Estimating the Effect of Cannabis Legalization on Labour Productivity in Canada using the Synthetic Control Method

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Abstract

In 2018, Canada legalized the production, distribution, sale and consumption of recreational cannabis for adults. Given the potential negative impacts of cannabis use on cognitive function, we hypothesize that this policy shift caused a negative impact on labour productivity in Canada. Employing the synthetic control method, we estimate that the policy caused a decline in labour productivity by $0.43 USD per hour worked by the year 2023. However, we conclude that this effect is not significant.

I. Introduction

In recent years, the global landscape of drug policy has shifted toward acceptance and regulation of recreational cannabis. In a landmark policy shift, Canada enacted the *Cannabis Act* in October 2018, legalizing the production, distribution, sale, and consumption of cannabis for recreational purposes. While the primary objectives of this framework were to decrease violence, displace the illicit market and restrict youth access, the policy has raised concerns about its broader socio-economic implications (Government of Canada, 2021).

Existing research provides mixed evidence of the impacts of cannabis on labour market outcomes. Some findings indicate that cannabis use is associated with lower wages, lower educational attainment and cognitive function (Mullin & Cservenka, 2024; Van Ours, 2007). This suggests a mechanism by which labour productivity can be negatively impacted by cannabis use. By contrast, some argue that with regulation, cannabis use can actually improve productivity in certain sectors via pain alleviation and stress management (Dave et al., 2022).

Recently, more countries have legalized recreational cannabis, including Luxembourg in 2023 and Germany in 2024. Despite this growing movement, to our knowledge, no studies have attempted to quantify the impact of legalizing cannabis on labour productivity in Canada. This information could help policymakers better design policies that meet their goals while minimizing the socio-economic impacts. As such, the goal of our research is to investigate the causal effect of Canada's legalization of recreational cannabis in 2018 on labour productivity.

Given the limited number of countries that have legalized recreational cannabis, conventional cross-country empirical strategies for studying this question are constrained. Consequently, we use the synthetic control method to construct a "synthetic Canada" that enables us to discern the potential impact of such a policy on labour productivity in Canada.

I.1 Literature Review

Existing research presents mixed evidence regarding the effects of cannabis on labour market outcomes. Cannabis use may reduce productivity through an impairment mechanism, negatively impacting cognitive functioning and educational attainment. However, empirical studies often struggle to find robust evidence of these negative aggregate effects.

Several studies have utilized Difference-in-Differences estimators to isolate the impact of cannabis liberalization policies. Sabia and Nguyen (2018) examined Medical Marijuana Laws (MMLs) and found that while marijuana usage increased, there was no substantial evidence that MMLs negatively impacted wages or unemployment.

Similarly, Dave et al. (2022) explored Recreational Marijuana Laws (RMLs) and found results consistent with Sabia and Nguyen. While they noted limited evidence of changes in employment and wages, they also identified a potential counter-mechanism whereby regulated cannabis use might actually improve productivity by alleviating pain and managing stress (Dave et al., 2022).

Despite the lack of strong evidence regarding labour market impacts in some studies, concerns regarding human capital remain. Research by Fergusson and Boden (2008) and Zuckermann et al. (2020) identified a negative relationship between cannabis use and educational outcomes. This suggests that while immediate wage effects may not always be significant, the long-term impact on cognitive development remains a concern. Dave et al. (2022) acknowledge this limitation, noting that restricted post-treatment periods in current data may fail to capture these longer-term cognitive effects.

The lack of consensus in the literature may be linked to methodological inconsistencies. Popovici and French (2013) demonstrated that results are highly sensitive to model specification. In their analysis, they found a significant negative relationship between cannabis use and employment and income, but it disappeared when controlling for unobserved heterogeneity (fixed effects).

In sum, these results suggest a possible impairment mechanism by which cannabis may reduce labour productivity. Motivated by these findings, this study seeks to whether the 2018 legalization of cannabis in Canada caused labour productivity to decline.

II.   Data

The study uses two main sources of data: the Organisation for Economic Co-operation and Development (OECD) and World Bank. Measures of labour productivity (GDP per hour worked) are obtained from the OECD *Productivity Database* which provides cross-country indicators for labour productivity per hour. The data for educational attainment is also from the OECD dataset, *Adults' educational attainment distribution, by age group and gender.*

The remaining macroeconomic level variables are retrieved from the World Bank API in Python. We use variable World Bank World Development Indicators (WDI) which have corresponding codes (see Table 1).

Source	Variables
World Bank Data	Gross Fixed Capital Formation as a share of GDP (World Bank Indicator Code: NE.GDI.FTOT.ZS)
	Inflation, consumer prices (annual %) (World Bank Indicator Code: FP.CPI.TOTL.ZG)
	Exports (World Bank Indicator Code: NE.EXP.GNFS.ZS)
	Imports (World Bank Indicator Code: NE.IMP.GNFS.ZS)
	Industry (including construction), value added (% of GDP) (World Bank Indicator Code: NV.IND.TOTL.ZS)
	Agriculture (World Bank Indicator Code: NV.AGR.TOTL.ZS)
	Population growth (annual %) (World Bank Indicator Code: SP.POP.GROW)
OECD Data	Pre-treatment productivity (GDP Per Hour Worked)
	Education attainment (Percentage of population in the same sex and age with Upper secondary education)

Table 1: Data Sources and Variables

III. Methodology

III.1 Synthetic Control Method

To estimate the causal effect of the 2018 cannabis legislation on labour productivity in Canada, we aim to compare Canada's observed outcomes against a counterfactual scenario where the legislation was not enacted. However, because the policy was implemented nationwide, a direct control group is unavailable, making causal identification difficult. To address this, we employ the Synthetic Control Method (SCM). SCM constructs a "synthetic" counterfactual by generating a convex combination of untreated units (the "donor pool") that best reproduces the characteristics and productivity trends of the treated unit during the pre-intervention period. The treatment effect is then measured as the difference between the observed outcomes in Canada and those of the synthetic control following the intervention.

Formally, for a time period $t \in \{1, ..., T\}$ and a unit $j \in \{1, ..., J+1\}$, let $Y_{j,t}$ be the labour productivity for the country j in period t. We refer to Canada as unit 1 so that the donor pool (non-treated units) consist of the remaining J countries. Given that the United States and the Netherlands have some form of cannabis legalization at either the country or state level during the period of study, we exclude them from our analysis to avoid biasing our results. Other countries

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which have legalized recreational cannabis (e.g., Germany) did so after the end of our period of study, therefore we allow them to remain in our donor pool. Therefore, our donor pool consists of 35 countries.

To use synthetic control, we require data for every year in our study for every country studied; as such, the earliest year in the pre-treatment period with available data is 1997. Therefore, the pre-treatment period is from $1997 - 2018$ and the post-treatment period is from $2019 - 2023$. Given that the cannabis legislation was implemented in October 2018, we assume that any impacts of the legislation would not be realized until the next year.

Also, let $Y_{1,t}^N$ be the labour productivity in Canada in the absence of the intervention after treatment year $T_0 = 2018$. Therefore, the treatment effect we will estimate is defined as:

$$\alpha_t = Y_{1t} - Y_{1t}^N \tag{1}$$

We only observe Y_{1t} after T_0, so we define our synthetic control as:

$$\hat{Y}_{jt}^N = \Sigma_{j=2}^{J+1} \ w_j Y_{jt} \tag{2}$$

Following Abadie et al. (2010), we use a weighted combination of outcomes and characteristics of the donor pool countries, subject to the restriction that the weights, $w = (w_2, ..., w_{j+1})$, are non-negative and sum to one. Therefore, we choose the vector w that minimizes the distance:

$$||X_1 - X_0 W|| = (\Sigma_{h=1}^k \ v_h \ (X_{h1} - \Sigma_{j=2}^{J+1} \ w_j X_{hj})^2)^{1/2} \tag{3}$$

where X_1 is the $(K \times 1)$ matrix of K pre-treatment variables in Canada, X_0 is the $(K \times J)$ matrix of K pre-treatment variables for the J countries in the donor pool and v_h is the importance of assigned to each variable before the intervention.

Using the *scpi* package in Python, we solve the optimization problem in (3), following the method in Facure (2022, Chapter 15) by choosing our vs such that each variable has equal importance for predicting the outcome variable. This is an assumption we have made for the simplicity of the analysis.

III.2   Covariate Selection

Pre-treatment variables typically consist of pre-intervention characteristics that may affect the post-treatment outcomes in absence of the intervention (Barr et al. 2022). Previous synthetic control studies that have evaluated the impact of interventions on labour productivity have employed various covariates such as pre-treatment labour productivity, tertiary education rates, inflation rates, industry and agriculture (% GDP), imports and exports (% GDP), population growth rates, and gross fixed capital formation (% GDP) (Zhuang et al. 2023b).

To select the pre-treatment variables used to estimate (3), we use a data driven approach discussed in Abadie (2021), where we evaluate the predictive power of alternative sets of predictors. First, we divide our pre-treatment period into an initial training period (1997-2008) and a validation period (2009-2018), letting $T_0 = 2009$. We estimate synthetic control weights like in equation (3) using the training period only. Then, we select the set of predictors that result in the best fit for

the observed untreated outcome for the treated unit in the validation period.

Figure 1 displays various synthetic controls generated using different combinations of covariates. Based on these results, the combination of covariates in (a) results in the best fit of labour productivity between Canada and the synthetic unit during the validation period. As such, we will use pre-treatment labour productivity, industry value added (% GDP), investment (% GDP) as the covariates using in our syntehtic control analysis going forward.

(a) Productivity, Investment and Industry

(b) Productivity, Investment and Exports

(c) Productivity and Population Growth
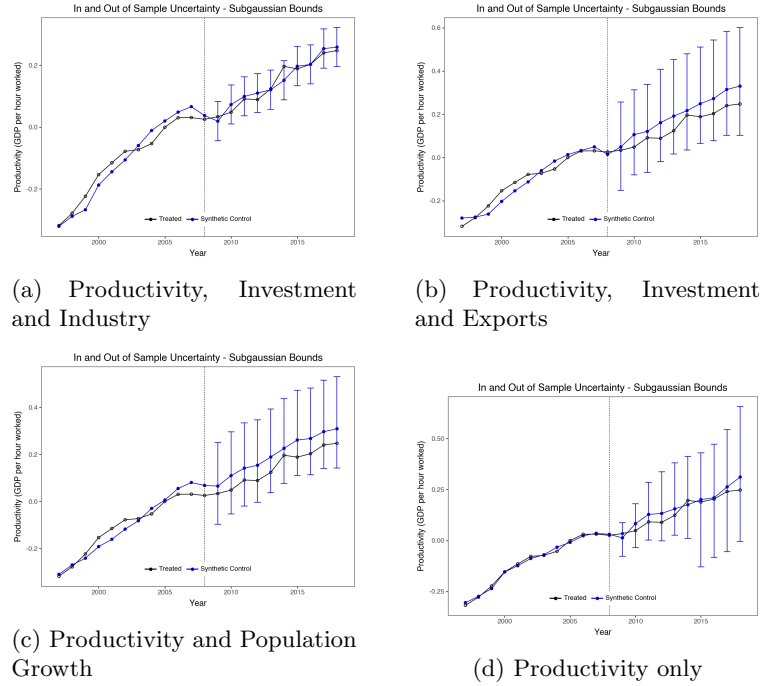
(d) Productivity only

Figure 1: Covariate Selection using different combinations of covariates
*Note: productivity on the y-axis is scaled so that it has zero mean and unit variance

IV.   Results

As a result of the optimization described in Section III.2, we construct a synthetic unit by weighing donors (see Table 2) and computing the treatment effect by computing the gap between Canada and the synthetic unit's productivity for each year in the post-intervention period (see Table 3).

Country	Weight
AUS	0.094
BEL	0.191
COL	0.256
FIN	0.218
FRA	0.071
MEX	0.105
NOR	0.065

Table 2: Donor countries with non-zero synthetic control weights for Canada.

Year	Country	Productivity (Canada)	Productivity (Synthetic Unit)	Treatment Effect
2019	CAN	58.407	58.716	-0.309
2020	CAN	62.914	60.257	2.657
2021	CAN	60.376	59.954	0.422
2022	CAN	59.954	59.356	0.598
2023	CAN	58.862	59.291	-0.429

Table 3: Labour Productivity, Synthetic Unit Productivity, and Treatment Effects for Canada in the post-treatment period (2019–2023).

Figure 2 (a) plots labour productivity for Canada and the synthetic unit over time. As one can see, in the pre-intervention period, the synthetic control unit does not reproduce the treated unit (Canada) exactly; this suggests we are not overfitting the model. Furthermore, we can see that after the legislation is implemented in 2018, labour productivity is similar between Canada and the synthetic unit, suggesting that the policy did not have a large impact on labour productivity in Canada.

Figure 2 (b) plots the gap in labour productivity between Canada and the synthetic unit across time. One can clearly see that this gap remains close to zero in the pre- treatment period. In the post-treatment period, this gap is our estimated treatment effect. We see there is a small negative effect following treatment in 2019 then a spike in 2020, coinciding with the COVID-19 pandemic. However, the gap between Canada and the synthetic unit eventually declines to just below zero in 2023, the last year of data we have in the post-treatment period.

Given that we expect cannabis to gradually cause cognitive decline in workers, we also expect the negative effects of the 2018 legalization to be slowly realized after the policy intervention. Our results suggest that the cannabis legislation in 2018 may have led to a decrease in labour productivity by $-\$0.43$ USD per hour worked in 2023. This effect is small. To explore whether these results are significant, we conducted placebo tests and report our results in the next section.
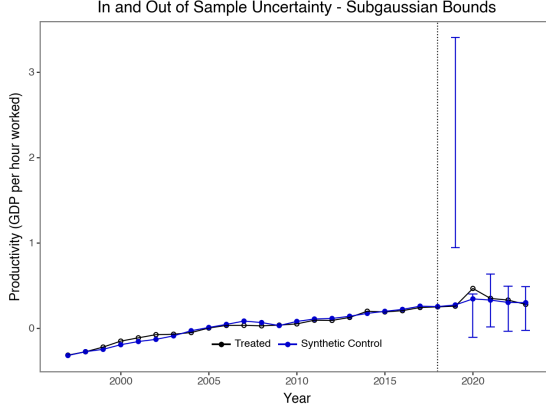
(a) Labour Productivity Over Time in Canada and the Synthetic Unit. The cannabis legislation was implemented in Canada in 2018, shown by the dashed line. Labour productivity on the y-axis is in scaled unit (zero mean; unit variance).
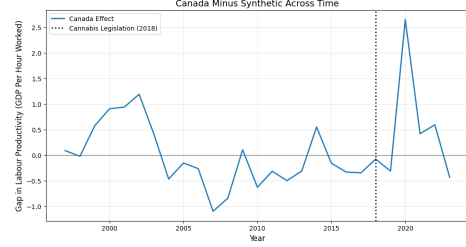
(b) Gap in Productivity between Canada and the Synthetic Unit across Time

Figure 2: Synthetic Control Results

IV.1 Permutation Inference

To evaluate the significance of our estimates, we ask whether our results are driven only by chance. How often would we get results of these size if a random country received the intervention instead of Canada? Using the method discussed in Abadie et. al (2010), we run placebo tests by applying the synthetic control method to the countries that did not legalize recreational cannabis during the sample period of our study. If the placebo tests result in gaps in productivity ("placebo effects") the same size as Canada, then we would conclude that there is no significant evidence that the 2018 legalization negatively affected labour productivity in Canada. Otherwise, if the gap in labour productivity in Canada was unusually large relative to the gaps for countries that did not implement such a legislation, we would conclude that our analysis provides significant evidence that there was a negative effect of the legislation on labour productivity in Canada.

We conduct placebo studies by iteratively applying the same synthetic control method used to estimate the effect of the cannabis legislation in Canada to all 35 countries in the donor pool. In each iteration, we treat one of the countries in the donor pool as the treated unit instead of Canada as if they had implemented the intervention in 2018. We compute the estimated placebo effect for each donor to generate a distribution of the estimated effects where there was no intervention. In Figure 2, we plot all the placebo effects along with the actual treatment effect in Canada.

Figure 3 (a) displays the results for the placebo tests using all donor countries. The grey lines show the difference in labour productivity between each country in the donor pool and its respective synthetic unit (convex combination of the other donor countries). The blue line shows the gaps for Canada. After 2018, the plot shows the placebo effects for the 35 donor countries and the treatment effect for Canada.

As Figure 3 (a) shows, the synthetic control method provides a good fit for labour productivity

in Canada prior to the 2018 cannabis legislation. We calculate the pre-intervention mean squared prediction error (MSPE) (equation 4) in Canada (the average of the squared discrepancies between labur productivity in Canada and in its synthetic counterpart during 1997-2018) is about 0.331. The median pre-intervention MSPE among the 35 donor countries is 0.395.These values are quite small, suggesting that the synthetic control method provides a good fit for labour productivity before the 2018 intervention for the majority of donor countries (Abadie et al. 2010). However, we can also see in this figure that labour productivity during the pre-treatment period cannot be reproduced well for some donor countries via the synthetic control. For example, the pre-MSPE for Ireland, Colombia and Norway are approximately 130, 58 and 25, respectively. This is to be expected since countries can have very different characteristics that impact productivity which cannot be matched by convexly combining other countries as we have attempted.

$$MSPE = \frac{1}{N}\Sigma(Y_t - \hat{Y_t}^{Synth})^2 \tag{4}$$

If the synthetic unit poorly fits Canada poorly fits labour productivity in the pre-treatment period, then our interpretation of the treatment effect could be due to poor fit instead of the true effect of the 2018 cannabis legalization. For this reason, following Abadie et. al (2010), we will measure the relative rarity of the observed treatment effects for only well-fitted countries. To do this, we exclude donor countries that exceed a certain level of pre-MSPE and plot the results in Figure 3 (b)-(d).

In Figure 3 (b), we exclude countries that have a pre-MSPE more than 20 times the pre-MSPE of Canada; we exclude four of 35 donor countries. We repeat this process for five and two times Canada's pre-MSPE and plot them similarly in Figure 3 (c) and (d), respectively. As we can see in all three figures, Canada's gap line is within the same range as those for the placebo effects of the donor countries in the post-treatment period. These results suggest that the treatment effects that we see for Canada in the 2019-2023 period are not unusual and are likely due to chance. This interpretation is the same even if we include all 35 donor countries like in Figure 3 (a).
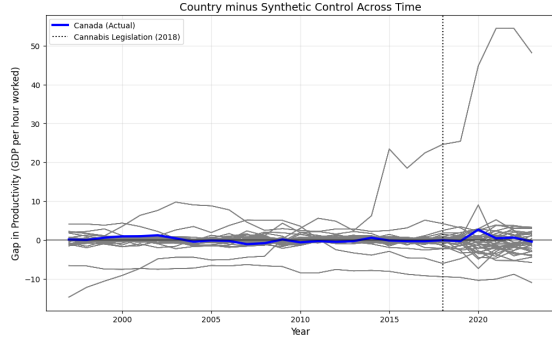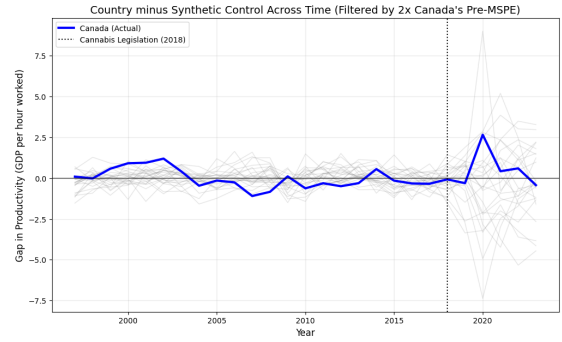
(a) All placebo effects (35 donors).
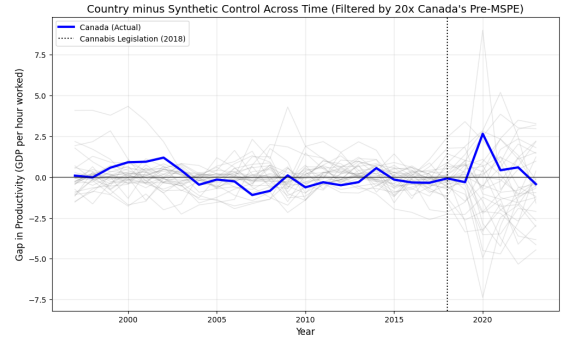
(b) Filtered by 20x Canada's pre-MSPE.
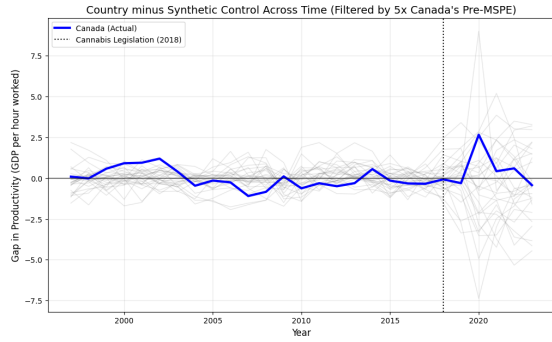
(c) Filtered by 5x Canada's pre-MSPE.

(d) Filtered by 2x Canada's pre-MSPE.

Figure 3: Placebo Effects in Productivity for Canada vs. Synthetic Control Donor Countries, Under Various Pre-MSPE Filters

Finally, following the method in Facure (2022, Chapter 15), we derive p-values from our results to see how many times the effects we observe are below the effect in Canada. We want to test the one-sided hypothesis that the effect of the legislation in Canada is negative, so we estimate the p-value as the proportion of times the effect in Canada is bigger than all of the estimated effects:

$$PV = \frac{1}{N} \Sigma 1\{\hat{\tau}_{CAN} > \hat{\tau}_j\} \tag{5}$$

where $1\{\hat{\tau}_{CAN} > \hat{\tau}_j\}$ is an indicator function equal to 1 if the treatment effect of Canada is greater than the estimated placebo effects.

Table 4 summarizes the resulting p-values. Echoing our previous results, we see that the effect of the cannabis legislation did not have a significant impact on labour productivity in the post-treatment period spanning 2019-2023.

Year	Treatment Effect	Rank	P-Value
2019	-0.309131	11/36	0.305556
2020	2.656671	31/36	0.861111
2021	0.422231	22/36	0.611111
2022	0.597807	22/36	0.611111
2023	-0.428916	18/36	0.500000

Table 4: Post-treatment effects, ranks, and permutation-based p-values using the method in Facure (2022, Chapter 15)

In Figure 5, we plot the distribution of treatment and placebo effects in each year of the post-treatment period. The grey bars reflect the placebo (fake) effects for countries that did not legalize cannabis, i.e, the donor countries. Canada's estimated treatment effect is plotted in red within this distribution. If Canada's effect was extreme relative to the placebo effects, this would indicate a statistically meaningful impact of legalization.

The question we try to address here is whether Canada experienced a significant decline in productivity due to the cannabis legislation. If so, we would expect the red bar in each of the plots in Figure 5 to be on the extreme left of the distribution. This would be interpreted as Canada's labour productivity being unusually negative compared to the other countries. However, we do not see the red bars being in the left extreme in any of the post-treatment years. This implies that the legislation did not have any significant impact on labour productivity in Canada in any of the post-treatment years.
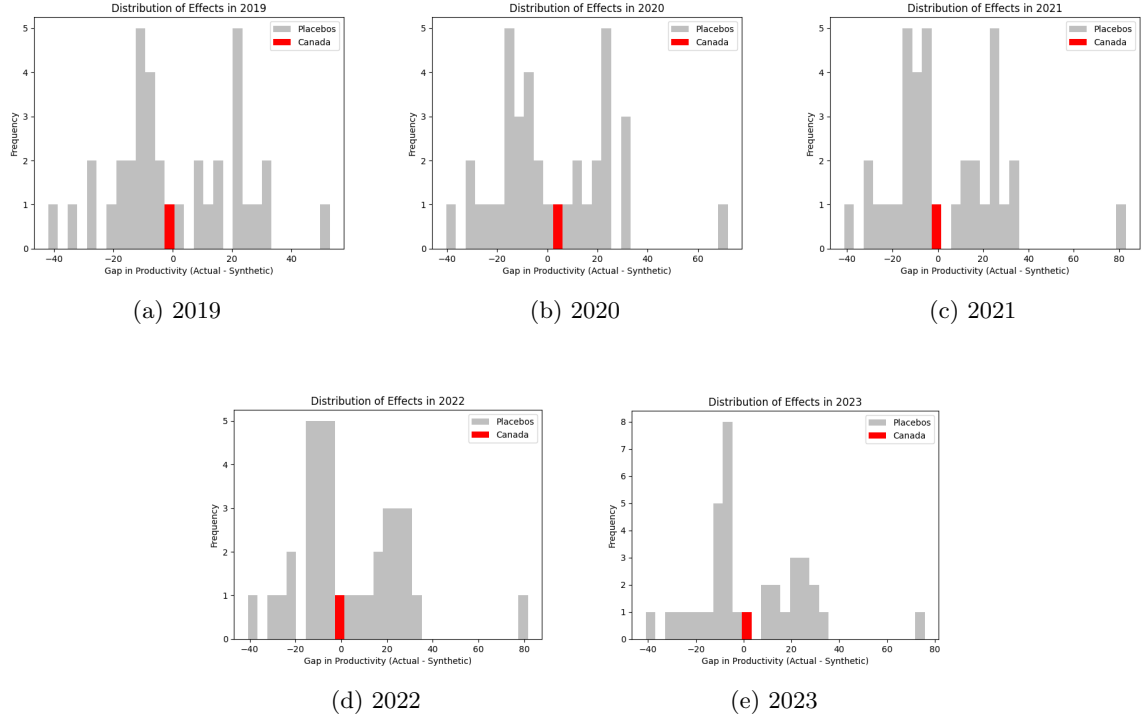
(a) 2019   (b) 2020   (c) 2021

(d) 2022   (e) 2023

Figure 4: Distribution Effects for 2019–2023.

V.   Conclusion

In 2018, Canada became one of the first countries in the world to legalize access to recreational cannabis. Since then, several countries have followed suit, including Germany and Luxembourg. Despite evidence that cannabis can negatively impact cognition and educational attainment, few studies have examined its impact on economic outcomes. To our knowledge, we are the first to evaluate the impact of cannabis legalization on labour productivity in Canada.

We employed the synthetic control method to construct a "synthetic Canada" as a counterfactual with which to compare the impact of the policy on labour productivity in Canada. While we observe a small, negative impact of the policy on labour productivity in Canada compared to the synthetic unit in 2023, we conclude that this effect is not significant.

While our results are not significant, this may be due to the lack of availability of a long post-treatment period following the 2018 legislation. Given that the cognitive impacts of cannabis may not be fully realized until after several years of use, revisiting this question after more years of data become available may produce different results.

Moreover, it is possible that the effects of cannabis use may have other labour market outcomes as suggested by previous research, so future studies could also explore the effects of cannabis legalization outcomes such as unemployment rates, to provide a more comprehensive understanding of the policy's effects.

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