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1961/
real_daily_bracero55_1961_et.pdf")
event_study_plot(result_hourly_ln_61, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1961/
log_hourly_bracero55_1961_et.pdf")
event_study_plot(result_daily_ln_61, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers",
               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
                                 save = T, output_path = "output/figures/regression/1961/
log_daily_bracero55_1961_et.pdf")


# Look for distinction between treatment exposure ------------------------------------

## High -------------------------------------------------------------------

#ban
domestic = feols(domestic_seasonal ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS
+ time_q, cluster = ~State_FIPS, data = tab_high)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
local = feols(Local_final ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab_high)
intrastate = feols(Intrastate_final ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
interstate = feols(Interstate_final ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
local_ln = feols(ln_local ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab_high)
intrastate_ln = feols(ln_intrastate ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
interstate_ln = feols(ln_interstate ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)

#regulation
domestic = feols(domestic_seasonal ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) | State_FIPS
+ time_q, cluster = ~State_FIPS, data = tab_high)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
local = feols(Local_final ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab_high)
intrastate = feols(Intrastate_final ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
interstate = feols(Interstate_final ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
```

```
local_ln = feols(ln_local ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) | State_FIPS +
time_q, cluster = ~State_FIPS, data = tab_high)
intrastate_ln = feols(ln_intrastate ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)
interstate_ln = feols(ln_interstate ~ i(distance_treat_1961_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_high)

#ban
domestic_ban = retrieve_result(domestic)
domestic_ln_ban = retrieve_result(domestic_ln)
local_ban = retrieve_result(local)
intrastate_ban = retrieve_result(intrastate)
interstate_ban = retrieve_result(interstate)
local_ban_ln = retrieve_result(local_ln)
intrastate_ban_ln = retrieve_result(intrastate_ln)
interstate_ban_ln = retrieve_result(interstate_ln)

event_study_plot(domestic_ban, title = "Effect of Bracero worker exclusion on domestic employment
of seasonal workers \n in most exposed states",
                x_label = "Distance to treatment (quarter)", y_label = "Employment (thousand)",
save = T,
                                                output_path = "output/figures/regression/1965/
domestic_employment_bracero55_high_et.pdf")
event_study_plot(domestic_ln_ban, title = "Effect of Bracero worker exclusion on domestic (log)
employment of seasonal workers \n in most exposed states",
                 x_label = "Distance to treatment (quarter)", y_label =  "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/
domestic_employment_ln_bracero55_high_et.pdf")
event_study_plot(local_ban, title = "Effect of Bracero worker exclusion on local employment \n
in most exposed states",
               x_label = "Distance to treatment (quarter)", y_label = "Employment (thousands)",
                                 save = T, output_path = "output/figures/regression/1965/
local_employment_bracero55_high_et.pdf")
event_study_plot(intrastate_ban, title = "Effect of Bracero worker exclusion on intrastate
employment \n in most exposed states",
               x_label = "Distance to treatment (quarter)", y_label = "Employment (thousands)",
                                 save = T, output_path = "output/figures/regression/1965/
intrastate_employment_bracero55_high_et.pdf")
event_study_plot(interstate_ban, title = "Effect of Bracero worker exclusion on interstate
employment \n in most exposed states",
               x_label = "Distance to treatment (quarter)", y_label = "Employment (thousands)",
                                 save = T, output_path = "output/figures/regression/1965/
interstate_employment_bracero55_high_et.pdf")
event_study_plot(local_ban_ln, title = "Effect of Bracero worker exclusion on local employment
(log) \n in most exposed states",
                 x_label = "Distance to treatment (quarter)", y_label = "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/
local_employment_ln_bracero55_high_et.pdf")
event_study_plot(intrastate_ban_ln, title = "Effect of Bracero worker exclusion on intrastate
employment (log) \n in most exposed states",
                 x_label = "Distance to treatment (quarter)", y_label = "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/
intrastate_employment_ln_bracero55_high_et.pdf")
```

```
event_study_plot(interstate_ban_ln, title = "Effect of Bracero worker exclusion on interstate
employment (log) \n in most exposed states",
                 x_label = "Distance to treatment (quarter)", y_label = "Employment (log)",
                                 save = T, output_path = "output/figures/regression/1965/
interstate_employment_ln_bracero55_high_et.pdf")

## Low ---------------------------------------------------------------------

hourly_full_low = feols(realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)
daily_full_low = feols(realwage_daily ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)
hourly_ln_low = feols(ln_realwage_hourly ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)
daily_ln_low = feols(ln_realwage_daily ~ i(distance_treat_1965_q, mex_frac_55, ref = -4) |
State_FIPS + time_q, cluster = ~State_FIPS, data = tab_low)

result_hourly_full_low = retrieve_result(hourly_full_low)
result_daily_full_low = retrieve_result(daily_full_low)
result_hourly_ln_low = retrieve_result(hourly_ln_low)
result_daily_ln_low = retrieve_result(daily_ln_low)

event_study_plot(result_hourly_full_low, title = "Effect of Bracero worker exclusion on real
hourly wage of seasonal workers in low exposed States in 1955",
                x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/
real_hourly_bracero55_low_et.pdf")
event_study_plot(result_daily_full_low, title = "Effect of Bracero worker exclusion on real
daily wage of seasonal workers in low exposed States in 1955",
                 x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage ($)",
                                 save = T, output_path = "output/figures/regression/1965/
real_daily_bracero55_low_et.pdf")
event_study_plot(result_hourly_ln_low, title = "Effect of Bracero worker exclusion on log real
hourly wage of seasonal workers in low exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Hourly Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_hourly_bracero55_low_et.pdf")
event_study_plot(result_daily_ln_low, title = "Effect of Bracero worker exclusion on log real
daily wage of seasonal workers in low exposed States in 1955",
               x_label = "Distance to treatment (quarter)", y_label = "Real Daily Wage (log)",
                                 save = T, output_path = "output/figures/regression/1965/
log_daily_bracero55_low_et.pdf")

# Year frequency -----------------------------------------------------

## All ---------------------------------------------------------------------
domestic = feols(domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)

# 1961
domestic_61 = feols(domestic_seasonal ~ i(distance_treat_1961_year, mex_frac_55, ref = -1) |
```

```
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
domestic_ln_61 = feols(ln_domestic_seasonal ~ i(distance_treat_1961_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab)

#ban
domestic_ban_year = retrieve_result(domestic)
domestic_ban_ln_year = retrieve_result(domestic_ln)

# regulation
domestic_ban_year_61 = retrieve_result(domestic_61)
domestic_ban_ln_year_61 = retrieve_result(domestic_ln_61)

#ban
event_study_plot(domestic_ban_year, title = "Effect of Bracero worker exclusion on domestic
employment of seasonal workers",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                                save = T, output_path = "output/figures/regression/1965/
domestic_employment_bracero55_year_et.pdf")
event_study_plot(domestic_ban_ln_year, title = "Effect of Bracero worker exclusion on domestic
employment of seasonal workers",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                                save = T, output_path = "output/figures/regression/1965/
domestic_employment_ln_bracero55_year_et.pdf")

#regulation
event_study_plot(domestic_ban_year_61, title = "Effect of Bracero worker regulation on domestic
employment of seasonal workers for exclusion in 1961",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                                save = T, output_path = "output/figures/regression/1961/
domestic_employment_bracero55_year_1961_et.pdf")
event_study_plot(domestic_ban_ln_year_61, title = "Effect of Bracero worker regulation on
domestic employment of seasonal workers for exclusion in 1961",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                                save = T, output_path = "output/figures/regression/1961/
domestic_employment_ln_bracero55_year_1961_et.pdf")

## High --------------------------------------------------------------------

# High exposed group
#ban
domestic = feols(domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)

#regulation
domestic_61 = feols(domestic_seasonal ~ i(distance_treat_1961_year, mex_frac_55, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)
domestic_ln_61 = feols(ln_domestic_seasonal ~ i(distance_treat_1961_year, mex_frac_55, ref =
-1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_high)

#ban
domestic_ban_year = retrieve_result(domestic)
```

```
domestic_ban_ln_year = retrieve_result(domestic_ln)

#regulation
domestic_reg_year_61 = retrieve_result(domestic_61)
domestic_reg_ln_year_61 = retrieve_result(domestic_ln_61)

#ban
event_study_plot(domestic_ban_year, title = "Effect of Bracero worker exclusion on domestic employment of seasonal workers \nin the most exposed states",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                                save = T, output_path = "output/figures/regression/1965/domestic_employment_bracero55_year_high_et.pdf")
event_study_plot(domestic_ban_ln_year, title = "Effect of Bracero worker exclusion on domestic employment of seasonal workers \nin the most exposed states",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                                save = T, output_path = "output/figures/regression/1965/domestic_employment_ln_bracero55_year_high_et.pdf")

#regulation
event_study_plot(domestic_reg_year_61, title = "Effect of Bracero worker regulation (1962) on domestic employment of seasonal workers \nin the most exposed states",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                                save = T, output_path = "output/figures/regression/1961/domestic_employment_bracero55_year_high_et_1961.pdf")
event_study_plot(domestic_reg_ln_year_61, title = "Effect of Bracero worker regulation (1962) on domestic employment of seasonal workers \nin the most exposed states",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                                save = T, output_path = "output/figures/regression/1961/domestic_employment_ln_bracero55_year_high_et_1961.pdf")

## Low ---------------------------------------------------------------------

#ban
domestic = feols(domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)

#regulation
domestic_61 = feols(domestic_seasonal ~ i(distance_treat_1961_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)
domestic_ln_61 = feols(ln_domestic_seasonal ~ i(distance_treat_1961_year, mex_frac_55, ref = -1) | State_FIPS + Year, cluster = ~State_FIPS, data = tab_low)

#ban
domestic_ban_year = retrieve_result(domestic)
domestic_ban_ln_year = retrieve_result(domestic_ln)

#regulation
domestic_reg_year_61 = retrieve_result(domestic_61)
domestic_reg_ln_year_61 = retrieve_result(domestic_ln_61)

#ban
```

```
event_study_plot(domestic_ban_year, title = "Effect of Bracero worker exclusion on domestic
employment of seasonal workers \nin the low exposed states",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                                save  =  T,  output_path  =  "output/figures/regression/1965/
domestic_employment_bracero55_year_low_et.pdf")
event_study_plot(domestic_ban_ln_year, title = "Effect of Bracero worker exclusion on domestic
employment of seasonal workers \nin the low exposed states",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                                save  =  T,  output_path  =  "output/figures/regression/1965/
domestic_employment_ln_bracero55_year_low_et.pdf")

#regulation
event_study_plot(domestic_reg_year_61, title = "Effect of Bracero worker regulation (1962) on
domestic employment of seasonal workers \nin the low exposed states",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                                save  =  T,  output_path  =  "output/figures/regression/1961/
domestic_employment_bracero55_year_low_et_1961.pdf")
event_study_plot(domestic_reg_ln_year_61, title = "Effect of Bracero worker regulation (1962)
on domestic employment of seasonal workers \nin the low exposed states",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                                save  =  T,  output_path  =  "output/figures/regression/1961/
domestic_employment_ln_bracero55_year_low_et_1961.pdf")

#                        Alternative                         method                         of
estimations -------------------------------------------------------------

## 1958 batch --------------------------------------------------------------
domestic  =  feols(domestic_seasonal  ~  i(distance_treat_1965_year,  mex_frac_58,  ref  =  -1)  |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)
domestic_ln = feols(ln_domestic_seasonal ~ i(distance_treat_1965_year, mex_frac_58, ref = -1) |
State_FIPS + Year, cluster = ~State_FIPS, data = tab)

#ban
domestic_ban_year = retrieve_result(domestic)
domestic_ban_ln_year = retrieve_result(domestic_ln)

#ban
event_study_plot(domestic_ban_year, title = "Effect of Bracero worker exclusion on domestic
employment of seasonal workers, 1958 batch",
                x_label = "Distance to treatment (year)", y_label = "Employment (thousands)",
                         save  =  T,  output_path  =  "output/figures/regression/1965/58_batch/
domestic_employment_bracero58_year_et.pdf")
event_study_plot(domestic_ban_ln_year, title = "Effect of Bracero worker exclusion on domestic
employment of seasonal workers, 1958 batch",
                 x_label = "Distance to treatment (year)", y_label = "Employment (log)",
                         save  =  T,  output_path  =  "output/figures/regression/1965/58_batch/
domestic_employment_ln_bracero58_year_et.pdf")

## Synthetic Control -------------------------------------------------------------------

### California ------------------------------------------------------------
cols = c("State", "Year","domestic_seasonal","realwage_hourly","realwage_daily","Cotton_machine","Sugarbeet_ma
      "Cotton","Tomatoes_total","Lettuce","Strawberries_total","Citrus","Cantaloupes","BrusselsSprouts",
```

```
         "Asparagus_total", "Celery", "Cucumbers_pickle")

tab_sc <- tab %>%
  select(all_of(cols)) %>%
  group_by(State, Year) %>%
  summarise(domestic_seasonal = mean(domestic_seasonal, na.rm = TRUE),
            # domestic_seasonal = ln_domestic_seasonal,
            realwage_hourly = mean(realwage_hourly, na.rm = TRUE),
            realwage_daily = mean(realwage_daily, na.rm = TRUE),
            Cotton_machine = mean(Cotton_machine, na.rm = TRUE),
            Sugarbeet_machine = mean(Sugarbeet_machine, na.rm = TRUE),
            Tractors = mean(Tractors, na.rm = TRUE),
            Cotton = mean(Cotton, na.rm = TRUE),
            Tomatoes_total = mean(Tomatoes_total, na.rm = TRUE),
            Lettuce = mean(Lettuce, na.rm = TRUE),
            Strawberries_total = mean(Strawberries_total, na.rm = TRUE),
            Citrus = mean(Citrus, na.rm = TRUE),
            Cantaloupes = mean(Cantaloupes, na.rm = TRUE),
            BrusselsSprouts = mean(BrusselsSprouts, na.rm = TRUE),
            Asparagus_total = mean(Asparagus_total, na.rm = TRUE),
            Celery = mean(Celery, na.rm = TRUE),
            Cucumbers_pickle = mean(Cucumbers_pickle, na.rm = TRUE),
            .groups = 'drop')

# Filter data to retain only complete rows for all relevant columns
#tab_sc_clean <- tab_sc %>%
  #  filter(complete.cases(domestic_seasonal,  Cotton,  Tomatoes_total,  Strawberries_total,
Tractors))

# Drop treated States
tab_sc_clean = tab_sc %>%
  filter(!State %in% c("TX", "AR", "AZ", "COL", "NM", "NV"))

# Synthetic control setup
synth_output <- tab_sc_clean %>%
  synthetic_control(outcome = domestic_seasonal,
                    unit = State,
                    time = Year,
                    i_unit = "CA",
                    i_time = 1965,
                    generate_placebos = TRUE) %>%
  generate_predictor(time_window = 1955:1964,
                     mean_cotton = mean(Cotton, na.rm = TRUE),
                     mean_tomatoes = mean(Tomatoes_total, na.rm = TRUE),
                     mean_strawberries = mean(Strawberries_total, na.rm = TRUE),
                     mean_tractor = mean(Tractors, na.rm = TRUE)) %>%
  generate_weights(optimization_window = 1955:1964,
                   margin_ipop = .02, sigf_ipop = 7, bound_ipop = 6) %>%
  generate_control()

# Plot trends
synth_plot <- synth_output %>% plot_trends()
ggsave(glue("output/sc/sc_plot_domestic_employment_CA.pdf"),  plot  =  synth_plot,  width  =  10,
```

```r
height = 8, dpi = 300)
synth_diff = synth_output %>% plot_differences()
ggsave(glue("output/sc/sc_diff_domestic_employment_CA.pdf"), plot = synth_diff, width = 10,
height = 8, dpi = 300)
synth_weights = synth_output %>% plot_weights()
ggsave(glue("output/sc/sc_wieghts_domestic_employment_CA.pdf"), plot = synth_weights, width =
10, height = 8, dpi = 300)
synth_placebo = synth_output %>% plot_placebos(prune = TRUE)
ggsave(glue("output/sc/sc_placebo_domestic_employment_CA.pdf"), plot = synth_placebo, width =
10, height = 8, dpi = 300)

### Texas ---------------------------------------------------------------
tab_sc <- tab %>%
  select(all_of(cols)) %>%
  group_by(State, Year) %>%
  summarise(domestic_seasonal = mean(domestic_seasonal, na.rm = TRUE),
            # domestic_seasonal = ln_domestic_seasonal,
            realwage_hourly = mean(realwage_hourly, na.rm = TRUE),
            realwage_daily = mean(realwage_daily, na.rm = TRUE),
            Cotton_machine = mean(Cotton_machine, na.rm = TRUE),
            Sugarbeet_machine = mean(Sugarbeet_machine, na.rm = TRUE),
            Tractors = mean(Tractors, na.rm = TRUE),
            Cotton = mean(Cotton, na.rm = TRUE),
            Tomatoes_total = mean(Tomatoes_total, na.rm = TRUE),
            Lettuce = mean(Lettuce, na.rm = TRUE),
            Strawberries_total = mean(Strawberries_total, na.rm = TRUE),
            Citrus = mean(Citrus, na.rm = TRUE),
            Cantaloupes = mean(Cantaloupes, na.rm = TRUE),
            BrusselsSprouts = mean(BrusselsSprouts, na.rm = TRUE),
            Asparagus_total = mean(Asparagus_total, na.rm = TRUE),
            Celery = mean(Celery, na.rm = TRUE),
            Cucumbers_pickle = mean(Cucumbers_pickle, na.rm = TRUE),
            .groups = 'drop')

# Filter data to retain only complete rows for all relevant columns
tab_sc_clean <- tab_sc %>%
     filter(complete.cases(domestic_seasonal,  Cotton,  Tomatoes_total,  Strawberries_total,
Tractors))

# Drop treated States
tab_sc_clean = tab_sc_clean %>%
  filter(!State %in% c("CA", "AR", "AZ", "COL", "NM", "NV"))

# Synthetic control setup
synth_output <- tab_sc_clean %>%
  synthetic_control(outcome = domestic_seasonal,
                    unit = State,
                    time = Year,
                    i_unit = "TX",
                    i_time = 1965,
                    generate_placebos = TRUE) %>%
  generate_predictor(time_window = 1955:1964,
                     mean_cotton = mean(Cotton, na.rm = TRUE),
```

```
                     mean_tomatoes = mean(Tomatoes_total, na.rm = TRUE),
                     mean_strawberries = mean(Strawberries_total, na.rm = TRUE),
                     mean_tractor = mean(Tractors, na.rm = TRUE)) %>%
  generate_weights(optimization_window = 1955:1964,
                   margin_ipop = .02, sigf_ipop = 7, bound_ipop = 6) %>%
  generate_control()

# Plot trends
synth_plot <- synth_output %>% plot_trends()
ggsave(glue("output/sc/sc_plot_domestic_employment_TX.pdf"), plot = synth_plot, width = 10,
height = 8, dpi = 300)
synth_diff = synth_output %>% plot_differences()
ggsave(glue("output/sc/sc_diff_domestic_employment_TX.pdf"), plot = synth_diff, width = 10,
height = 8, dpi = 300)
synth_weights = synth_output %>% plot_weights()
ggsave(glue("output/sc/sc_wieghts_domestic_employment_TX.pdf"), plot = synth_weights, width =
10, height = 8, dpi = 300)
synth_placebo = synth_output %>% plot_placebos(prune = TRUE)
ggsave(glue("output/sc/sc_placebo_domestic_employment_TX.pdf"), plot = synth_placebo, width =
10, height = 8, dpi = 300)
```