Watching the Grass Grow: Does Recreational Cannabis Legalization Affect Labor Outcomes?*

Sichao Jiang
Univ. of Oregon†

Keaton Miller
Univ. of Oregon‡

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Abstract

Over the past several years, cannabis has become legal for recreational use in several U.S. states and jurisdictions around the world. The opening of these markets has led to the establishment of hundreds of cannabis production and retail firms with accompanying demand for labor, leading to concerns about spillover effects on wages from incumbents. We study the markets for agricultural and retail labor in Washington and Colorado, early legalizers with now-established cannabis markets. Using a synthetic control technique to account for the possibility of border-state spillover effects and machine learning techniques for data imputation and variable selection, we find no evidence that cannabis legalization is associated with increases in per-employee wages, neither within industries most similar to cannabis production or retail, nor in more broad industry categories. We conclude that cannabis legalization is unlikely to negatively impact incumbent firms through the labor market channel.

JEL Codes: D00, I18, I28, J21, Q10

Keywords: Marijuana Legalization, Policy Change, Labor Market, Synthetic Control

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†sichaoj@uoregon.edu

‡Corresponding Author. keatonm@uoregon.edu

1 Introduction

The long-standing landscape of cannabis prohibition is rapidly changing. In the past decade, the median American voter moved from opposing to supporting legalization (Motel, 2015), more than a dozen U.S. states legalized the substance for adult use, and jurisdictions around the world loosened restrictions, including full legalization in Canada and Uruguay. One argument employed by supporters of legalization is the assertion that policy liberalization would lead to the creation of new jobs across multiple sectors (see e.g. Keys, 2020, Wallace, 2020). Indeed, according to Statistics Canada, the industry generated over 10,000 jobs within a year of legalization, with average hourly wages above the national average, and Barcott and Whitney (2019) estimate that the U.S. cannabis industry (including both medical and adult-use cannabis) directly employed more than 200,000 workers in 2019.

Cannabis, however, does not exist in a vacuum – the labor involved in cannabis production and retail is similar to that involved in other agricultural and retail markets and so cannabis legalization may induce workers to substitute between employers. Indeed, farmers of other crops in many areas have expressed concerns about the potential for upward pressure on agricultural labor wages as a consequence of cannabis legalization (Stoicheff, 2018, Smith et al., 2019, Valachovic et al., 2019, Washburn, 2020). In this paper, we investigate these concerns by measuring the impact of recreational cannabis legalization on labor markets using data collected from the U.S. Census Bureau. We focus on Washington and Colorado due to their early adoption of legalization policies and therefore the longest post-legalization period during which to measure any changes in labor market outcomes.

While this policy change may seem like a relatively clean quasi-experiment (as it is unlikely that the timing of legalization was driven by labor market conditions) and an opportunity for a differences-in-differences approach, we must overcome two challenges. First, given the spillover effects of legalization efforts both in terms of geography (Hansen et al., 2020c) and in product space (Miller and Seo, 2021), as well as the mobility of (particularly agricultural) labor (Thomas-Lycklama-Nijeholt, 2012, Holmes, 2013), it is difficult to choose an appropriate control group *a priori*. We therefore follow Hansen et al. (2020b), who study the impact of cannabis legalization on traffic fatalities, and use a synthetic control approach. We create a control group by choosing weights for states without legal cannabis markets to match moments characterizing each state in the pre-legalization period. By comparing post-legalization employment and wages in the treated states to their synthetic controls, we can estimate the causal impact of legalization on these outcomes of interest.

Implementing this approach for the retail sector is relatively straightforward – the elements of retail sectors which drive labor market outcomes (i.e. household income and population density) do so in a consistent way across states (Neumark et al., 2008, Blakely and Leigh, 2013). Agricultural sectors in different states, however, are significantly different due to variation in growing conditions and the characteristics of arable land. While many detailed industry measures are available, the set of measures changes frequently and often are not available for all states. Faced with a need to both select variables and impute certain values, we follow the approach of White et al. (2018) and implement machine learning techniques to accomplish these tasks algorithmically. In particular, we use LASSO for variable selection and classification and regression trees (CART) to impute missing values.

We start our analysis by verifying that the opening of cannabis markets in these states did in fact lead to increases in the level of employment in the relevant categories as defined by the North American Industry Classification System (NAICS). Our primary finding is a null result: we find little evidence of a significant difference in weekly wages per worker in either the most directly substitutable NAICS categories nor broader definitions of retail and agricultural employment. To ensure the results are not driven by an idiosyncratic selection of control weights or over-fitting, we perform placebo tests and find no change in our results.

This paper adds to the growing literature investigating the legalization of cannabis for adult (recreational) use and its effects on outcomes thought to be related to marijuana consumption. Smart and Pacula (2019) summarizes many of the policy implications of cannabis legalization. Specific examples include studies on student performance (Miller et al., 2017), traffic fatalities (Aydelotte et al., 2017, Hansen et al., 2020b), crime (Dragone et al., 2019, Hughes et al., 2020, Hao and Cowan, 2020) and the consumption of other "sin" goods and cannabis substitutes (Kerr et al., 2017, Baggio et al., 2018, Miller and Seo, 2021, Hansen et al., 2020a, Chan et al., 2020). More recently, the literature has begun to examine the cannabis industry as an economic entity of interest in and of itself and as a tool to investigate long-standing questions in industrial organization and policy design: Hansen et al. (2017) investigate the impact of a change in Washington's tax structure throughout the cannabis supply chain, Thomas (2018) considers the effect of Washington's licensing quota system, Hollenbeck and Uetake (2019) estimate the level and effects of market power in the industry, and Berger and Seegert (2020) use the cannabis industry to analyze the effects of financial exclusion on firms

Within this literature, the closest effort to that of our own is that of Chakraborty et al. (2020), who study the effects of Colorado's legalization on labor market outcomes at the county level exploiting the timing of retail entry across counties. Ultimately, they find, as we do, that while the entry of legal cannabis employers leads to increases in the number of employees in the relevant sectors, the impact on equilibrium wages is approximately zero. Relative to that work, we aggregate to the state level to avoid concerns about intra-state labor mobility, use states without legal cannabis markets as the bases for synthetic controls to avoid inter-state spillover effects, and add an additional treated unit (Washington).

We proceed in Section 2 by describing labor in the cannabis industry relative to other agricultural and retail industries. In Section 3, we describe our data on labor market outcomes and our methodology. In Section 4, we present our findings. We conclude in Section 5 with a discussion of the policy implications and suggestions for future research.

2 Labor in the Cannabis Industry

Relative to many commodity agriculture crops such as corn and wheat, cannabis production is labor intensive owing in large part of the dioecious nature of plants in genus *Cannabis*. Buds with high concentrations of the psychoactive cannabinoids tetrahydrocannabinol (THC) and cannabidiol (CBD) (among others) are only produced by female plants prior to pollination (Chandra et al., 2017). Thus, in contrast to other dioecious agriculture operations, such as fruiting trees where males are necessary for fruit production, cannabis growers must identify and remove male cannabis plants from growing areas as even a small number of male plants can provide pollen for an entire crop, triggering seed production in females, a diminished set of flowers, and a corresponding reduction in cannabinoid production.[1] A relevant analogy in traditionally-legal agricultural products is hops (*Humulus lupulus*); producers of hops remove male plants to prevent pollination (Shepard et al., 1999).

The prevalence of indoor growing facilities complicates direct comparisons between cannabis and other plants. According to an industry report, 60% of legal producers operate indoor facilities, and 41% operate greenhouses – only 12% of firms grow cannabis in the outdoors alone.[2] The use of indoor and greenhouse spaces allows for more precise control of the growing environment, leading to more potent output (Aizpurua-Olaizola et al., 2016), and enables production regardless of the outdoor agricultural season. However, the amount of labor hours needed per pound produced is likely higher for indoor and greenhouse operations than for outdoor operations (Caulkins, 2010).

After budding, plants must be harvested and trimmed of buds – a process which takes four to six hours per pound manually (Cervantes, 2006). While mechanized trimmers are available, hand-trimmers are able to extract higher quality buds from plants which can

[1] Though there are processes that "feminize" seeds, the costs of a single male plant are high enough that farmers employ laborers to identify and destroy them before flowering.

[2] See https://www.cannabisbusinesstimes.com/article/2020-state-of-the-industry-report-nexus-greenhouse-systems/

command higher prices from consumers; the majority of products sold to consumers (by revenue) consists of dried and cured buds and thus the visual appearance of the buds is directly relevant to demand (Miller and Seo, 2021). As a consequence, skilled trimmers can earn more than twice the average hourly wage of other laborers in crop, nursery, and greenhouse operations (Krissman, 2017).

These features of the cannabis industry imply that it is at least plausible that a small number of cannabis producers (relative to the number of other agricultural producers using greenhouses) could sufficiently impact the aggregate demand for agricultural labor to significantly change equilibrium wages. However, relative to other agricultural products, the market for cannabis labor is tightly regulated. In each state with an operating recreational market, individuals must pass a background check before working for a cannabis producer – and to pass that check, the worker must have legal immigration status and (in most states) must not have recent felony convictions related to Schedule I or Schedule II drugs. According to the U.S. Department of Labor, approximately 47% of the U.S. agricultural labor industry are undocumented immigrants, though agricultural industry sources estimate the share is closer to 75% (Jordan, 2020). If the labor markets are bifurcated due to immigration status, the effects of legalization on wages may be minimal at best. Furthermore, as the highest wages available within the cannabis industry are paid to workers with cannabis-specific skills, the substitutability of that labor (and therefore the upwards pressure on equilibrium wages) may be limited.

The process of retail sales of cannabis prodcuts also differ from most retail businesses. In most jurisdictions, psychoactive cannabis inventory must be strictly and securely separated from the sales floor, which is often required to be separated from pedestrian access through secure doors so that customer ages can be verified before entry. Inventory must be tracked in real-time for compliance with federal guidelines and state seed-to-sale traceability regulations. Audits are frequent and penalities for non-compliance include civil and criminal liability for firm owners and managers (Hansen et al., 2018). These additional layers of security and related regulations imply that, relative to other retailers with similar footprints, cannabis retailers may demand additional labor hours.

Finally, though Colorado and Washington set up recreational markets in the same time period, the regulatory structures vary in an important way. While Washington required vertical separation between production and retail, Colorado initially required retailers to produce 70% of the products they sell through vertically integrated production facilities (Hansen et al., 2021). As a consequence, while firms in both Washington and Colorado set up production operations, production facilities in Washington more directly competed with other greenhouse agricultural facilities for labor.

3 Data and Methodology

We begin our analysis of the relationship between cannabis legalization and labor market outcomes by obtaining labor market data from the Quarterly Census of Employment and Wages compiled by the U.S. Bureau of Labor Statistics (BLS). BLS categorizes employers according to the North American Industry Classification System (NAICS) – a system of 2-6 digit codes which classifies employers in narrowing groups according to their output or primary business activity. Our outcomes of interest include the number of establishments, the total number of workers, the total real wages, and the average weekly real wage per worker. We collect these outcomes at the NAICS-state-quarter level from 2000-2019, aggregate to the annual level, and deflate to 2019 dollars using the Consumer Price Index.

To capture time-varying characteristics of labor markets which may influence outcomes, we collect demographic data from the U.S. Census Bureau and Department of Education including state-level high school and college graduation rates, population density, the aggregate unemployment rate, and per-capita GDP. Agricultural labor markets differ widely from state to state due to differences in the characteristics of arable land and growing seasons and therefore to capture other time-varying characteristics of agricultural markets which may influence relevant labor market outcomes, we additionally collect state-year-level survey data from the National Agricultural Statistics Service from 2000-2019 and state-level data from the U.S. Censuses of Agriculture for 2002, 2007, and 2012. A challenge we face in using this data is the prevalence of missing values which stem in part from changes in the survey questions from year to year. To create a panel data set for analysis, we focus on variables for which there are at least 30 state-level observations per year. These variables largely sort into clear topic areas: demographics, land statistics including rental prices, counts of farm establishments, and variables capturing output for corn, wheat, hay, and fruits and vegetables.

Despite this restriction, the data still contain many missing values complicating any analysis effort. Following White et al. (2012, 2018), we use the Van Buuren et al. (2006) modification of the Classification and Regression Trees (CART) algorithm to impute missing values. The algorithm uses a Gibbs sampling procedure to generate a plausible value for each missing value. Key to our application, the algorithm uses "chained" imputation: for each unit of observation (i.e. each state-year observation), the most recent generated imputation for each column is used as a predictor for the next column to minimize bias (Van Buuren and Groothuis-Oudshoorn, 2010, Murray and Reiter, 2016, Michalowsky et al., 2020). In other words, suppose the vector of independent variables for observation t is $X_T = [x_{1t}, x_{2t}, \cdots]$. Suppose x_{1t} is known for some t but x_{2t} is missing. The algorithm uses a Gibbs sampler to draw a value from x_{2t} using the empirical distribution of x_2 conditional on x_{1t}. Now suppose x_{3t} is also missing for t. The algorithm uses both the observed value x_{1t} and the imputed x_{2t} to draw a value of the x_3 distribution conditional on both x_1 and x_2.

We next turn to the issue of variable selection. The number of potential control units (i.e. states other than Washington and Colorado) is less than the number of potential covariates. Instead of manually choosing covariates based on some prior hypothesis, we use the LASSO algorithm to select appropriate covariates (Tibshirani, 1996, Duncan et al., 2019). For each outcome variable, we fit prediction models to the pre-legalization data (i.e. data from 2000-

2012) using the `glmnet` method of Friedman et al. (2010) and select the covariates with the highest frequency for each of the outcome variables. The final covariate matrix X has 23 columns.[3]

The agricultural census data is collected every five years – the last collection was in 2017. At the time of the last collection, only four states – Alaska, Colorado, Oregon, and Washington – had legalization cannabis for recreational use, and within those states, Colorado and Washington legalized earliest (voting in 2012, markets opening in 2014). To focus on the longest post-legalization period possible, we follow Hansen et al. (2020b) and focus on Colorado and Washington as the treated states.[4]

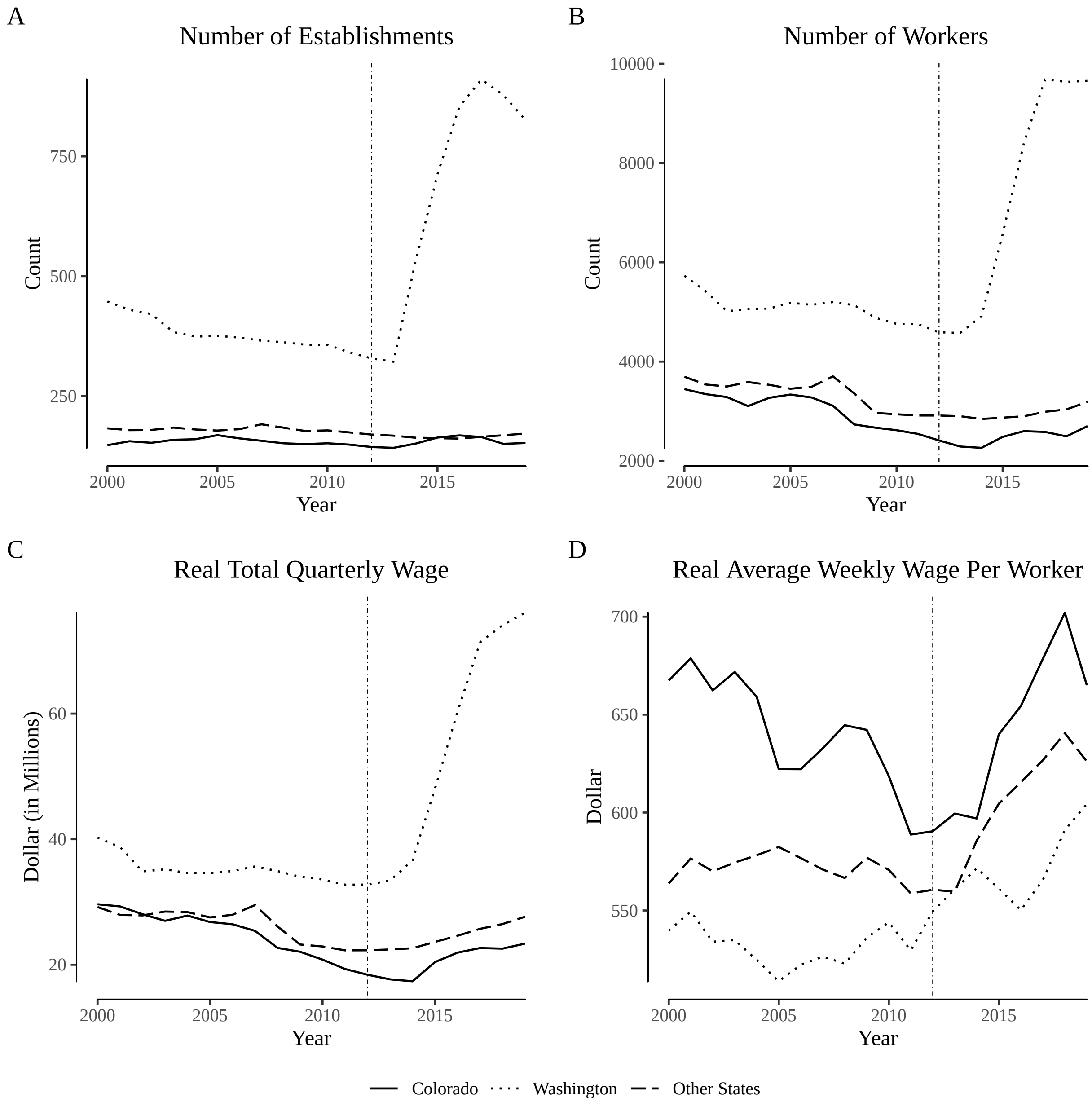
Figure 1 plots outcomes by year for Colorado, Washington, and the average of other states for the "greenhouse, nursery, and floriculture production" category (NAICS 1114, the category containing cannabis production firms). Notably, the establishment count for Washington increased by roughly 500 between legalization and a peak in late 2015, which is similar to the count of cannabis production licenses issued by the state around the same time period as reported by Hansen et al. (2017). Washington experienced a similarly-shaped increase in the number of workers in the sector and the total wages paid, but those outcomes in Colorado and other states remained largely constant. Despite the increase in labor quantity observed in Washington, the real average weekly wage per week increased after legalization relatively uniformly everywhere.

Figure 2 reports analogous outcomes in the "store retailers not specified elsewhere" category (NAICS 453998, the category containing cannabis retailers). As with the agricultural

[3] They are "Barley for grain (acres)"; "Land in orchards (acres)"; "Snap beans harvested for sale (acres)"; "Cherries (acres)"; "Pears (acres)"; "Commercial fertilizer, lime, & soil conditioners (acres treated)"; "2000 Resident population 65 years & over, percent"; "2000 Savings institutions (FDIC-insured)-total deposits"; "2000 Civilian labor force unemployment rate"; "Federal Government expenditure-grants FY 2000"; "Federal Government insurance FY 2000"; "2000 Resident population: Black alone, percent"; "2000 Resident population: Two or more races, percent"; "2000 Resident population: Hispanic or Latino Origin, percent"; "2000 Resident population: total females, percent"; "Social security: retired workers-benefit recipients (Dec.) 2000"; "Corn grain production"; "Farm operations"; "Hay production"; "Labor hired wage rate ($ per hour)"; "Rent cash cropland expense ($ per acre)"; "Vegetable total production"; "Wheat production"

[4] Anecdotally, both Oregon and Alaska experienced significant supply issues in months immediately post market-opening and thus any impact on agricultural labor is potentially more difficult to observe and/or interpret from the short post-legalization period available.

Figure 1: Narrowly-Defined Agricultural Employment and Wage Outcomes



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Greenhouse and Nursery Production" category (NAICS 1114).

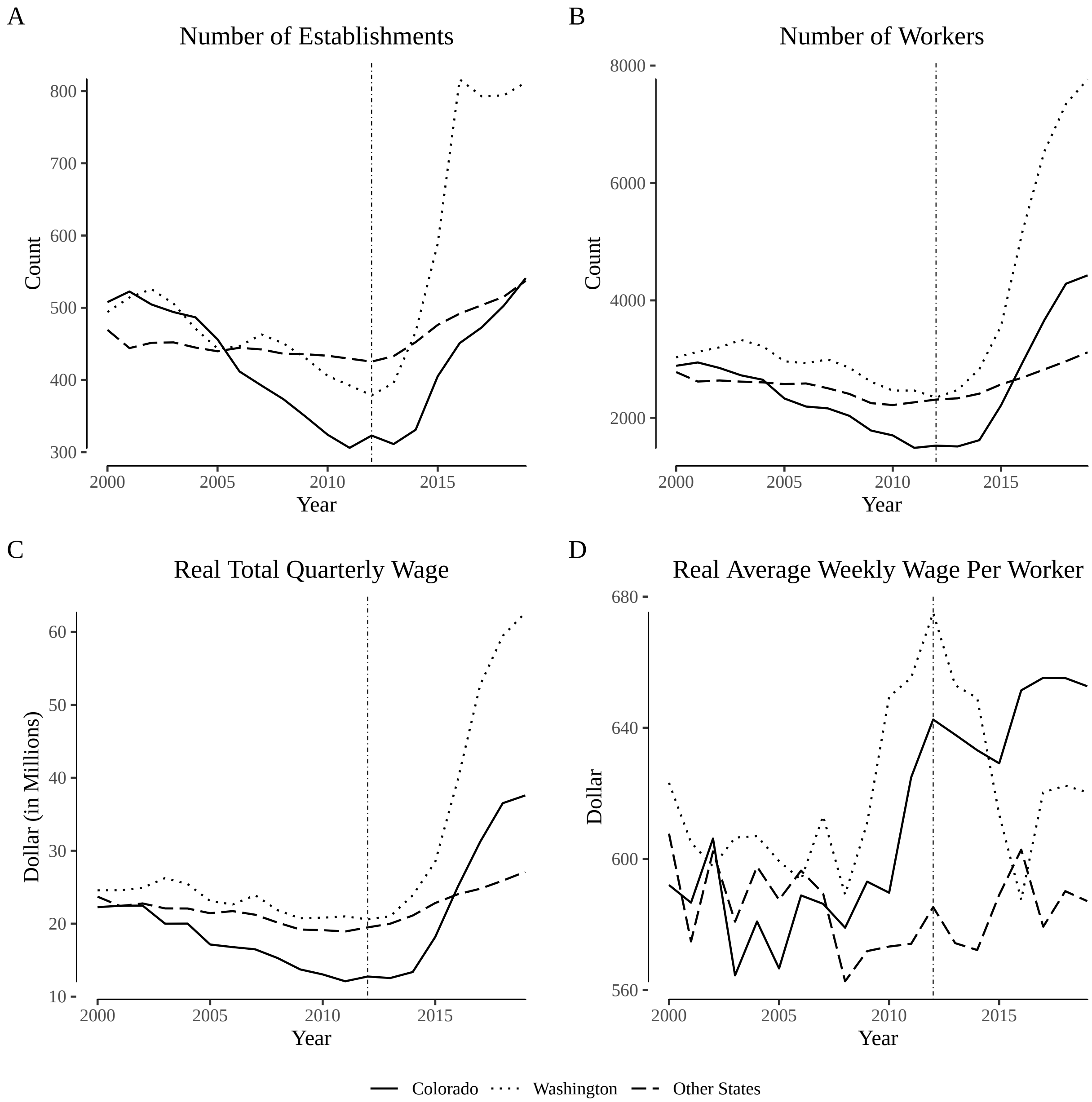
sector, the establishment count in Washington increased by several hundred immediately post-legalization corresponding to descriptive statistics found in the literature (Thomas, 2018). Colorado also experienced an increase of roughly 200 establishments over the same time period. Increases of similar magnitude occured for worker counts and total wages paid in conjunction with the opening of these establishments. As in the agricultural sector, however, there are no clear patterns in the average weekly wage per worker; while the mean post-reform wage in Colorado is above the mean pre-reform wage, wages had begun increasing in the years prior to the passage of the ballot measure.

While the raw data suggest that the legalization of cannabis led to significant changes in employment in each state corresponding to their different regulatory structures, it is not clear that cannabis legalization caused these changes. Estimating a causal effect requires identifying an appropriate set of control units. While neighboring states might seem like a natural control group, Hansen et al. (2020c) find evidence of substantial inter-state cannabis demand, and it is reasonable to believe that laborers may also move across state lines in response to cannabis legalization, particularly if cannabis producers are indeed offering higher wages.[5]

To address this concern, we apply the synthetic control approach of Abadie and Gardeazabal (2003), Abadie et al. (2010, 2015). We construct synthetic control units separately for Washington and Colorado based on pre-legalization data and then estimate the effect of marijuana legalization on our outcomes of interest by calculating the post-legalization difference between the outcomes for our treated states and for our synthetic controls. Our synthetic control units are convex combinations of non-treated states selected in such a way to match the pre-legalization outcomes. In addition to previous work on cannabis legalization and traffic fatalities (Hansen et al., 2020b), the synthetic control approach has been used to analyze the effects of policy changes across a variety of domains, including economic liberalization (Billmeier and Nannicini, 2013), pediatric health (Bauhoff, 2014), tropical de-

[5]This is a particular concern for Washington, where many retailers are located close to the Oregon and Idaho borders.

Figure 2: Narrowly-Defined Retail Employment and Wage Outcomes



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Store retailers not specified elsewhere" category (NAICS 453998).

forestation (Sills et al., 2015), foreign exchange rates (Chamon et al., 2017), and tobacco policies (Chelwa et al., 2017) among many others.

We first select a "donor pool" of control units (i.e. states) which may be used to construct the synthetic control units. We start with all U.S. states and exclude any states which legalized cannabis after 2012. We also exclude states which are adjacent to the treated states to avoid spillover effects. For each treated unit $s \in \{\text{Washington, Colorado}\}$, we then select weights w_j for each of the control units j (with $0 \leq w_j \leq 1$ and $\sum w_j = 1$) to minimize the weighted difference between the synthetic control and the treated unit on the pre-treatment covariates identified above. The weight matrix V (which is a $23 * 23$ matrix) used to form the distance measure is chosen such that the mean square prediction error is minimized for the pre-intervention period following Abadie et al. (2010). We report the weights W^* chosen for each treated unit and outcome variable in the Appendix. We then obtain point estimates of the effect of recreational marijuana legalization with a standard differences-in-differences estimating equation. For outcome y for unit s (either a treated state or the synthetic control for that state) in year t, we estimate the parameters of

$$y_{st} = \beta_0 + \beta_1 * Legal_t + \beta_2 * Treated_t + \beta_3 * Legal_t * Treated_t + \epsilon_{st}. \tag{1}$$

To perform hypothesis testing, we use the "in-space" placebo tests described in Abadie et al. (2015). In particular, we apply the synthetic control model to each of our potential control units and interpret the results as placebos. For each outcome Y (and corresponding sequence of state-year outcome observations Y_{jt}), we then calculate the empirical distribution of the *ratio of the mean squared prediction errors* (RMSPE) where

$$\text{RMSPE} = \left(\frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \right)^2 \right)^{1/2} \tag{2}$$

and T_0 is the positive number of pre-intervention periods. The p-value is then simply the fraction of placebo effect estimates which are greater than or equal to the effect estimated for the treated unit (Firpo and Possebom, 2016):

$$p := \frac{\sum_{j=1}^{J+1} \mathbb{1}\left[\text{RMSPE}_j \geqslant \text{RMSPE}_1\right]}{J+1}$$

Finally, it is plausible that, from the perspective of workers, jobs in the cannabis industry are substitutes for jobs beyond the narrowly-defined NAICS categories described above. We repeat this analysis for a broader set of categories taking advantage of the hierarchical nature of the NAICS inclusive of cannabis firms; for agriculture, we use "agriculture, forestry, fishing, and hunting" (NAICS 11) and for retail, we aggregate the "health and personal care stores" (NAICS 446), "general merchandise stores" (NAICS 452) and "miscellaneous store retailers" (NAICS 453) categories.

4 Results

4.1 Narrowly-defined industries

Figure 3 illustrates agricultural labor market outcome measures in Colorado and its synthetic control unit (control weights are reported in Table A.1) for the "greenhouse, nursery, and floriculture production" NAICS category. Following Figure 1, Panel (a) illustrates the log of the number of establishments, Panel (b) illustrates the log of the number of worker, Panel (c) illustrates the log of the real total quarterly wage, and Panel (d) illustrates the log of the real average weekly wage. In general, the synthetic control closely follows both the trends and the level of Colorado's outcomes over the pre-legalization period. In the post-legalization period, the number of establishments temporarily grows relative to its synthetic control, but the number of workers tracks closely with its synthetic control, as do wages.

Figure 4 illustrates the analogous comparisons for Washington. As in Colorado, the synthetic control tracks closely with the Washington data in the pre-legalization period.

However, the number of establishments increases significantly immediately after legalization, as does the number of works and (as a consequence), the total quarterly wages paid. Though the average weekly wage in Washington does increase post-legalization, the increase is also seen in the synthetic control.

Figures 5 and 6 repeat the exercise for outcomes for the "store retailers not specified elsewhere" NAICS category in Colorado and Washington, respectively. For Colorado, the synthetic control approach struggles to match the full volatility of the pre-reform data for the number of establishments and the number of workers. However, the method performs better (in a mean-squared-error sense) when matching per-reform average weekly wages per worker. Across outcomes, the synthetic control generally moves in the same direction as the Colorado data post reform, suggesting that other trends in Colorado contributed to the increase in establishments and workers seen in Figure 2. The synthetic control approach performs better for Washington, where pre-trends are closely matched for most outcomes.

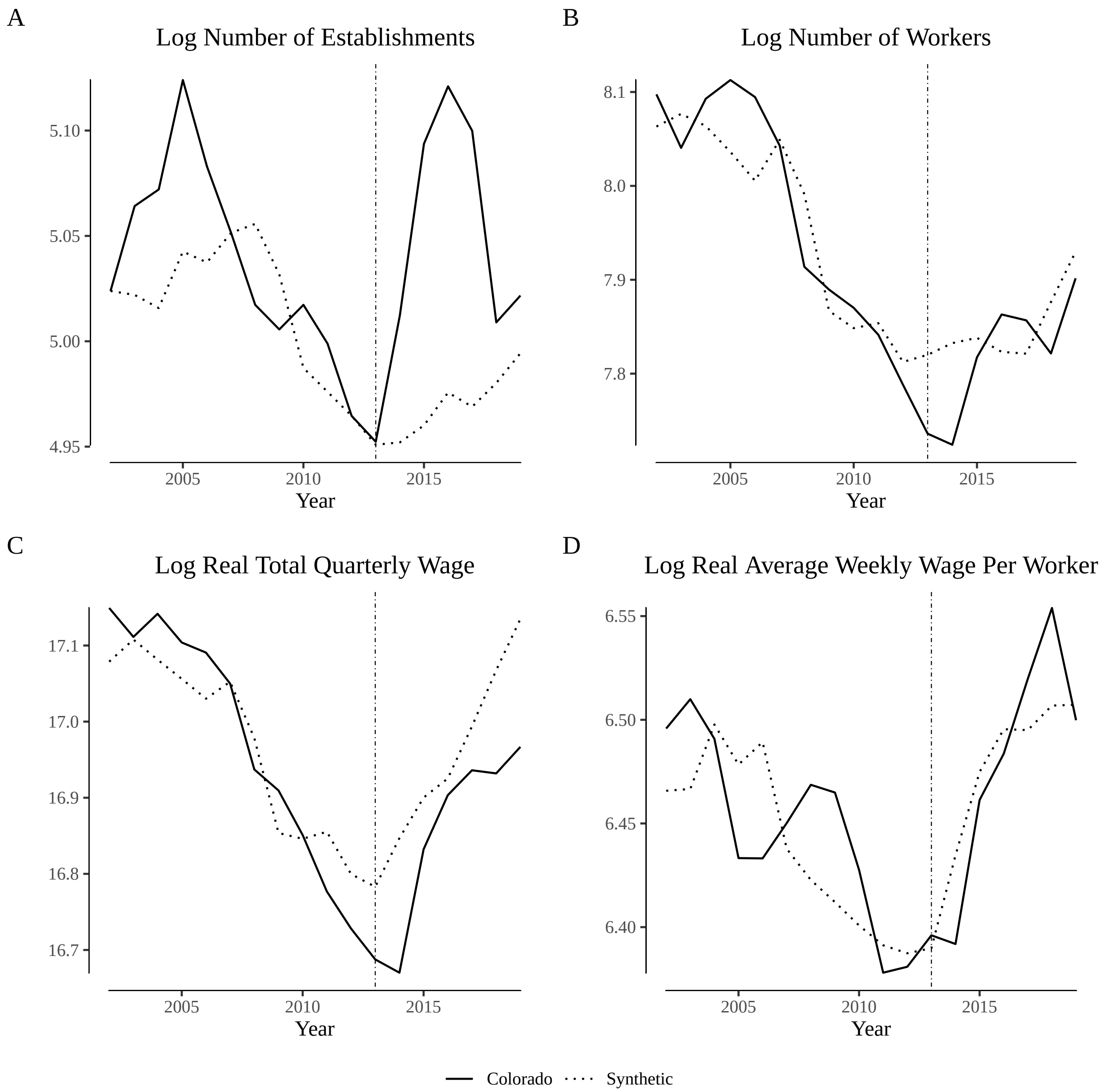
Point estimates of the effects seen in these Figures (i.e. estimates of β_3 in Equation (1)) are reported in Table 1. Several of the changes in the number of establishments, employees, and total wages are significant according to our permutation test at the 10% and 5% levels. However, the change in average weekly wage is either imprecisely estimated or negative for both sectors in both states.[6]

4.2 Broadly-defined industries

While the above results verify that the legalization of cannabis led to changes in the number of establishments and employees working in the categories which contain cannabis firms, they provide no evidence that legalization led to wage spillovers. Indeed, there is little evidence that legalization affected the Colorado labor market at all. One possibility is that although cannabis production facilities are coded as members of the green house and nursery

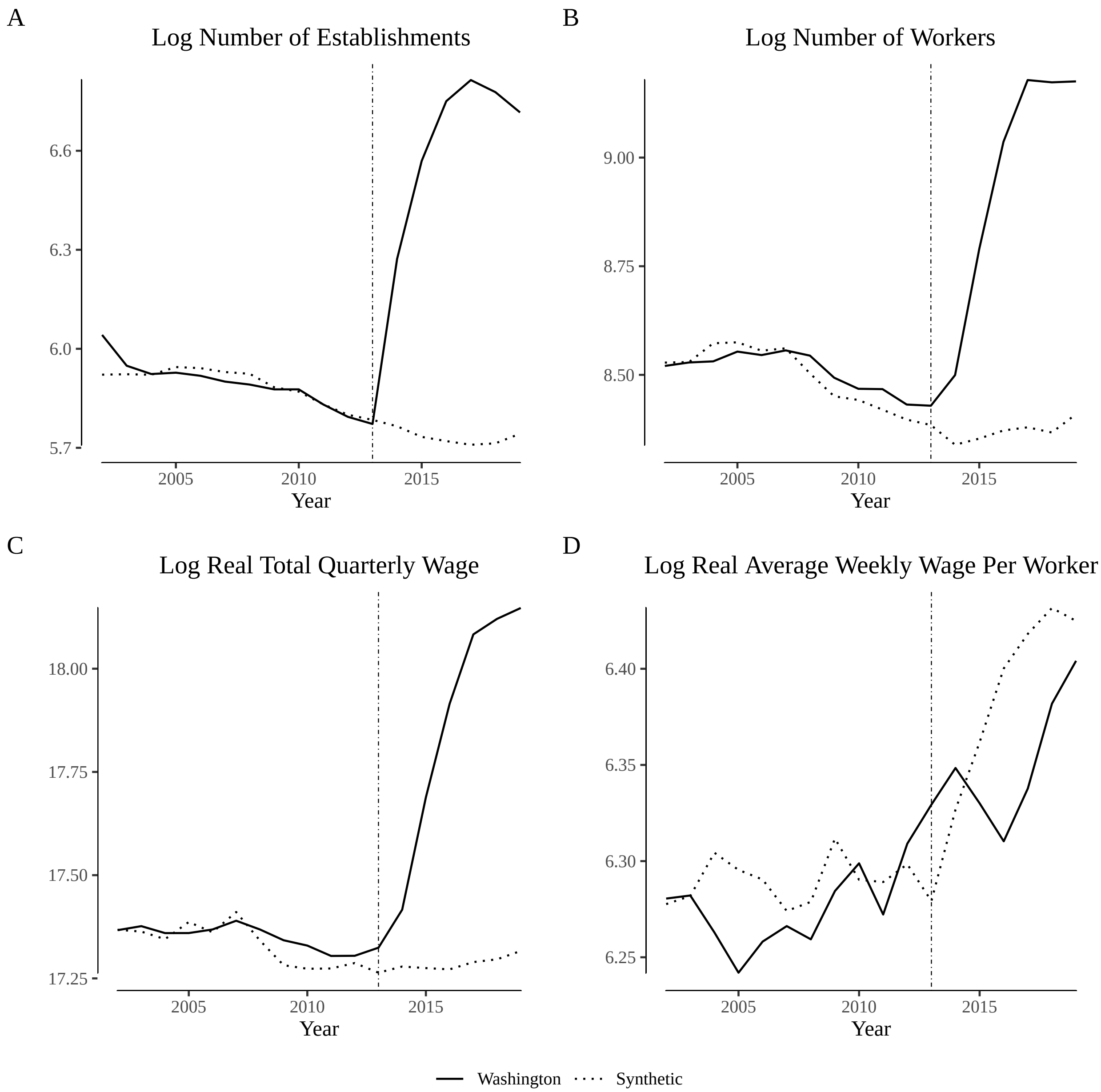
[6] Our exclusions reduce the number of placebo permutations available, thus somewhat reducing the potential power of this analysis. However, given our aim (in part) to evaluate claims that equilibrium wages have increased, we are still able to reject those hypotheses.

Figure 3: Comparing narrowly-defined agricultural labor market outcomes in Colorado and its synthetic control



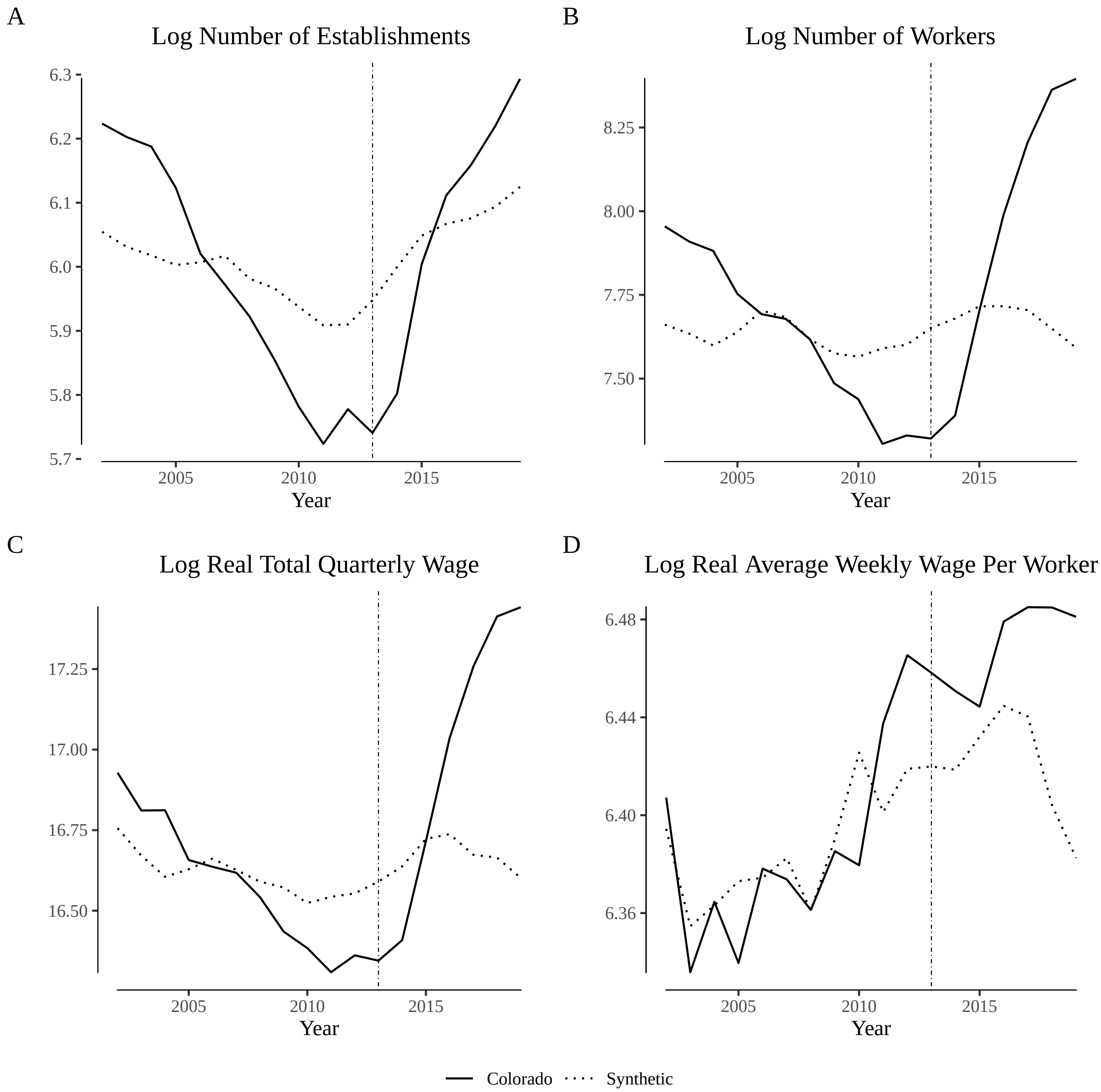
Notes: Outcomes are for "Greenhouse and Nursery Production" (NAICS 1114).

Figure 4: Comparing narrowly-defined agriculture labor market outcomes in Washington and its synthetic control



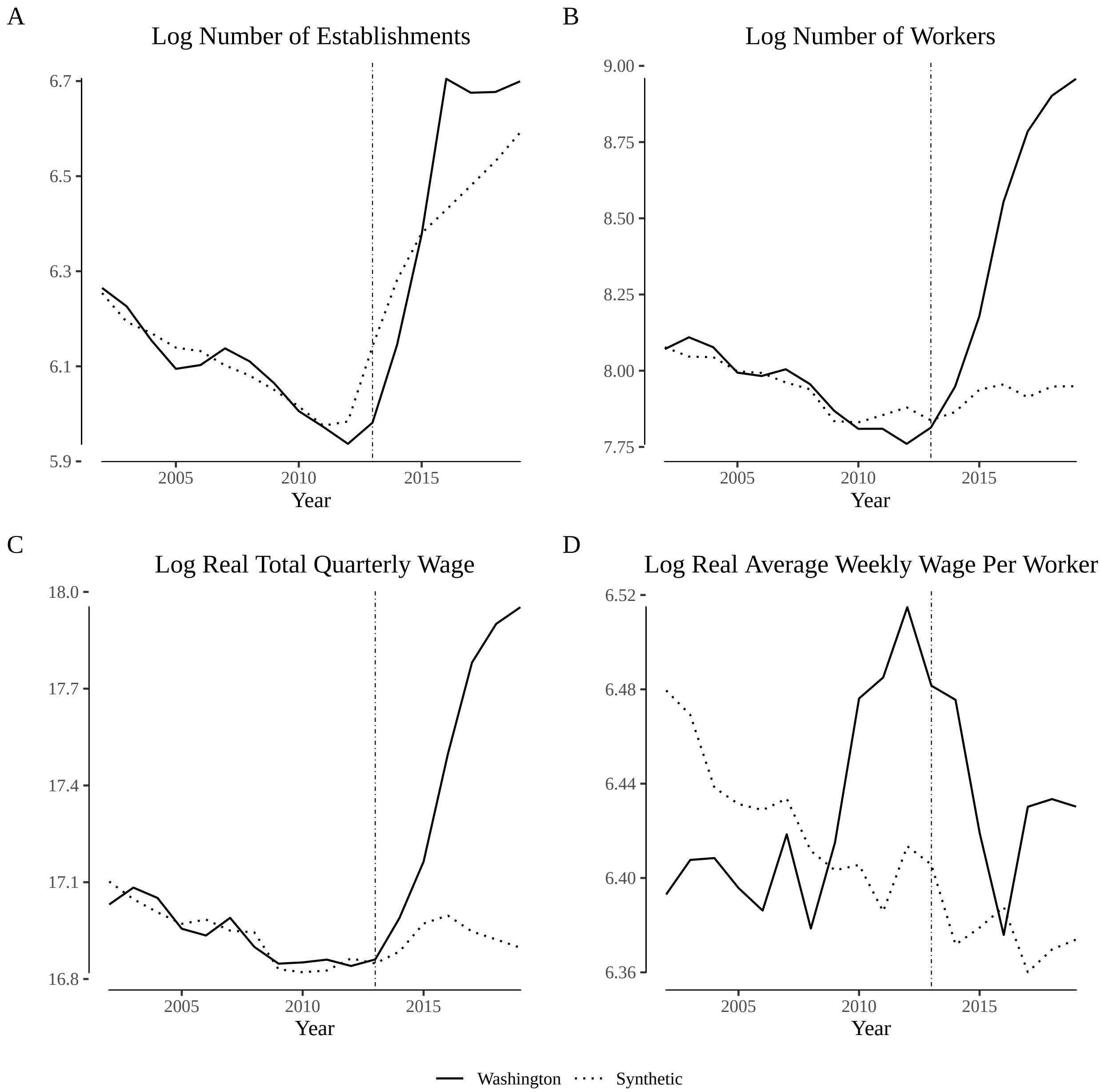
Notes: Outcomes are for "Greenhouse and Nursery Production" (NAICS 1114).

Figure 5: Comparing narrowly-defined retail labor market outcomes in Colorado and its synthetic control



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Store retailers not specified elsewhere" category (NAICS 453998).

Figure 6: Comparing narrowly-defined retail labor market outcomes in Washington and its synthetic control



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Store retailers not specified elsewhere" category (NAICS 453998).

Table 1: Synthetic control estimates of the effect of recreational cannabis legalization on narrowly-defined labor market outcomes

	Colorado			
	Log number establishments	Log number of employees	Log total quarterly wages	Log weekly wage
Narrowly-defined Agriculture				
RML	0.056**	-0.042	-0.113	-0.007
P-value	[0.030]	[0.303]	[0.303]	[0.576]
Narrowly-defined Retail				
RML	0.000	0.220	0.306*	0.050
P-value	[0.818]	[0.152]	[0.091]	[0.212]
	Washington			
	Log number establishments	Log number of employees	Log total quarterly wages	Log weekly wage
Narrowly-defined Agriculture				
RML	0.783*	0.516*	0.513**	-0.013*
P-value	[0.061]	[0.061]	[0.030]	[0.091]
Narrowly-defined Retail				
RML	0.063	0.535**	0.525**	0.059
P-value	[0.152]	[0.030]	[0.030]	[0.606]

Notes: This table reports difference-in-difference estimates of the effect of recreational marijuana legalization on labor market outcomes using synthetic controls for the treated units. *Agriculture* is the "Greenhouse and Nursery Production" (NAICS 1114) industry. *Retail* is the "Store retailers not specified elsewhere" category (NAICS 453998). P-values are calculated via a permutation test. Stars indicate standard significance levels: *10%, **5%, ***1%.

sector, cannabis facilities do not compete with other members of that sector for labor. To explore this possibility, we repeat the analysis for NAICS 11, which includes all "agriculture, forestry, fishing, and hunting" firms. While this change is straightforward for Colorado, some modifications are necessary to create an appropriate synthetic control unit for Washington. In particular, our baseline analysis excludes Alaska, Oregon, and California from the pool of potential control units as these states legalized cannabis during our study period. NAICS 11 includes both forestry, a significant industry in Washington, Oregon and California, and fishing, a significant industry in Washington, Oregon and Alaska. We thus reintroduce those states into the set of potential control units for Washington.

The results are reported in Table 2 under the headings for "Broadly-defined Agriculture" – the relevant Figures are available in the Appendix. It is first useful to compare the estimates for Washington to those reported in Table 1. As the category considered here is more aggregated, the point estimates are attenuated and more noisily estimated; the cannabis industry is small relative to the entire NAICS category 11. For Colorado, the estimates indicate small and marginally significant increases in employees and total wages, though once again for both states there is no increase in average weekly wages.

The difference in results between Colorado and Washington is potentially driven by the vertical integration requirement in Colorado and the vertical dis-integration requirement in Washington. In particular, firms in Colorado may classify themselves completely as cannabis retailers, as opposed to cannabis producers. While it is unlikely that these firms would compete with other agriculture firms for labor (and indeed even if firms are classified in this way, we see no effect on agricultural wages in Tables 1 and 2), it is possible that firms organized in this way have an effect on wages paid in the retail sector. We thus repeat the analysis once more for firms in related NAICS retail categories 446, 452, and 453. The results are reported in Table 2 under the heading "Broadly-defined Retail." As expected, the estimates are attenuated from the more narrowly defined category. We find limited evidence to support the hypothesis that weekly per-worker wages increased in Colorado (the point

Table 2: Synthetic control estimates of the effect of recreational cannabis legalization on broadly-defined labor market outcomes

	Colorado			
	Log number establishments	Log number of employees	Log total quarterly wages	Log weekly wage
Broadly-defined Agriculture				
RML	0.007	0.064**	0.108**	0.008*
P-value	[0.242]	[0.030]	[0.030]	[0.091]
Broadly-defined Retail				
RML	-0.044	0.035**	0.055**	0.015*
P-value	[0.576]	[0.030]	[0.030]	[0.061]
	Washington			
	Log number establishments	Log number of employees	Log total quarterly wages	Log weekly wage
Broadly-defined Agriculture				
RML	-0.056	0.054	0.074	-0.032
P-value	[0.472]	[0.750]	[0.778]	[0.389]
Broadly-defined Retail				
RML	0.013	0.112	0.147*	0.014
P-value	[0.121]	[0.121]	[0.061]	[0.333]

Notes: This table reports difference-in-difference estimates of the effect of recreational marijuana legalization on labor market outcomes using synthetic controls for the treated units. *Broadly-defined Agriculture* is the "Agriculture, Forestry, Fishing, and Hunting" (NAICS 11) industry. *Broadly-defined Retail* is the combination of 'NAICS 446 Health and personal care stores', 'NAICS 452 General merchandise stores', and 'NAICS 453 Miscellaneous store retailers'. P-values are calculated via a permutation test. Stars indicate standard significance levels: *10%, **5%, ***1%.

estimate of a 1.5% increase is significant at the 10% level) and no evidence to support such a hypothesis in Washington.

5 Policy Implications and Conclusions

Over the past decade, U.S. voters have undergone a rapid shift towards supporting the legalization of cannabis in some form and policy has changed to follow this support. These changes, however, have not come without frictions generated by broad society-wide concerns about (among other issues) public health and safety (Hall and Lynskey, 2016, Kilmer, 2019), educational outcomes (van Ours and Williams, 2015), and interactions with other substances (Miller and Seo, 2021). Other frictions have been caused by more immediate financial concerns: agricultural firms in areas with legal cannabis production have expressed concerns about upward wage pressures leading to reduced international competitiveness and domestic agricultural output. Indeed, Bampasidou and Salassi (2019) identify a number of instances of labor shortages in particular U.S. agricultural industries and regions around the time of the first successful cannabis legalization campaigns. At the same time, supporters of legalization have pointed to substantial employment within the nascent industry as a sign of success. Taken together, it is natural to suggest that cannabis legalization may be contributing to a highly competitive labor market from the perspective of agricultural employers.

We investigate the relationship between cannabis legalization and labor market outcomes across both the agricultural and retail sectors. Using a synthetic control approach paired with machine learning techniques including LASSO to select appropriate covariates on which to generate synthetic control units and CART for chained imputation of missing values, we ask whether equilibrium wages increased after legalization in Washington and Colorado, the first states to legalize. We find limited evidence to support this assertion; while the number of workers in the relevant sectors increased following the entry of cannabis producers and retailers, the wage per worker remained effectively constant.

Our results indicate that cannabis is not likely to be responsible for the broader changes in the agricultural or retail labor markets experienced during our study period. Indeed, others have pointed to the changes in the H-2A guest worker program (Luckstead and Devadoss, 2019) and changes in immigration policy enforcement (Escalante and Luo, 2017) as key contributing factors to changes in agricultural labor markets. On the retail side, aggregation in brick-and-mortar retailers (Neumark et al., 2008) and the increase in online shopping (Bram and Gorton, 2017) have been identified as key drivers of changes in retail employment outcomes. Relative to these broader labor market trends, cannabis legalization may well be the proverbial "drop in the bucket".

These results may give policymakers currently considering cannabis liberalization confidence that such a policy change is unlikely to significantly negatively impact labor market outcomes for existing retailers and agricultural firms in the short term. Indeed, legalization is likely to improve labor market outcomes for job-seekers, if only by slightly increasing demand for labor—though long-term cannabis use may affect labor market outcomes at the individual level (Sabia and Nguyen, 2018). That said, it is still possible that cannabis legalization may impact incumbent firms through alternative mechanisms, including competition for retail store locations and/or agricultural land and product market substitution. Our work is necessarily limited to a relatively short postlegalization time period – as cannabis production continues to grow, it is possible that other purchasers of agricultural and retail labor may experience effects they did not in the past.

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Appendices

A Additional tables and figures

Table A.1: Synthetic control weights assigned to each state for narrowly-defined agriculture labor market outcomes

	Log Number of Establishments	Log Number of Workers	Log Real Total Quarterly Wage	Log Real Average Weekly Wage Per Worker
Colorado				
Arizona	0.00	0.00	0.00	0.04
Georgia	0.19	0.00	0.38	0.00
Hawaii	0.00	0.25	0.00	0.00
Maryland	0.00	0.00	0.00	0.33
Minnesota	0.00	0.00	0.00	0.25
Montana	0.00	0.22	0.20	0.11
New Hampshire	0.19	0.00	0.00	0.00
South Carolina	0.00	0.00	0.00	0.23
Texas	0.45	0.53	0.41	0.04
Vermont	0.17	0.00	0.00	0.00
Washington				
Arizona	0.00	0.03	0.11	0.00
Connecticut	0.00	0.02	0.00	0.07
Florida	0.10	0.04	0.00	0.00
Georgia	0.00	0.00	0.00	0.37
Hawaii	0.00	0.05	0.01	0.07
Illinois	0.08	0.00	0.00	0.00
Kentucky	0.00	0.00	0.08	0.00
Michigan	0.54	0.40	0.05	0.00
Minnesota	0.28	0.37	0.00	0.00
Montana	0.00	0.00	0.00	0.14
South Dakota	0.00	0.00	0.00	0.15
Texas	0.00	0.08	0.66	0.19
West Virginia	0.00	0.00	0.09	0.00

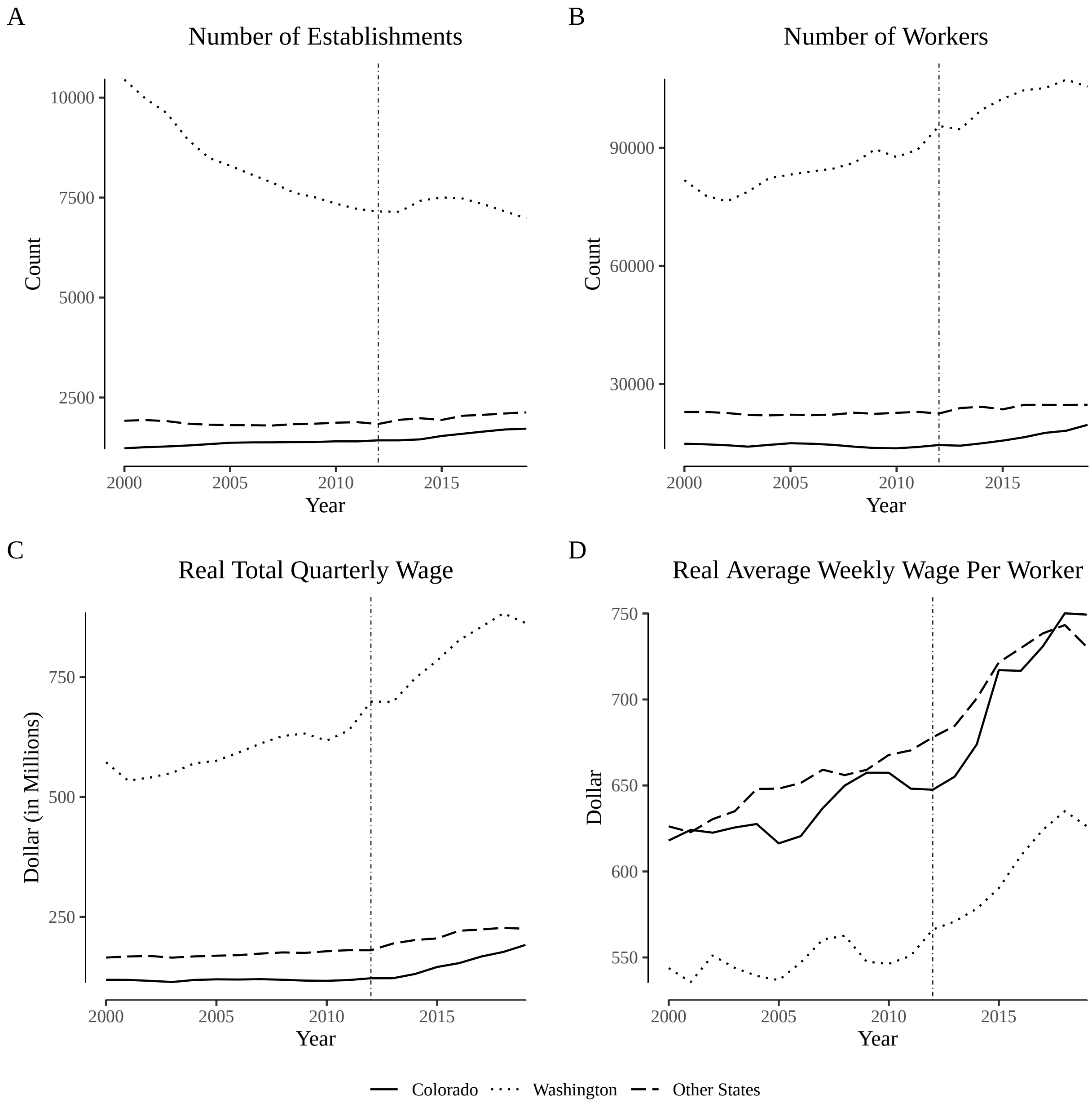
Notes: The table provides the weights assigned to states for the synthetic controls used to estimate the "narrowly-defined agriculture" models in Table 1. All states except those which legalized cannabis during our study period and those bordering either Washington or Colorado were included in the pool of potential control units. Only states which received positive weight for at least one outcome are included in the table.

Table A.2: Synthetic control weights assigned to each state for narrowly-defined retail labor market outcomes

	Log Number of Establishments	Log Number of Workers	Log Real Total Quarterly Wage	Log Real Average Weekly Wage Per Worker
Colorado				
Georgia	0.07	0.11	0.19	0.00
Iowa	0.41	0.26	0.18	0.00
Kentucky	0.10	0.00	0.01	0.33
Louisiana	0.20	0.28	0.21	0.00
Minnesota	0.00	0.28	0.18	0.00
Mississippi	0.00	0.00	0.00	0.11
Missouri	0.00	0.00	0.01	0.00
New Hampshire	0.00	0.00	0.00	0.14
Pennsylvania	0.00	0.00	0.00	0.22
South Dakota	0.00	0.00	0.00	0.19
Texas	0.22	0.06	0.05	0.00
Wisconsin	0.00	0.00	0.18	0.00
Washington				
Connecticut	0.00	0.27	0.31	0.00
Illinois	0.00	0.38	0.36	0.00
Iowa	0.35	0.00	0.00	0.21
Michigan	0.33	0.04	0.05	0.07
Mississippi	0.05	0.00	0.00	0.00
New York	0.00	0.00	0.02	0.00
North Carolina	0.12	0.18	0.00	0.53
Pennsylvania	0.15	0.00	0.00	0.08
South Carolina	0.00	0.13	0.26	0.11

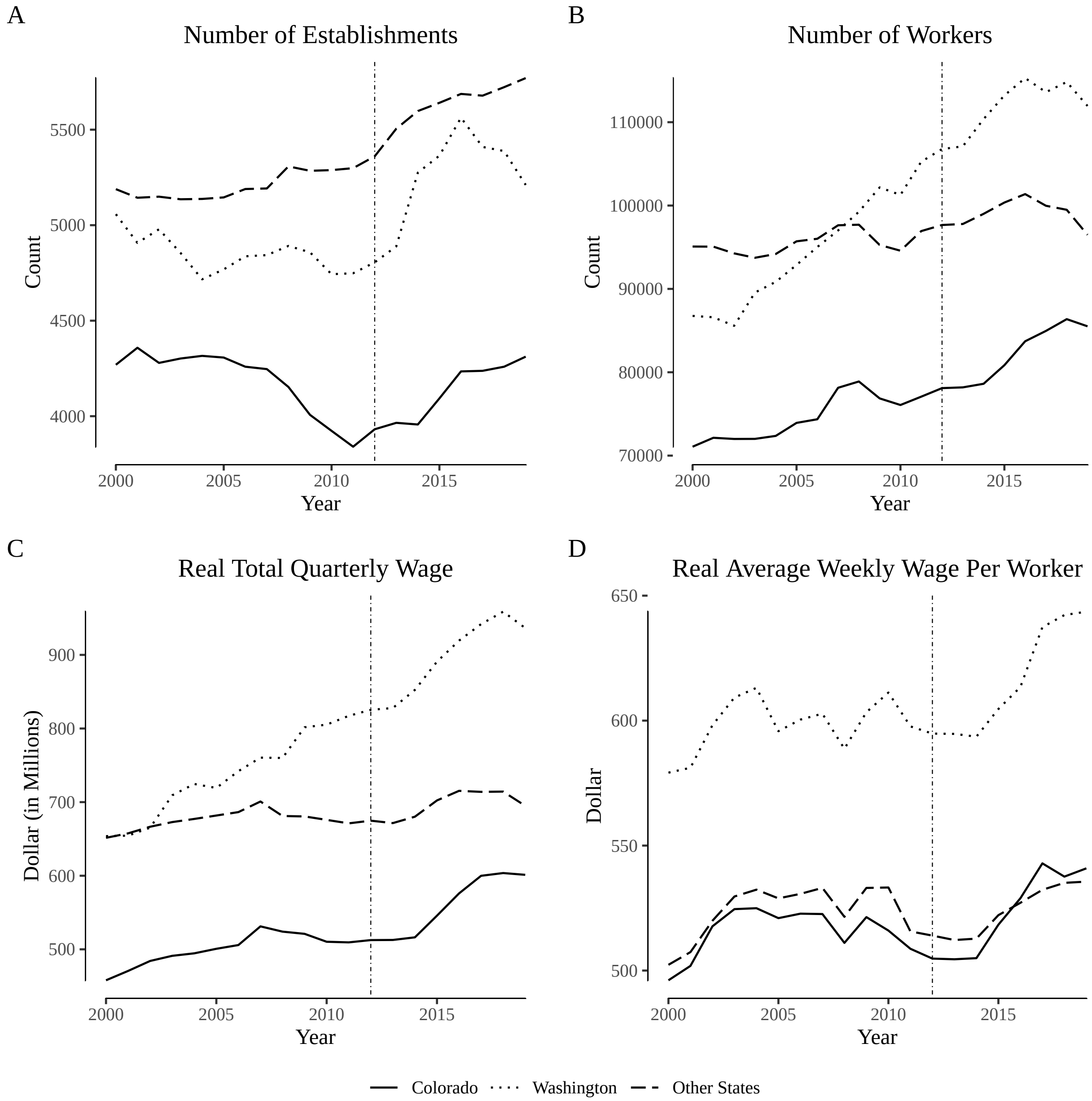
Notes: The table provides the weights assigned to states for the synthetic controls used to estimate the "narrowly-defined retail" models in Table 1. All states except those which legalized cannabis during our study period and those bordering either Washington or Colorado were included in the pool of potential control units. Only states which received positive weight for at least one outcome are included in the table.

Figure A.1: Employment and Wage Outcomes for the Broader Agriculture Industry



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Agriculture, Forestry, Fishing, and Hunting" category (NAICS 11).

Figure A.2: Broadly-Defined Retail Employment and Wage Outcomes



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are aggregated over "health and personal care stores" (NAICS 446), "general merchandise stores" (NAICS 452) and "miscellaneous store retailers" (NAICS 453) categories.

Table A.3: Synthetic control weights assigned to each state for broadly-defined agriculture labor market outcomes

	Log Number of Establishments	Log Number of Workers	Log Real Total Quarterly Wage	Log Real Average Weekly Wage Per Worker
Colorado				
Arizona	0.19	0.26	0.12	0.00
Georgia	0.52	0.00	0.10	0.02
Hawaii	0.01	0.02	0.01	0.00
Kentucky	0.00	0.00	0.00	0.16
Minnesota	0.00	0.24	0.10	0.43
Montana	0.07	0.27	0.08	0.00
New Hampshire	0.00	0.05	0.22	0.00
South Dakota	0.21	0.00	0.00	0.00
Texas	0.00	0.15	0.29	0.02
Virginia	0.00	0.00	0.08	0.37
Washington				
Alaska	0.00	0.00	0.01	0.00
Arizona	0.00	0.00	0.00	0.35
California	0.70	0.66	0.36	0.03
Michigan	0.00	0.00	0.00	0.34
Montana	0.24	0.34	0.08	0.00
Oregon	0.04	0.00	0.52	0.28

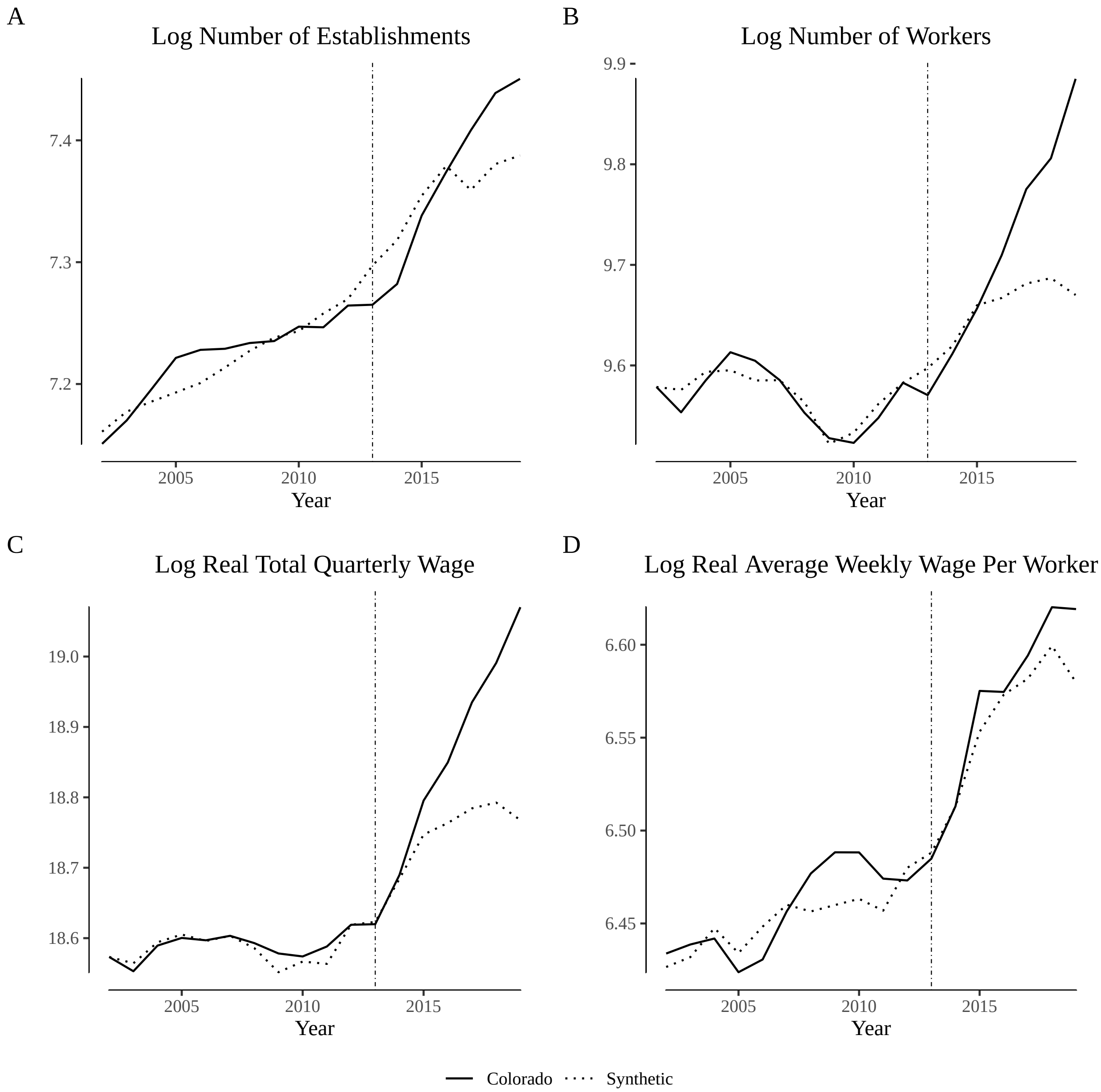
Notes: The table provides the weights assigned to states for the synthetic controls used to estimate the "broadly-defined agriculture" models in Table 2. All states except those which legalized cannabis during our study period and those bordering either Washington or Colorado were included in the pool of potential control units; Alaska, California,, and Oregon were added to the pool for Washington due to the similarity in their agriculture, forestry, and fishing industries. Only states which received positive weight for at least one outcome are included in the table.

Table A.4: Synthetic control weights assigned to each state for broadly-defined retail labor market outcomes

	Log Number of Establishments	Log Number of Workers	Log Real Total Quarterly Wage	Log Real Average Weekly Wage Per Worker
Colorado				
Alabama	0.02	0.01	0.02	0.02
Arizona	0.02	0.18	0.11	0.02
Arkansas	0.02	0.01	0.03	0.03
Connecticut	0.23	0.00	0.00	0.01
Florida	0.00	0.00	0.00	0.01
Georgia	0.02	0.00	0.01	0.02
Hawaii	0.04	0.00	0.01	0.00
Illinois	0.01	0.00	0.01	0.03
Indiana	0.02	0.00	0.01	0.03
Iowa	0.02	0.01	0.02	0.05
Kentucky	0.02	0.01	0.01	0.02
Louisiana	0.03	0.01	0.02	0.05
Maryland	0.02	0.00	0.00	0.01
Michigan	0.01	0.00	0.01	0.02
Minnesota	0.02	0.01	0.03	0.07
Mississippi	0.02	0.01	0.03	0.03
Missouri	0.02	0.01	0.02	0.03
Montana	0.03	0.35	0.29	0.03
New Hampshire	0.03	0.00	0.01	0.03
New Jersey	0.07	0.00	0.00	0.01
New York	0.12	0.00	0.00	0.00
North Carolina	0.01	0.00	0.01	0.02
Ohio	0.01	0.00	0.00	0.02
Pennsylvania	0.01	0.00	0.00	0.02
South Carolina	0.02	0.00	0.01	0.02
South Dakota	0.03	0.04	0.04	0.06
Tennessee	0.02	0.00	0.01	0.01
Texas	0.01	0.34	0.28	0.19
Vermont	0.03	0.00	0.00	0.02
Virginia	0.02	0.00	0.01	0.04
West Virginia	0.02	0.01	0.01	0.03
Wisconsin	0.02	0.01	0.01	0.04
Washington				
Alabama	0.00	0.00	0.00	0.01
Connecticut	0.38	0.00	0.00	0.00
Georgia	0.00	0.00	0.00	0.01
Hawaii	0.00	0.00	0.00	0.09
Illinois	0.28	0.00	0.00	0.01
Iowa	0.00	0.24	0.01	0.00
Michigan	0.00	0.00	0.00	0.01
Minnesota	0.00	0.00	0.00	0.01
Missouri	0.00	0.00	0.00	0.01
New York	0.02	0.01	0.00	0.49
North Carolina	0.01	0.31	0.01	0.01
Pennsylvania	0.01	0.00	0.00	0.00
South Carolina	0.27	0.22	0.23	0.00
Texas	0.00	0.00	0.00	0.31
Vermont	0.00	0.00	0.00	0.01
Virginia	0.00	0.21	0.74	0.00

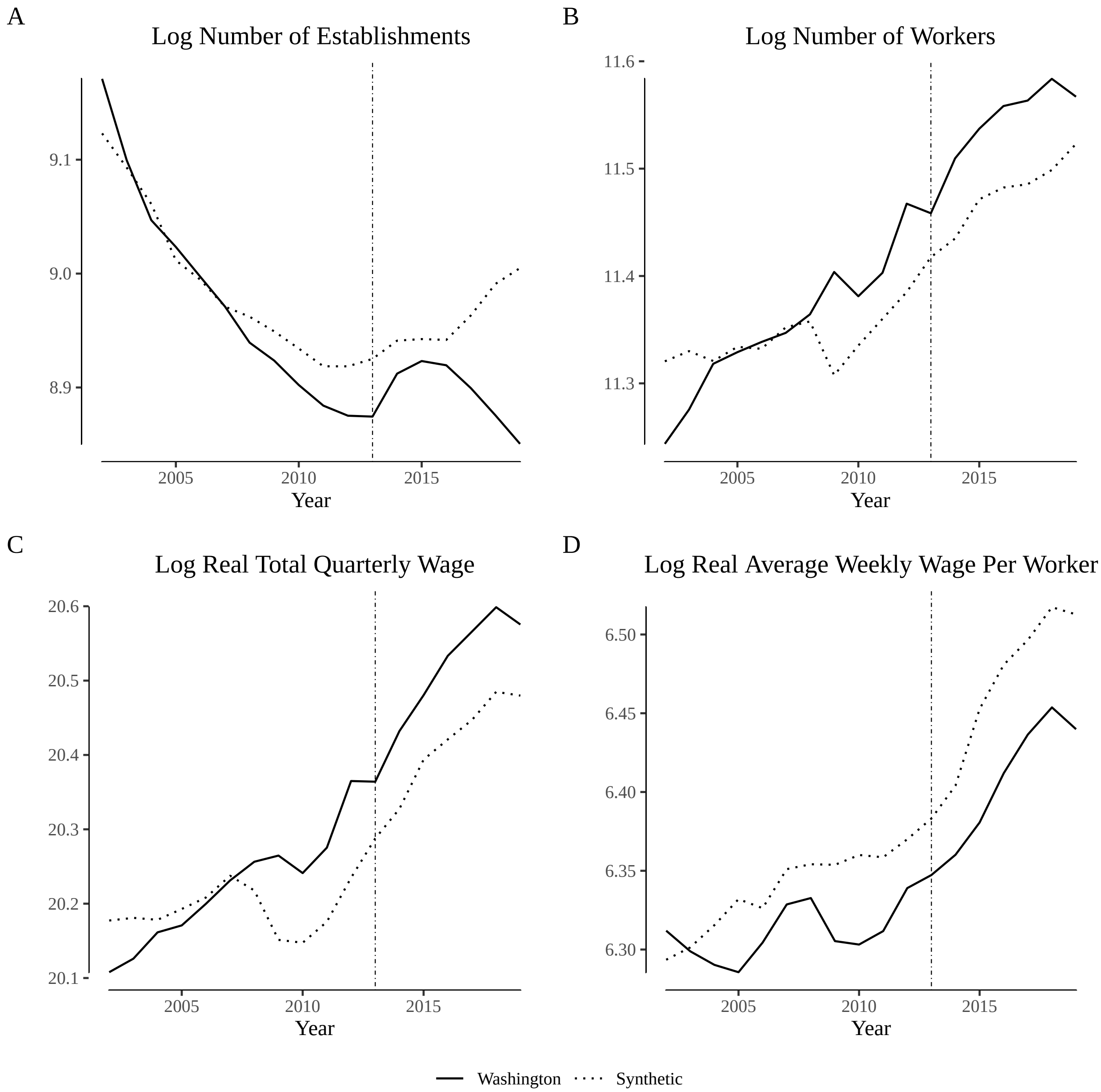
Notes: The table provides the weights assigned to states for the synthetic controls used to estimate the "broadly-defined retail" models in Table 2. All states except those which legalized cannabis during our study period and those bordering either Washington or Colorado were included in the pool of potential control units. Only states which received positive weight for at least one outcome are included in the table.

Figure A.3: Comparing broadly-defined agriculture labor market outcomes in Colorado and its synthetic control



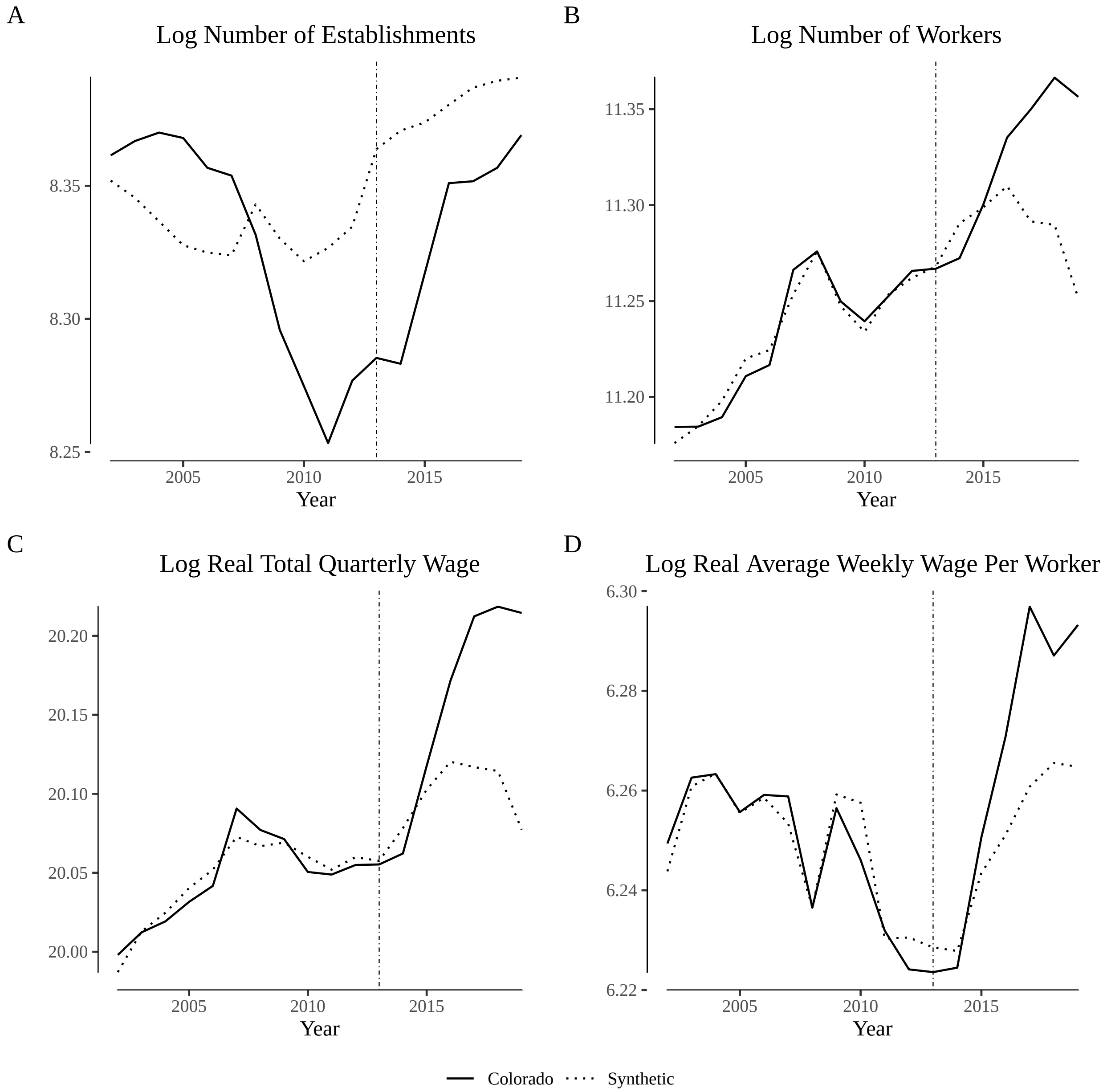
Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Agriculture, Forestry, Fishing, and Hunting" category (NAICS 11).

Figure A.4: Comparing broadly-defined agriculture labor market outcomes in Washington and its synthetic control



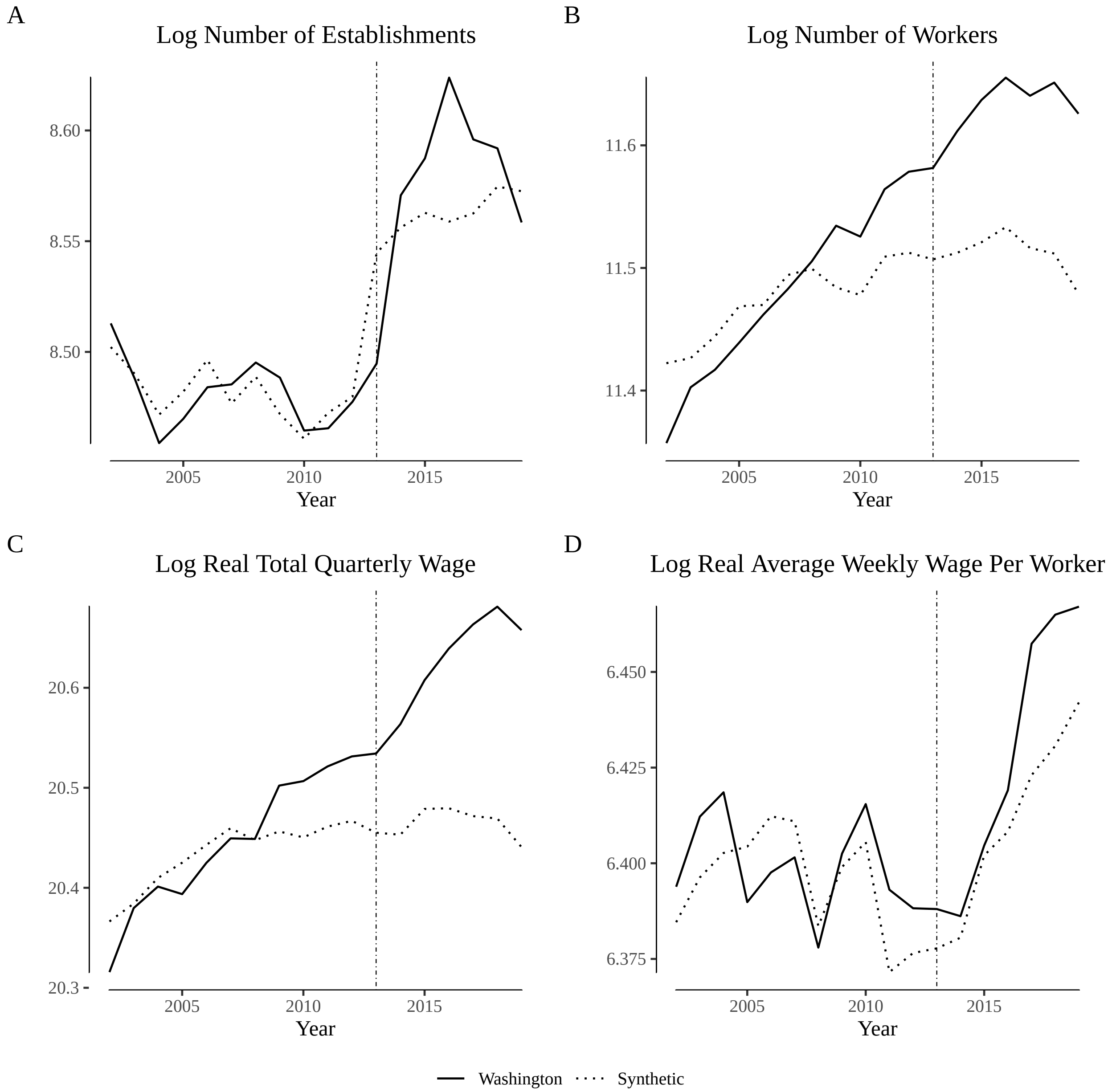
Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are for the "Agriculture, Forestry, Fishing, and Hunting" category (NAICS 11).

Figure A.5: Comparing broadly-defined retailer labor market outcomes in Colorado and its synthetic control



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are aggregated over "health and personal care stores" (NAICS 446), "general merchandise stores" (NAICS 452) and "miscellaneous store retailers" (NAICS 453) categories.

Figure A.6: Comparing broadly-defined retailer labor market outcomes in Washington and its synthetic control



Notes: Data come from the Quarterly Census of Employment and Wages. Outcomes are aggregated over "health and personal care stores" (NAICS 446), "general merchandise stores" (NAICS 452) and "miscellaneous store retailers" (NAICS 453) categories.

B Declarations

B.1 Ethics approval and consent to participate

Not applicable.

B.2 Consent for publication

Not applicable.

B.3 Availability of data and materials

All data are taken from publicly available United States government sources.

B.4 Competing interests

The authors declare no competing interests.

B.5 Funding

The authors declare no sources of funding.

B.6 Authors' contributions

Keaton Miller conceived of and designed the study. Data collection, curation, analysis, and visualization were performed by Sichao Jiang under the oversight of Keaton Miller. Keaton Miller and Sichao Jiang wrote and edited the manuscript.