Do Carbon Taxes Kill Jobs? Firm-level Evidence from British Columbia *

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Abstract

This paper investigates the employment impacts of British Columbia's revenue neutral carbon tax. Using the synthetic control method with firm-level data, we find considerable heterogeneity in employment responses to the policy. We show that firm size matters. In particular, the carbon tax had a negative impact on large emission-intensive firms, but simultaneous tax cuts and transfers increased the purchasing power of low income households, substantially benefiting small businesses in the service sector and food/clothing manufacturing. Furthermore, we find that aggregate employment was not adversely affected by the policy. Our results provide additional insight for the "job-shifting hypothesis" of revenue neutral carbon taxes.

Key Words: Carbon tax; Employment; Unilateral climate policy; Firms
JEL Codes: E24, H23, J2, Q5

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1. Introduction

For decades there has been a consensus in the economics literature that carbon taxes are efficient, but their precise economic impact has remained hotly debated. At one extreme of the debate, "carbon taxes kill jobs." At the other extreme, carbon taxes are claimed to generate economic growth and "spur innovation."[1] The concerns by politicians are that they displace workers, depress economic growth, and are regressive. These can make many governments hesitant to adopt such a tax. However, it is unclear how these concerns play out when the carbon tax revenues are redistributed back to the economy. To better inform this debate on costs and benefits, this paper investigates the employment effects of the most aggressive and comprehensive revenue-neutral carbon tax globally, implemented in British Columbia (BC), Canada.[2]

On July 1st, 2008, BC became the first jurisdiction in North America to implement a revenue-neutral carbon tax. Anecdotal evidence suggests the policy is a success — achieving large reductions in pollution at a relatively modest cost to the economy.[3] The policy intervention has a number of characteristics that make it an ideal natural experiment with which to study employment impacts. First, the BC carbon tax is a textbook pollution tax — subjecting almost all sources of carbon pollution in the region to a uniform price per tonne of carbon emitted, making it easy to connect the predictions of theory to an empirical test. Second, the speed with which the policy was implemented made it a surprise to most stakeholders, ruling out the possibility that polluters would adjust their behaviour in anticipation of the regulation.[4] Third, the relatively high tax rate adopted meant that it provided

[1] The latter claim is referred to as the "Porter hypothesis" (Porter, 1991; Porter and van der Linde, 1995).

[2] The tax rate was initially \$10/tonne CO_2e when it was implemented in 2008, then increased \$5/tonne annually until it reached \$30/tonne in 2012 until April of 2018, when it increased to \$35 and will further increase to \$50 until 2021. Carbon dioxide equivalent (CO_2e) is a unit of measurement used to compare the global warming potential of various greenhouse gas (GHG) emissions to the global warming potential of CO2. In 2013, CO_2 made up 78% of BC's GHG emissions methane made up 16%, while N_2O made up 3% (measured in CO_2e) (Environment Canada, 2015).

[3] See https://www.cbc.ca/news/canada/british-columbia/b-c-carbon-tax-cut-fuel-use-didn-t-hurt-economy-1.1309766

[4] The policy was announced on February 2008 and then implemented on July 2008.

a strong signal to polluters to change their behaviour when the policy was introduced.

By treating the BC carbon tax as a natural quasi-experiment, our empirical strategy is based on a difference-in-differences (DID) method, comparing the changes in employment for industries in BC with changes in employment in the rest of Canada (ROC) before and after the implementation of the carbon tax. We find, however, that for a large percentage of industries, the parallel trend assumption is likely to be violated.[5] This is mainly because the BC carbon tax was implemented at a time period of major macroeconomic shifts that may have affected industries differently, such as the Great Recession, rapid migration, and oil price shocks.[6] We, hence, employ the synthetic control method (SCM), which allows us to correct the pre-treatment trend of the counterfactual BC to become statistically parallel to the observed BC trend.[7] In our setting, we face the challenge that there are only ten provinces in Canada, and so we would only have a maximum of 9 control units per industry only.[8] This is particularly problematic for inference when using placebo tests as the statistical significance level of the SCM estimates depends on the number of control units available in the donor pool.

To overcome this inference problem, we use the most comprehensive and confidential firm-level employment data, Longitudinal Employment Analysis Program (LEAP), to construct "representative firms" from all individual firms in each province-industry-firm size category.

[5] We also develop a way to succinctly display the support for or lack of parallel pre-treatment trends of employment between BC and ROC. The results are presented in Section 4.III.

[6] Yip (2018) shows that the employment trends between BC and the rest of Canada are parallel only over the period 2005-2008. As we estimate the employment effect industry by industry, the parallel trends assumption must be satisfied for each industry. Thus, checking the parallel trends assumption at the province-level, such as Yip (2018), is not sufficient for the identification.

[7] Roth (forthcoming) shows that conventional pre-trends tests used in DID settings often have low power and that therefore conditioning the analysis on the result of a pre-test can bias the point estimates and provide underestimated confidence intervals. Our study also shows that most of our pre-trends on the industry level are non-parallel, and therefore we feel uncomfortable using DID. By using SCM, we correct for these issues, but our suggestive parallel trend between the treatment and the synthetic control in principle is subject to the same critique as in Roth (forthcoming). Ultimately, for future work Roth suggests calculating the power of the pre-tests against the hypothesized trends, but not relying on these tests solely but providing economic context and intuition to argue how the parallel trends could be violated.

[8] For inference, one runs placebo tests using the other provinces (non-BC) as placebo treatments. For many industries, we would have fewer than nine controls due to data suppression by Statistics Canada for confidentiality reasons with publicly available data.

Then we run the SCM using these representative firms.[9] With this approach, we can now obtain a much higher number of control units in each province-industry pair for the placebo tests. We test this method in a Monte Carlo simulation to illustrate its feasibility.

With our new approach, we first show that employment responses are heterogeneous across industries, yet aggregate employment is not adversely affected by the policy. In particular, we find a decrease of aggregate employment of 0.86%, with an upper bound of a 1.12% increase and a lower bound of a 2.42% decrease in employment, making the point estimate insignificant at the 10% level.

Second, we further explore the heterogeneity and show that firm size matters. We find that the policy caused large companies in emission-intensive manufacturing sectors to contract, while it increased employment in small service sectors, such as health services (e.g., massage therapists, dental), restaurants, tourism, small food manufacturers, and small clothing companies.[10] Although not formally tested, we argue that the positive employment effect is a result of the revenue-recycling feature of the policy. It uses the revenues from the carbon tax to provide transfers and income tax reductions, possibly increasing the purchasing power of low income households. This causes (in addition to the small business tax and corporate tax reduction) the positive impact of the overall policy on small businesses in the service and clothing/food manufacturing. These findings provide an important additional insight to the "job-shifting hypothesis" of a revenue-neutral carbon tax in the literature, first documented in Yamazaki (2017). Yamazaki showed that jobs shift away from the emission-intensive industries to the clean domestic service industries. We further show that such "job shifts" mainly take place from large manufacturing firms to small firms in the service industry.

We can highlight three additional results: i) we find that the metal manufacturing industry is hardest hit and lost around 5,700 jobs, equivalent to a 15.3% decrease in jobs per capita in this industry. This percentage decrease is even larger, at 18.6%, for large firms in

[9]In addition, implementing the SCM directly to a firm-level data would be extremely computationally slow. Our SCM approach improves computational efficiency as well.

[10]This result is consistent with Hafstead and Williams (2018), in which the authors directly model the impact of a carbon tax on employment and find that the policy reallocated workers from dirty to clean industries.

the metal manufacturing industry; ii) Small firms in the food and clothing manufacturing industry experience a statistically significant increase in employment per capita of over 25%; iii) Small companies in the healthcare and social assistance industry see a 23.9% increase in employment per capita.

This paper makes several important contributions. First, on the employment effect of carbon taxes, the empirical literature is still scant and inconclusive.[11] To our knowledge, there are only two empirical papers which examine the employment effects of the BC carbon tax.[12] Using a DID framework, Yamazaki (2017) finds that BC's aggregate employment increased by 4.5% over the six years following the implementation of the policy. In contrast, Yip (2018), also using DID, finds that the policy sharply increased unemployment by 1.3 percentage points, which would be enormous as it would explain 41% of BC's total unemployment rate.[13] Our finding for the aggregate employment effect is in sharp contrast to these results, especially to Yip (2018). We provide important additional evidence to the literature that is currently inconclusive due to the mixed findings.

Our second contribution is that, to the best of our knowledge, this is the first paper to study the employment effect of a carbon tax using firm-level data, which includes the entire universe of employment in Canada. This highly confidential and rich dataset allows us to include more industries/provinces whose data is suppressed in the public datasets used by

[11] Rivers and Schaufele (2014) focus on the tax's effect on agricultural trade, finding that it did not adversely affect the sector's trade. Antweiler and Gulati (2016) investigate the tax's effect on gasoline consumption as well as vehicle choice, concluding that the policy has resulted in fuel demand per capita being 7% lower and the fuel efficiency of the average vehicle in the province being 4% higher than it otherwise would be. Thus far, only Martin, de Preux and Wagner (2014) investigated the effect of the UK's carbon tax, the Climate Change Levy (CCL), on manufacturing activities. Their results found no statistically significant impact of such tax on employment. This paper differs from Martin, de Preux and Wagner in several ways. First, although the CCL is considered a carbon tax, the CCL and BC carbon tax are designed differently, especially in sectoral coverage and exemptions. Second, this paper investigated the net effect of the carbon tax by considering many different sectors while Martin, de Preux and Wagner focused on the manufacturing sector. In addition, Petrick and Wagner (2014) and Martin et al. (2014) investigate the effects of carbon pricing in the context of the European Trading Scheme.

[12] Carbone et al. (2020) also examine the employment effect of the BC carbon tax. As their empirical analysis is a replication of Yamazaki (2017), we do not see their finding to be a contribution to the literature on the employment effect of the BC carbon tax.

[13] Using a calibrated version of the theoretical model presented in the online appendix of Yamazaki (2017), we show in Appendix B that this wide range of results is theoretically possible, highlighting the need for further empirical research to pin down the impact.

previous researchers. In addition, the firm-level data has the advantage that we can explore the heterogeneous employment impacts at the more granular level, i.e., firm size. We can investigate further and better understand the mechanisms behind the employment responses to a carbon tax.

Lastly, this paper provides a method to deal with the common situation where not enough control units exist in the donor pool when implementing the SCM. This is a particularly pertinent issue for studies which focus on small regions.[14] We overcome this issue by using individual-level data to construct representative firms.

The majority of countries globally today are actively debating which policies to implement to curb GHG emissions in order to achieve national emissions targets. In fact, the BC carbon tax has now been actively discussed in many policy forums as a role model for carbon tax implementation (World Bank Group, 2018). This paper speaks directly to this important global debate. The results are also timely for Canada as the federal government mandates the provinces to implement carbon pricing of $50/tonne by 2022.

The remainder of the paper is structured as follows. Section 2 describes the design of the BC carbon tax. Section 3 explains the data while section 4 presents the research design. The empirical findings are presented in section 5. Finally, section 6 discusses the possible limitations of the paper and section 7 concludes. Estimation receipt, calibration exercises, and additional tables are provided in Appendix.

[14] If we were to use the traditional SCM with the industry-level data, at most nine control units (9 non-BC provinces) are available for the placebo test. However, because not all industries exist in all nine provinces, there are less than nine control units for most industries. This issue is even more severe with the publicly available data as the data for many industries in small provinces is suppressed. Given that at least nine control units are required to interpret the estimates with a pseudo-10% statistical significance level, using the publicly available industry-level data or even constructing industry-level data from the firm-level data is problematic. Furthermore, because at least 19 control units are required for the pseudo-5% statistical significance level, it is impossible to interpret the estimates with the 5% or even higher statistical significance when using the industry-level data.

2. BC Carbon Tax: Background

The British Columbia Ministry of Finance formally announced its intention to implement a carbon tax in its budget plan in February 2008. Only five months later, the policy was initiated on July 1st, 2008. It was introduced to reduce emissions by a minimum of 33% below the 2007 levels by 2020 (Ministry of Finance, 2013). Given past political actions taken by the Liberal government in the province, the announcement of the carbon tax took the public by surprise (Harrison, 2013).

Starting at \$10/tonne CO2e, the rate increased by \$5/tonne CO_2e annually until it reached \$30 in 2012, making it among the highest carbon prices in the world (Murray and Rivers, 2015). The rate was kept at \$30 until 2018; however, it increased to \$35 on April 1, 2018, and is expected to annually increase by \$5 until it reaches \$50/tonne in 2022 (Ministry of Finance, 2017). These increases are set to meet the carbon pricing requirements in the Pan-Canadian Framework on Clean Growth and Climate Change. This framework is a collective plan set out by the federal government to reduce emissions in Canada. British Columbia joined this framework in 2016. Under this framework, the carbon tax rate is required to be at \$50 by 2022. As each fuel has different carbon contents, the rate is adjusted accordingly. For example, the carbon tax increased the price of gasoline by 2.34 cents per liter in 2008, rising gradually to 6.67 cents per liter by 2012 (Ministry of Finance, 2010). Table 1 provides the tax rate per unit volume for selected fuel types and the percent of the final fuel price that the tax is responsible for.

The revenue neutrality of the policy is implemented in two ways. Firstly, the bottom two income tax brackets in BC were reduced by 5% (Ministry of Finance, 2012). This resulted in BC having the lowest income tax rate in Canada for individuals earning up to \$122,000 (Ministry of Finance, 2012). A "low-income climate action" tax credit, and the Northern and Rural Homeowner benefit, further distribute the revenue collected by the policy (Ministry of Finance, 2012). Second, the general corporate tax rate was initially reduced from 12% to 11% in 2008 and was reduced further to 10.5% and 10% in 2010 and 2011 (Ministry of

Table 1: Tax rate for selected fuel type

Fuel type	Tax rate (2013)	Tax % of final fuel price (2013)
Gasoline (cents/liter)	6.67	5.10
Diesel (cents/liter)	7.67	5.74
Natural Gas (cents/m$\hat{3}$)	5.7	50.68
Propane (cents/liter)	4.62	18.67

Notes: Tax rate per unit volume for selected fuel types and the tax % of the final fuel price for 2013. This table is adapted from Table 2 in Murray and Rivers (2015). Gasoline and diesel data were obtained from CANSIM Table 326-0009, natural gas data were obtained from Natural Resources Canada (2015), and propane data were obtained from National Energy Board (2014).

Finance, 2012). It was reverted back to the 2008 level of 11% in 2014. The small business corporate income tax rate was also reduced from 4.5% to 2.5% in 2008 (Ministry of Finance, 2012).[15] A number of additional tax credits, which make up a relatively small portion of the redistributed revenue, have also been implemented since 2008 (Ministry of Finance, 2012). These tax credits range from the BC Seniors Home Renovation Tax Credit to the Film Incentive BC tax credit. According to the Budget and Fiscal Plan (Ministry of Finance, 2015), the carbon tax had raised about $1.2 billion in revenue annually since 2012, when the rate stopped increasing at $30/tonne CO_2e.

The carbon tax covers nearly all carbon emissions from fuel combustion in BC, which amounts to about 75% of all greenhouse gas (GHG) emissions in the province (Murray and Rivers, 2015). Exemptions are made for fuels exported from BC, all GHG emissions that are not directly produced from the combustion of fossil fuels (e.g., methane produced from landfills), and all emissions produced outside BC's borders (Ministry of Finance, 2014). These exemptions result in a significant portion of emissions from the air transportation and non-metallic mineral product manufacturing industry being exempt from the tax. Additionally, since the carbon tax is only levied on fossil fuels, emissions from non-fossil fuel sources, such as fugitive emissions or from chemical processes, are not covered by the tax.[16]

[15] In BC, "Small business" for tax purposes is defined as a company with corporate income of less than $500,000/year (before 2010, the limit was $400,000/year).

[16] The non-metallic mineral product manufacturing industry includes the cement and concrete manufacturing industry which, as a result of chemical processes involved in cement manufacturing, produces large volumes of CO_2 (Gibbs, Soyka and Coneely, 2000)). Therefore, since this CO_2 is not produced from fuel combustion, it is not covered by the BC carbon tax. In 2012, greenhouse vegetable and horticulture growers

Table 2: Summary Statistics for the LEAP data

Sector (NAICS)	British Columbia				Rest of Canada			
	Mean	SD	Total L		Mean	SD	Total L	
			Pre	Post			Pre	Post
Agriculture, forestry, fishing and hunting (11)	5.22	15.62	30,595	29,239	3.27	18.33	115,543	122,826
Mining, quarrying, and oil and gas extraction (21)	18.66	-	25,402	40,775	27.69	245.33	125,877	179,614
Utilities (22)	68.75	-	1,294	1,635	179.87	1370.34	19,977	27,425
Construction(23)	5.53	23.10	91,489	113,620	6.68	53.32	516,218	723,231
Food + clothing manufacturing (31)	20.79	70.16	23,263	26,392	33.86	198.65	211,212	197,074
Paper + chemicals manufacturing (32)	25.23	141.99	52,550	54,927	31.84	148.84	344,754	345,000
Metal + electrical manufacturing (33)	12.76	48.74	43,089	48,545	25.05	230.97	602,897	631,101
Wholesale trade (41)	10.09	37.07	69,471	81,752	12.84	93.05	535,652	614,343
Retail trade (cars, furniture, groceries) (44)	17.75	218.56	143,503	175,640	17.88	278.31	885,210	1,081,246
Retail trade (online, department stores, hobby) (45)	13.44	183.97	41,963	49,217	17.82	324.29	296,783	348,931
Air, rail, truck, and pipeline transportation (48)	11.79	159.54	57,447	72,668	9.59	155.51	325,924	406,895
Postal and warehousing (49)	31.32	-	16,174	19,653	34.54	569.36	93,882	103,672
Information and cultural industries (51)	14.86	151.21	33,280	40,070	27.10	315.33	198,645	244,495
Finance and insurance (52)	13.89	156.55	56,091	69,475	21.42	403.24	439,983	538,234
Real estate and rental and leasing (53)	3.52	16.36	28,382	34,458	4.90	34.44	165,734	197,179
Professional, scientific and technical services (54)	4.53	30.23	71,405	92,548	5.46	61.17	486,856	614,043
Management of companies and enterprises (55)	5.21	25.79	9,981	10,627	7.08	40.82	56,480	65,838
Administrative and support, waste services (56)	10.79	122.26	66,259	83,235	13.83	110.16	485,919	565,055
Educational services (61)	54.04	478.11	99,976	121,372	96.86	755.32	639,043	812,763
Healthcare and social assistance (62)	13.13	268.28	149,775	191,785	17.95	241.79	971,494	1,254,037
Arts, entertainment and recreation (71)	11.70	90.13	27,779	33,841	12.58	121.26	144,774	181,798
Accommodation and food services (72)	17.03	86.51	127,069	168,206	15.65	87.23	622,783	816,831
Other services (except public administration) (81)	4.97	22.76	56,656	69,398	4.95	29.92	362,257	442,777
Public administration (91)	328.98	-	92,778	118,109	304.74	4872.45	779,074	982,460

Note: We calculated the average firm-level employment over the sample period for each sector, presented in columns "Mean." SD stands for standard deviation for the firm-level employment. We also calculated the total employment for each sector, presented separately for the pre-policy and post-policy periods. NAICS stands for the North American Industry Classification System. Pre means 2001-2007 while Post means 2008-2013. L means average labour unit (ALU).

3. Data Sources

To estimate the employment effect of the BC carbon tax policy, we use firm-level data to estimate the overall impact of the policy. This data is the most detailed firm-level employment dataset available in Canada, the Longitudinal Employment Analysis Program (LEAP). It is confidential and consists of the universe of employment data from all Canadian firms covering the time period from 2001 to 2013. The employment measure used in this dataset is the average labour unit (ALU). The ALU employment estimate is derived by dividing the business's annual payroll (collected from Canadian business tax data) by the average annual earnings per employee in the corresponding industry/province/firm size (compiled from the *Canadian Survey of Employment, Payroll and Hours*). Summary statistics are presented in Table 2.

Between 2001-2013, the LEAP contains data on approximately 4 million firms; however, approximately 30% of these firms have zero employment throughout our period of analysis. After dropping these firms with zero employment and those with consecutive missing observations, there are approximately 2.1 million firms in Canada, representing around 91% of employment in Canada.[17]

4. Methodology

This section discusses the econometric design in estimating the industry-specific employment effects of the carbon tax. Section 4.I explains our new approach to implement the SCM

were exempted. Given that this exemption represents a small fraction of our data, we do not believe it would be a primary concern.

[17]After dropping the firms with no employment, there are still 40 million observations, consisting of 2.5 million firms. Among them, there are 437,780 firms in BC, which is 16% of the data. Among the 2.5 million firms, 11% of them have zero(s) that are surrounded by non-zero. The breakdown is: 1 year: 6%, 2 years: 2%, 3 years: 1.2%, 4 years: 0.7%, 5 years: 0.5%, 6 years or more: 0.85%. For any single zero and double zero surrounded by non-zeros, we interpolated the employment data by the surrounding years' employment data. Any firms reporting three or more subsequent years of zeros are dropped from the dataset. These non-reports are likely due to late tax filings or delays in the reporting system. Although it is theoretically possible that this interpolation may bias the results, we do not believe that this would fundamentally have impacted the results of our paper as these non-reports are likely due to late tax-filings or other administrative data issues.

applied to firm-level data. In Section 4.II, we provide Monte Carlo simulations to demonstrate the characteristics of our SCM approach. Then Section 4.III explores the validity of the parallel trends assumption with our approach.

I. A New Approach to Implement SCM

We implement the SCM according to how it is outlined in Abadie, Diamond and Hainmueller (2010). Let Y^I_{jpt} be employment in industry j in province p at time t which receives the policy intervention, and Y^N_{jpt} be the employment in that industry if it does not receive the intervention. Then we can write the effect of the intervention measured at time t as $\alpha_{jpt} = Y^I_{jpt} - Y^N_{jpt}$. In this study, the parameter of interest is $\alpha_{j,\mathrm{BC},2013}$ to capture the total effect of the policy as the final increase of the BC carbon tax rate was completed in 2012. In addition, starting with 2013/14, the tax revenues were used more for targeted support subsidies of particular industries in BC (among others, most prominently the movie industry), and hence the tax lost its notion of being a "textbook" example of a revenue-neutral carbon tax. Abadie, Diamond and Hainmueller (2010) show that $\alpha_{j,\mathrm{BC},t}$ can be estimated by substituting $Y^N_{j,\mathrm{BC},t}$ for a synthetic control group which is defined as the inner product of a vector of weights and the vector of the outcome variable for the firms from ROC, where the vector of weights is such that the difference between the pre-treatment values of chosen variables of the treatment unit and the synthetic control group is minimized. See Abadie, Diamond and Hainmueller (2010) for a detailed discussion of the SCM.

Representative firm approach

Given that our primary interest is the industry-specific employment effect, the SCM is employed for each industry. This implies that the synthetic control group will be constructed out of 12 potential control units (nine non-BC provinces and three territories) from the donor pool if we are to use the industry-level data. However, the SCM tests the statistical significance of the estimates using placebo tests, and the level of significance depends on the number of placebos available in the donor pool. Consequently, we require at least nine control groups in the donor pool to obtain a significance level of 10%.[18] Nevertheless, due to data suppression and missing values in the publicly available industry-level data from Statistics Canada, only 15 out of the 24 2-digit North American Industry Classification System (NAICS) sectors have at least nine control units. As these 15 sectors account only for about 60% of total employment in Canada, the SCM applied to this industry-level data would only allow us to present results with a significance level of 10% for a limited fraction of Canadian employment. To increase the numbers of placebos and therefore use a significance level of at least 10% for all industries, we use a new approach to the SCM applied to firm-level data and test the feasibility of our method by Monte Carlo simulation.

For each sector (2-digit NAICS), we create up to five "representative firms" for each province delineated by firm size. Because our Monte Carlo simulations (presented in Section 4.II) show that each representative firm must include a "large number of firms," here equal to 100, for the results of our analysis to be consistent, the exact definition of this representative firm depends on the number of firms that exist in a given province's industry during our sample period. Therefore, in all cases, the representative firm is the sum of at least 100 firms within one industry-province-size class combination. In particular, if there are 500 or more firms in a given industry-province pair, a representative firm is created for each quintile (i.e., each quintile contains the same number of firms, whereby the first (fifth) quintile is the quintile with the least (maximum) number of employees).[19] If there are 400 to 499 firms in a given industry-province pair, a representative firm is created for each quartile. This same pattern is applied to industry-province pairs with 300 to 399 and 200 to 299 firms. If there are 100 to 199 firms in the industry-province pair, then only one representative firm is created, and if there are less than 100 firms in the industry-province pair, then the representative firm is dropped. The only exception to this rule is made for the utilities industry, in which the number of firms is less than 100 for all provinces. In this case, one representative firm

[18] We need at least 19 control groups to obtain a significance level of 5%, which is more than all the potential control units in Canada. This calculation of the significance level is based on the number of control units in the donor pool, which is the same as that used in Abadie, Diamond and Hainmueller (2010).

[19] Firm-size category (e.g., quintile, quartile, etc.) is calculated based on firms' pre-policy average employment. We avoid using post-policy employment for this calculation because it is the outcome variable.

is made for each province which has more than 40 firms. As a result of the above rules, BC has 5 representative firms in each industry except two: the utilities industry with one representative firm and the public administration industry with 4 representative firms.

The SCM is then run for each BC representative firm in each industry, with the firms in BC as the treatment group and using all representative firms outside BC as the donor pool.[20] Depending on the particular industry, we obtain a minimum of five donors (utilities) and up to 41 donors (accommodations & food services and retail trade (cars, furniture, groceries)). This methodology results in multiple employment effect estimates (one estimate per BC representative firm). To obtain one estimate, we take the average of the estimates weighted by the number of employees within each estimate's associated representative firm. We explain this estimation procedure step by step in Appendix A.

Placebo tests are then carried out on each representative firm to test for the "significance."[21] To do this, we re-run the SCM, but where the treatment group is replaced by a representative firm from the donor pool, with the placebo donor pool being all representative firms in other provinces. If the estimated employment effect lies outside the range of the 90% of the estimates obtained by the placebos, then we say that the estimate is "significant at the 10% level."[22] Specifically, this "pseudo confidence interval" is constructed by taking the set of placebo estimates produced for each industry, dropping any outliers, dropping the top and bottom 5% of these estimates, and then taking the maximum and minimum of the left-over set.[23] Since each industry-province pair contains a different number of representative firms, the number of placebos available for each industry's estimation varies. In some cases, this

[20] To improve the fit of the pre-treatment trends between the treated and synthetic control groups, additional predictor variables are often included in the estimation. We included the average provincial retail gasoline and fuel price as well as provincial governmental expenditure. The gasoline and fuel price data come from Statistics Canada's CANSIM Table 326-0009, while government expenditure data comes from CANSIM Table 385-0001 and 385-0041.

[21] Here and in the following, we use the conventional terms of the "significance" and "confidence interval," although statistically the SCM produces pseudo-confidence intervals only. See Abadie, Diamond and Hainmueller (2010) regarding the interpretation of the placebo test inference methods.

[22] We call this 90% placebo range, a pseudo-confidence interval (pseudo-CI). For a discussion of the inference techniques used in this paper, see Abadie, Diamond and Hainmueller (2010).

[23] We define outliers by calculating the kernel density for each distribution of placebos and then storing the calculated density value for each placebo. We then drop any placebo that is assigned a density of less than 0.35.

leads to the significance level being higher than 10%.

While our SCM addresses the issue of non-parallel pre-treatment trends between treated and control groups, identifying the treatment effect also requires that there are no spillovers from the treated group to the control group, i.e., general equilibrium effects.[24] Although this is not testable econometrically, Carbone et al. (2020) show that the potential spillover effects do not bias the employment effect of BC carbon tax identified by a difference-in-differences estimation.[25] This suggests that the employment effects we identify using our SCM approach would not likely be contaminated by the general equilibrium effects either.

Another potential issue for the identification is that employment growth before and after the policy implementation is notably different across provinces, shown in Table 3. For example, BC's employment growth prior to the carbon tax is similar to that of Québec; however, in the post-tax period, it drops to about one-fifth of its employment growth in the previous period, whereas Québec's employment growth drops to about one half of what it was in the previous period.

Unless this difference is entirely due to the carbon tax, this change proves problematic for running the SCM using employment in levels to isolate the effect of the tax on employment at the industry level. This is because the SCM implicitly assumes that the employment growth in each industry due to macroeconomic conditions stays the same. Thus, if Québec is given a large weight in the SC, the employment effect estimate will be biased by the higher aggregate employment growth rate in Québec, assuming that this higher rate of growth is not solely due to the carbon tax.

To address this concern, we control for labour force changes due to migration and natural population growth over the time period from 2001 to 2013 by using the log of employment per capita as our dependent variable rather than the log of employment in levels. Furthermore, we take the opinion that this change in the aggregate employment growth rate is primarily

[24] This assumption is referred to as the stable unit treatment value assumption (SUTVA).

[25] They use a computable general equilibrium (CGE) model to generate two "pseudo-data," the one with the general equilibrium responses and the other without them. Then they estimated the employment effect using these two datasets by the difference-in-differences model. They show that regardless of the data choice, the results are almost identical in their magnitudes and significance.

Table 3: Employment growth rate (%)

Province	2001-2007	2007-2013
Newfoundland and Labrador	7	12
Prince Edward Island	7	8
Nova Scotia	8	1
New Brunswick	8	-1
Québec	12	6
Ontario	11	4
Manitoba	8	6
Saskatchewan	10	12
Alberta	22	12
British Columbia	15	3

Notes: This table presents employment growth rate (%) in the period before and after the implementation of the carbon tax in BC.
Source: CANSIM Table 282-0008

due to changes in migration patterns throughout Canada as well as the Great Recession, and not due to the carbon tax.[26]

While our representative firm approach allows us to better utilize the firm-level data in employing the SCM, we also directly use the firm-level data to estimate the employment effect with a traditional DID approach. Following Bohn, Lofstrom and Raphael (2014) and Jones and Goodkind (2019), we augment the DID approach with the weights generated by our representative firm SCM approach. This allows us to construct the counterfactual more systematically by only using firms that are included in representative firms with the SCM weight. Each firm is given a weight such that the cumulative weight within the representative firm matches the SCM weight for this representative firm. With these weights, we estimate

[26] To substantiate this claim, consider the employment growth in the two periods shown in Table 3 for Prince Edward Island and Nova Scotia. Prior to the carbon tax being implemented, they had similar employment growth rates; however, in the following period in which the Great Recession took place, their employment growth rate was substantially different. Hence, since a major policy change such as a carbon tax did not occur across either of these provinces during this time, this comparison suggests that this change in employment growth across provinces was largely influenced by the Great Recession. Further, Metcalf (2016) finds that the BC carbon tax did not have an economic impact at the aggregate level, corroborating our view that the large change in the employment growth rate in the period after 2008 is not likely due to the carbon tax. This assumption is contrary to the methods used in the previous literature, which could explain the large unemployment effect found in Yip (2018).

the following equation:

$$\ln L_{ipt} = \beta(\text{BC}_p \times \text{Post}_t) + X_{pt} + \phi_i + \gamma_{jt} + \epsilon_{ipt} \tag{4.1}$$

where $\ln L_{it}$ is the log of employment for firm i in province p at time t. BC_p is a dummy variable for BC while Post_t is a dummy variable for the post-policy period (2008-2013). X_{it} is a vector of control variables at province by year level, such as population growth, oil price, and etc. ϕ_i are firm fixed effects. γ_{jt} are (3-digit NAICS) sub-industry by time fixed effects. Finally, ϵ_{it} is an error term that captures idiosyncratic changes in employment. We estimate Eq.(4.1) for each industry at 2-digit NAICS level.

II. Monte Carlo Simulations

We run Monte Carlo (MC) simulations to demonstrate the characteristics of our representative firm approach to the synthetic control estimator. The primary goal of these simulations is to illustrate the fact that the synthetic control estimator in our new approach is consistent. Hence, we use these MC simulations to show that the estimator in this technique converges to the true value of $\alpha_{j,2013,\text{BC}}$ as the number of firms that are aggregated into the representative firm is increased. Similarly, we show that the probability of committing type 2 error decreases as the number of firms that are aggregated into the representative firm is increased. To show this, we run the following four sets of MC simulations.

The simulations are set up using a simple fake dataset with 100 provinces, each containing one industry, which contains n firms. The employment of each firm is randomly generated from a normal distribution. For simplicity, the standard deviation of this normal distribution is the same across all firms and provinces. Four years are included in the simulation, two before the imposed treatment and two after. In all simulations, the MSPE is minimized over the two years before the treatment. In each simulation, we run the SCM with BC as the treatment state but also with all other 99 control states as placebo tests. We then rank the α_{jpT}'s (smallest $\alpha_{jpT} = 1$, highest $\alpha_{jpT} = 100$) that are produced by these 99 placebo units

Table 4: Parameters of the four Monte Carlo simulations

Simulation	Mean of Control $E(yc)$	Mean($y_{\text{BC, Post}}$)	SD(y)	# of Firms per province
1	20	20	2	1
2	20	18	2	1
3	20	18	2	5
4	20	18	2	100

Note: Four Monte Carlo simulations were run to demonstrate the characteristics of the synthetic control estimator in our analysis of the homogeneous treatment effect using firm-level data. Specifically, the first simulation is designed to test whether the estimator rejects the null hypothesis consistent with basic probability theory, while the second, third, and fourth simulations illustrate the fact that the synthetic control estimator is consistent as the number of firms increases. This table summarizes the parameters of each simulation.

and 1 the one treatment unit, where T is the final year of the simulation. The alternate hypothesis is that the BC $\alpha_{j,\text{BC},T}$ is different than zero, H_A: $\alpha_{j,\text{BC},T} \neq 0$. The null hypothesis is that the BC $\alpha_{j,\text{BC},T}$ is equal to zero, H_0: $\alpha_{j,\text{BC},T} = 0$. If $\alpha_{j,\text{BC},T}$ is ranked 1st, 2nd, 99th, or 100th, then at a significance level of 4% , the null hypothesis is rejected, and we conclude that the $\alpha_{j,\text{BC},T}$ is significantly different from zero.[27]

In the first simulation, the mean of this normal distribution remains the same across all years, and the number of firms in each province is one, $n_i = 1$ for all j. Thus, on average, employment in the treatment province, BC, should not be significantly different from employment in the synthetic control province. Additionally, in simulation 1, the normal distributions from which BC and the control's employment are drawn are equal. Thus, we expect that the null hypothesis gets rejected in only 4% of the simulations. This simulation is repeated 1000 times. Table 4 summarizes the defining parameters of each simulation.

The second, third, and fourth simulations differ from simulation 1 in that the mean of the normal distribution from which BC's employment is drawn changes in 2008 (i.e., when the carbon tax is introduced). In these simulations, it drops by one standard deviation, which in this case is 2. In the second simulation $n_i = 1$ for all j, in the third simulation $n_i = 5$ for all j, and in the fourth simulation $n_i = 100$ for all j. Indeed, simulation 1 leads to the null

[27]A significance level of 4% is used as since we only have 100 units, it is not possible to determine the 2.5th and 97.5th percentiles, which is required to use a significance level of 5%. Using 1000 control units was attempted so that we could use the standard 5% significance level; however, these simulations demanded large computational power and were estimated to take approximately three months to complete.

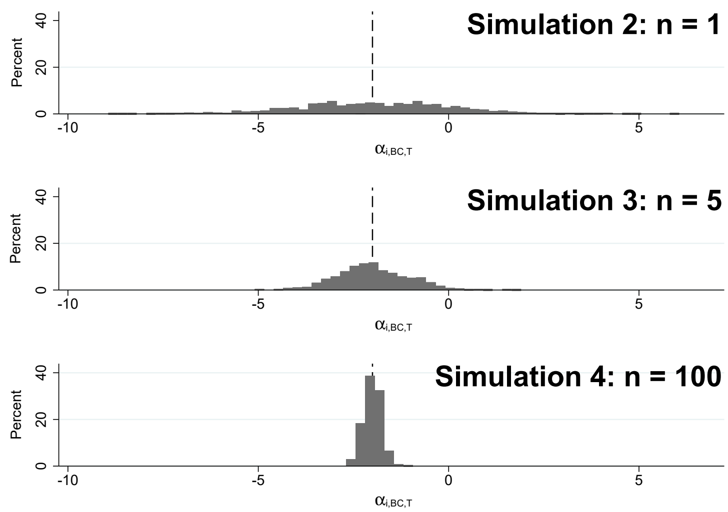

Figure 1: Distribution of treatment $\alpha_{j,\mathrm{BC},t}$'s

Note: This figure demonstrates the convergence of the estimator to the true treatment effect as the number of firms used to calculate the representative firm increases. The top panel presents a histogram of the results of simulation 2, in which there is one firm per province; the middle panel shows a histogram of the results of simulation 3, where there are five firms per province; and the bottom panel gives a histogram of the results of simulation 4, in which there are 100 firms per province. The true treatment parameter is -2, and from this figure, it is clear that, as the number of firms included in the representative firm increases, $\alpha_{jT,\mathrm{BC}}$ converges to the true value.
Source: Author's calculation.

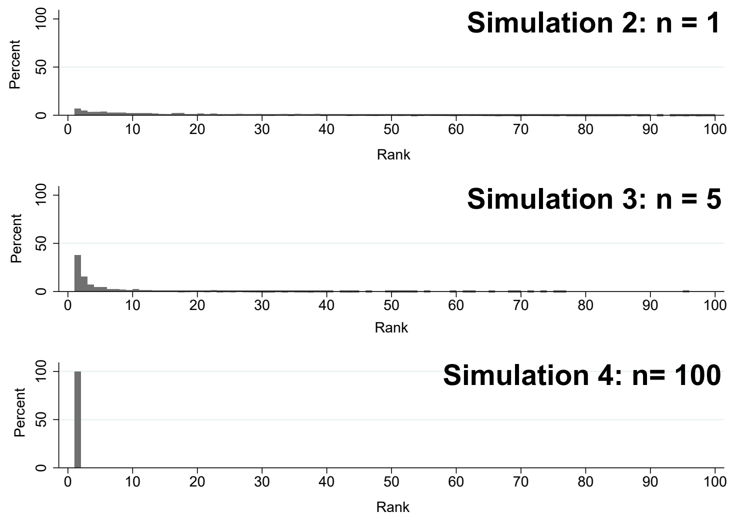

Figure 2: Distribution of the ranking of $\alpha_{i,T,\mathrm{BC}}$'s

Note: This figure shows that as the number of firms used to calculate the representative firm increases, the probability of committing type 2 error decreases. The top panel presents a histogram of the results of simulation 2, in which there is one firm per province; the middle panel shows a histogram of the results of simulation 3, where there are five firms per province; and the bottom panel gives a histogram of the results of simulation 4, in which there are 100 firms per province. Since the true treatment parameter in these simulations is -2, $\alpha_{jT,\mathrm{BC}}$ should be ranked 1st. Notice how, as the number of firms per province increases, the probability that $\alpha_{jT,\mathrm{BC}}$ will be correctly ranked first increases. In other words, as the number of firms per province increases, the probability of committing type 2 error decreases.
Source: Author's calculation.

hypothesis getting rejected in 3.2% of the simulations – close to the expected value of 4%.

In the simulations 2-4 the true treatment effect is a reduction of two units, $Y^I_{j,BC,T} - Y^N_{j,BC,T} = -2$. Fig.1 presents the distribution of treatment $\alpha_{j,\mathrm{BC},t}$'s for simulations 2–4. As expected, it shows, that as the number of firms per province increases, the $\alpha_{j,\mathrm{BC},T}$ estimate converges to the true value of -2.

Similarly, Fig.2 presents the distribution of the ranking of $\alpha_{iT,\mathrm{BC}}$'s for simulations 2–4 and demonstrates that as the number of firms per province increases, the probability that the $\alpha_{jT,\mathrm{BC}}$ will be found to be significant increases. Hence, we see that as the number of firms per province increases, the probability of committing type 2 error decreases.

III. Checking the pre-treatment trends

Before we present the results using our representative firm approach, we explore the validity of the parallel trends assumption by examining the pre-treatment trends of employment for industries in BC (treated group), ROC (control group), and synthetic BC (SC). Contrary to Yamazaki (2017) and Yip (2018), we need the parallel trends assumption at the industry level because we estimate the employment effect industry by industry, while Yamazaki (2017) and Yip (2018) need the assumption at the province level because they estimate the average employment effect for the province. To do this, we develop a way to succinctly display the support for or lack of the parallel pre-treatment trends.

To start, for each industry we calculate one representative firm for each group, BC and ROC. To test whether the pre-treatment trends are parallel between BC and ROC, we drop all data points from 2008 and onwards, and fit the following equation to the data:

$$\ln \tilde{L}_{ipt} = \mathrm{BC}_p + \beta(\mathrm{BC}_p \times \mathrm{Year}_t) + \mathrm{ROC}_p + \alpha(\mathrm{ROC}_p \times \mathrm{Year}_t) + \epsilon_{ipt} \tag{4.2}$$

where $\tilde{L}_{ipt}$ is the employment per capita, $L_{ipt}/\mathrm{population}_{pt}$, letting $\ln \tilde{L}_{ipt}$ be the log of employment per capita for firm i in province p at time t. BC_p is a dummy variable for BC and ROC_p is a dummy variable for the ROC. Year_t is the linear time trend variable. ϵ_{ipt} is the idiosyncratic error term. Finally, to test whether the trends in BC and ROC are parallel, we test the null hypothesis that the difference between β and α is zero. Rejecting the null hypothesis implies that the trends are not parallel between BC and ROC. We then apply the same method to check the pre-treatment trends between BC and SC, substituting ROC with the SC data generated from the methodology described in Section 4.I.[28]

Table 5 displays the median p-value for the results of these tests across each representative firm for each industry. We see that for 12 out of the 24 industries, the pre-treatment

[28]For each industry this test is carried out five times, as we divide firms in each province into quintiles based on size and then carry out the SCM on each size class. Hence, Table 5 presents the median p-value of these tests).

Table 5: Median p-value from parallel pre-treatment trends test for each industry

NAICS	ROC	SC
Agriculture, forestry, fishing and hunting	0.25	0.98
Mining, quarrying, and oil and gas extraction	0.03**	0.87
Utilities	0.51	0.71
Construction	0.00***	0.91
Manufacturing (food + clothing)	0.01***	0.95
Manufacturing (wood + plastic)	0.03**	0.98
Manufacturing (metal)	0.04**	0.98
Wholesale trade	0.00***	0.94
Retail trade (cars, furniture, groceries)	0.06*	0.97
Retail trade (online, department stores, hobby)	0.10	0.97
Transportation and warehousing (air, rail, truck, pipeline)	0.05*	0.98
Transportation and warehousing (postal, warehousing)	0.70	0.99
Information and cultural industries	0.23	0.97
Finance and insurance	0.71	0.96
Real estate and rental and leasing	0.36	0.99
Professional, scientific and technical services	0.18	0.95
Management of companies and enterprises	0.49	0.93
Administrative and support, waste services	0.10*	0.96
Educational services	0.01***	0.96
Healthcare and social assistance	0.01**	0.92
Arts, entertainment and recreation	0.02**	0.98
Accommodation and food services	0.26	0.96
Other services (except public administration)	0.28	0.96
Public administration	0.29	0.99

Notes: This table presents the main result of our parallel pre-treatment trends test. The median p-value for each industry presented in this table is calculated from the p-values generated for the parallel pre-treatment trends test for each representative firm within each industry, which are presented in Table C.1 in the Appendix. ROC stands for rest of Canada and SC stands for synthetic-BC.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

trends between BC and ROC control groups are not parallel. In comparison, when the SC is used as the control group, all industries show substantially higher p-values, failing to reject the null hypothesis. To supplement these, we also show Figs.3 and 4 to illustrate the correspondence between the estimation and the visualization of the trends. Fig.3 shows the trend of employment per capita in one representative firm for BC, ROC, and SC for the manufacturing (wood + plastic) sector. Table C.1 in the Appendix gives the p-values for all five tests in each industry (i.e., it is from these p-values that the median p-value presented

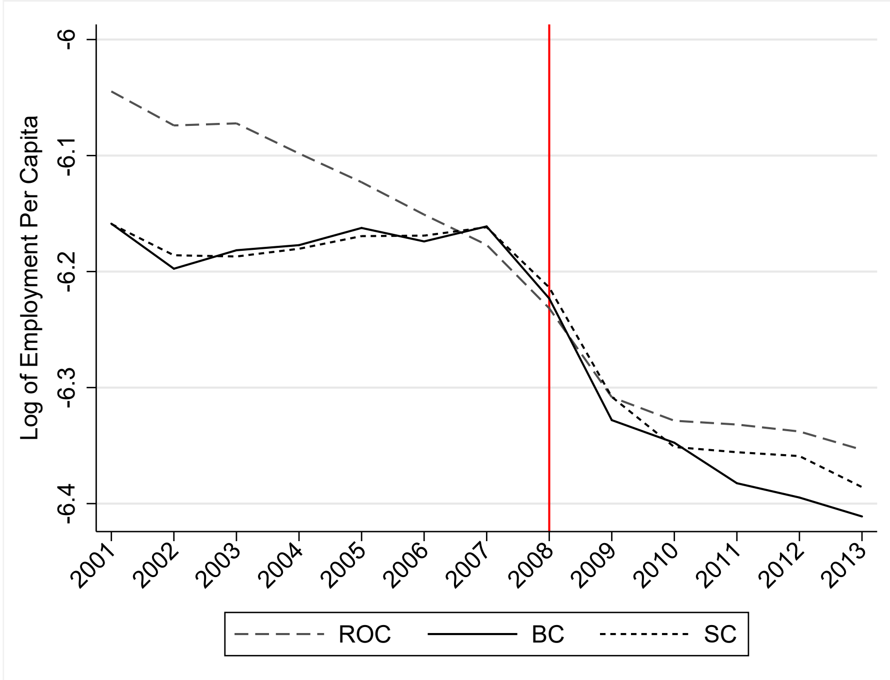

Figure 3: Employment per capita trends in manufacturing (wood and plastic) for BC, ROC, and SC

Note: This figure presents the evolution of one representative firm in the manufacturing (wood + plastic) industry log employment per capita in BC compared to the log employment per capita of the same quintile in this industry in the rest of Canada and to the SC. Notice that the pre-treatment trends, the trends prior to the vertical dashed line, are considerably different between BC and ROC. Hence, the parallel trend assumption is violated if the rest of Canada is used as the control for this industry. However, when the SC is used as the control, it seems to be well satisfied. The p-value which corresponds to the test between BC and ROC for this figure is 0.000024 and between BC and the SC it is 0.94.
Source: Author's calculation.

in Table 5 is calculated), and from this table, we see that the corresponding p-value for ROC vs. BC is 0.000024 and the p-value for the SC vs. BC is 0.94. Clearly, the pre-treatment trends for ROC and BC are significantly different; however, when the SC is used as the control group, the trends are far from being significantly different.

Fig 4, on the other hand, illustrates a case where neither the pre-treatment trend of ROC nor SC is parallel to that of BC. In this case, the p-value for ROC vs. BC is 0.014 and for the SC vs. BC is 0.84 for this particular representative firm. Clearly, from these two figures, we can see that p-values in the 0.8-0.9 range do not necessarily indicate a good match between the SC and BC. Fortunately, Table 5 shows that the large majority of industries have median p-values that are over 0.95.

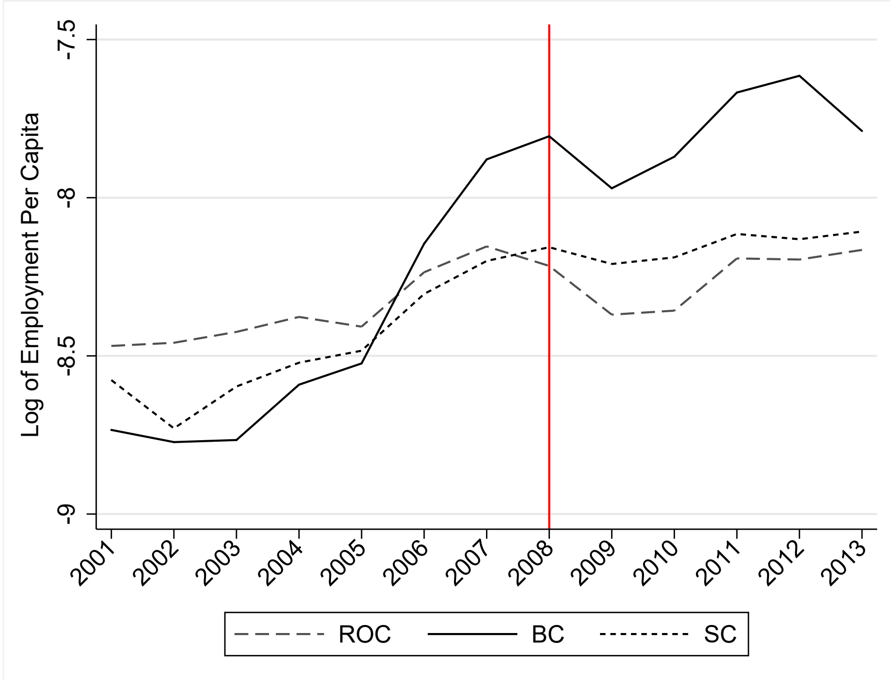

Figure 4: Employment per capita trends in mining, quarrying, and oil and gas extraction for BC, ROC, and SC

Note: This figure presents the evolution of one representative firm in the mining, quarrying, and oil and gas extraction industry log employment per capita in BC compared to the log employment per capita of the same quintile in this industry in the rest of Canada and to the SC. Notice that the pre-treatment trends, the trends prior to the vertical dashed line, are considerably different between BC and ROC and BC and the SC. Hence, the parallel trend assumption is violated if the rest of Canada is used as the control for this industry and is only slightly better, but likely still violated when the SC is used as the control. The p-value which corresponds to the test between BC and ROC for this figure is 0.014 and for BC and the SC it is 0.83. Source: Author's calculation.

5. Results

The results are presented in the following subsections.[29] Section 5.I presents the heterogeneous employment effects across industries. In section 5.II, we evaluate a hypothesis that the employment impacts would differ between small and large firms, while section 5.III presents the results for sub-industries within selected industries, such as manufacturing. Then, section 5.IV explores the relationships between the estimated employment effects and emission/trade intensity of industries.

[29]We also conducted a calibration exercise to illustrate that the employment effects could differ substantially across industries. The results are presented in Appendix B. We present results for two distinct industries, one clean industry (food and clothing manufacturing) and one dirty industry (metal and electrical manufacturing).

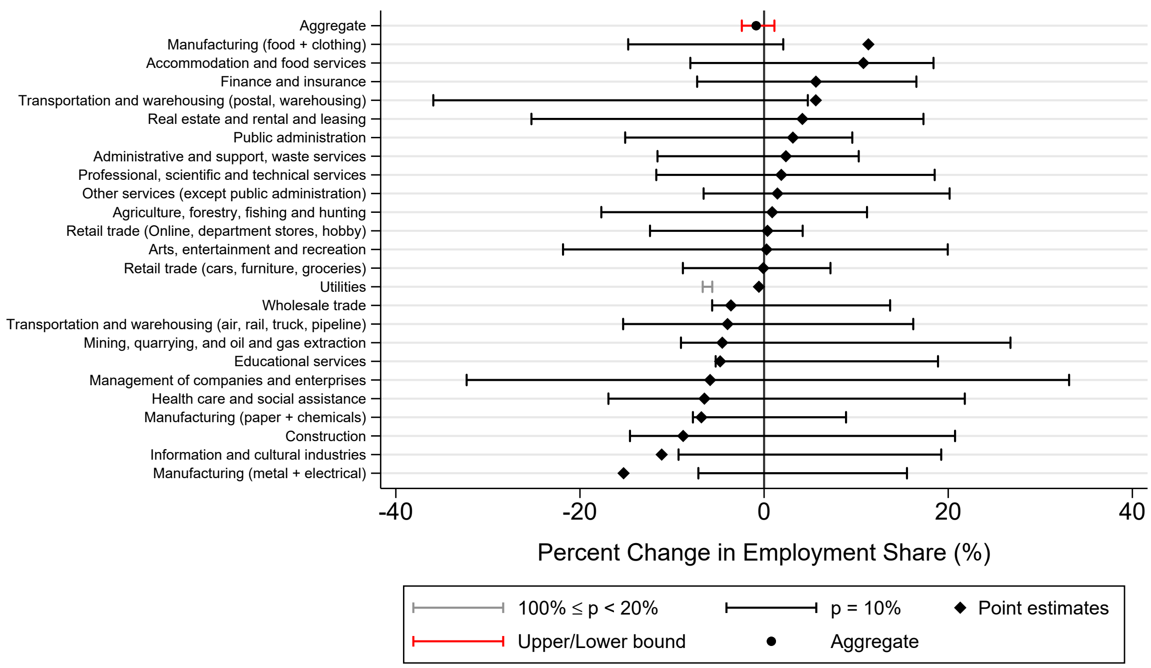

Figure 5: Percentage change in employment per capita, all firms

Note: This figure shows the estimated percent change in employment per capita for all industries. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. In order to apply the SCM to this firm-level dataset, firms are aggregated into "representative firms" which are then used as donor controls in the SCM. The results in this figure were produced using all firms in our cleaned dataset. The range presented (by dark-grey (10%) or light-grey (100%∼20%) line) for each industry is the pseudo confidence interval (pseudo-CI). In fact, the 10% pseudo-CI is used for all industries except utilities industry. If the estimate lies outside this pseudo-CI, then the estimate is significant at the corresponding significance level. If the estimate lies within the pseudo-CI, then the estimate is insignificant at the corresponding significance level. We also add the aggregate effect and its lower and upper bounds.
Source: Author's calculation.

I. Heterogeneous Employment Effects Across Industries

Representative firm approach

Fig.5 presents the results of the industry-level analysis using our representative firm SCM approach.[30] The figure displays $\alpha_{j,\mathrm{BC},2013}$, the treatment effect estimates for each industry j plotted along with a pseudo-confidence interval (CI). Fig.5 suggests that the carbon tax did have a statistically significant effect on four industries.[31] The manufacturing (metal)

[30]The corresponding table (Table C.2) is presented in Appendix C.

[31]The utility industry also shows a statistically significant employment effect, i.e., the point estimate is outside of the pseudo-CI. However, the significance level is much greater than 10% due to the insufficient number of placebos. Thus, we do not interpret the estimates to be statistically significant for the utility industry.

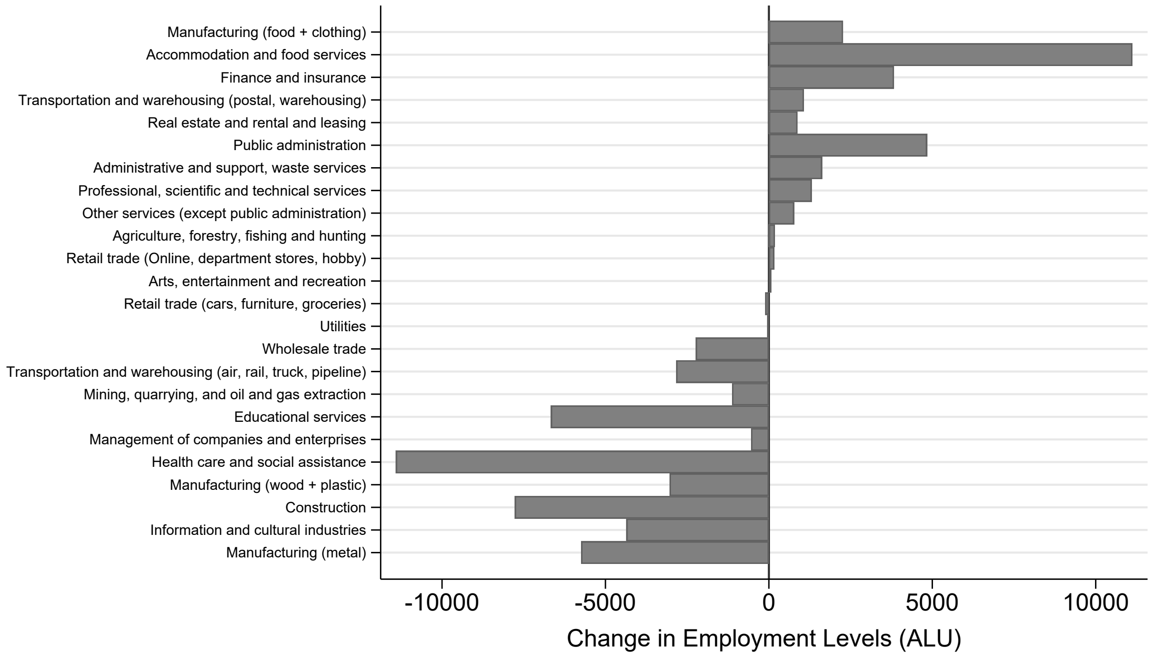

Figure 6: Change in level of employment, all firms

Note: Change in employment for all industries. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. In order to apply the SCM to this firm-level dataset, firms are aggregated into "representative firms" which are then used as donor controls in the SCM. The results in this figure were produced using all firms in our cleaned dataset.
Source: Author's calculation.

industry saw the carbon tax result in a decrease of 15% in jobs per capita, equivalent to a loss of 5,700 jobs. In contrast, the information and cultural industries saw a decrease of 11% in jobs per capita, equivalent to a loss of 4,400 jobs. In contrast, the carbon tax policy increased employment per capita in the manufacturing (food + clothing) industry by 11.5%, equivalent to a gain of 2,300 jobs, and increased employment per capita in the transportation and warehousing (postal + warehousing) industry by 5.5%, equivalent to a gain of 1,100 jobs. The results for the rest of the industries are statistically insignificant at the 10% level.

Fig.6 shows the above results converted into employment change in units of persons employed. The point estimate with the largest magnitude is a decrease in employment of 11,400 jobs in the healthcare and social services industry. This is followed closely by the construction industry, which saw a decrease in employment of 7,800 jobs. Large increases in employment in the accommodations and food services sector and public administration are offsetting these decreases. It should be noted that for all industries that see large changes in employment measured in jobs, except for manufacturing (metal), the corresponding estimate in percent change in employment per capita is insignificant. Hence, most of these large results in levels are also insignificant.

Despite the significance of the point estimates, this finding further supports the "job-shifting hypothesis" in response to the revenue-neutral carbon tax. Similar to Yamazaki (2017), jobs mainly shift away from emission-intensive industries to clean service industries.

By taking the sum of the employment effect estimates presented in Fig.6, we can obtain an aggregate employment estimate. Further, by converting the pseudo-CI's presented in Fig.5 into employment in levels, we can obtain a 90% pseudo-CI for this aggregate estimate.[32] The result is a decrease of aggregate employment of 0.86%, with an upper bound of a 1.12% increase and a lower bound of a 2.42% decrease in employment, making the estimate statistically insignificant at the 10% significance level. This -0.86% estimate is equivalent to a loss of 17,000 jobs.

Fixed effects model with SCM-weights

In addition to our SCM approach, we also estimate the industry-specific employment effects using the fixed effects model with SCM-weights. The results are presented in Fig.7.[33] One of the advantages of this approach is that the precision of estimates improves relative to our SCM approach. Despite the order of the employment effects across industries, this finding also suggests that jobs shift across industries. The employment effects range from -9% to 11%. Using employment share for each industry, the weighted average employment effect is -0.08%.[34] This small employment effect is consistent with the results from our SCM approach.

[32] We exclude the utilities sector in this calculation as it does not have a 90% pseudo-CI. Since the point estimate for the utilities industry is so small, this has a negligible effect on the aggregate estimate.

[33] The corresponding table (Table C.3) is presented in Appendix C.

[34] Yamazaki (2017) also estimated a similar estimation equation as Eq.(4.1) and found that the policy increased employment by 0.95% but not statistically significant. Although the signs are different between Yamazaki (2017) and ours, these results are not statistically different from each other as our weighted average employment effect lies within the confidence interval of the result in Yamazaki (2017).

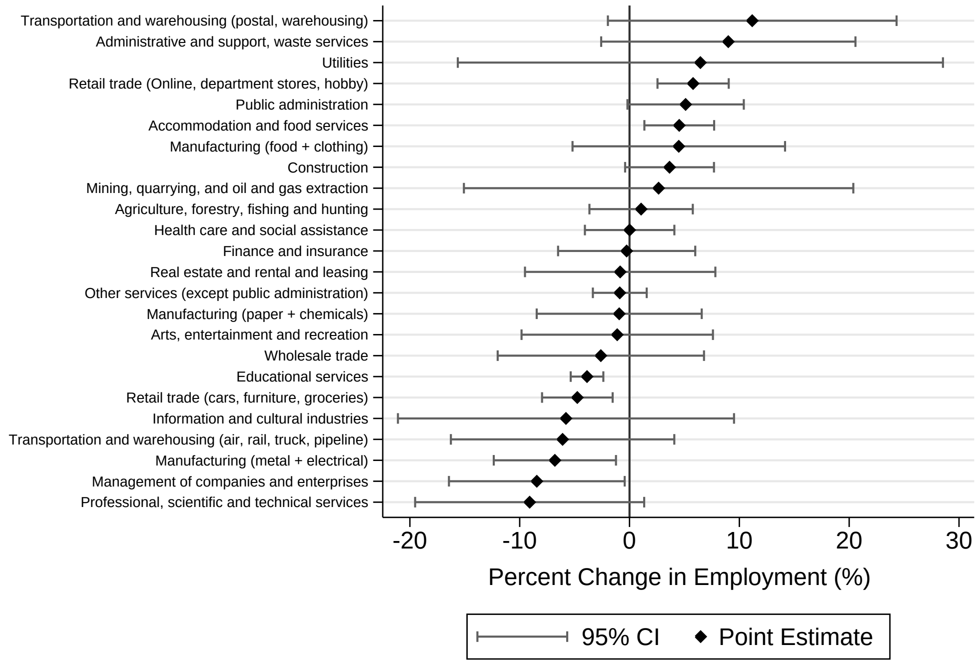

Figure 7: Percentage change in employment by SCM-weighted FE model

Note: This figure plots the employment effects and the corresponding 95% confidence interval for all 2-digit NAICS industries. These employments are estimated using the SCM-weighted fixed effects methodology.
Source: Author's calculation.

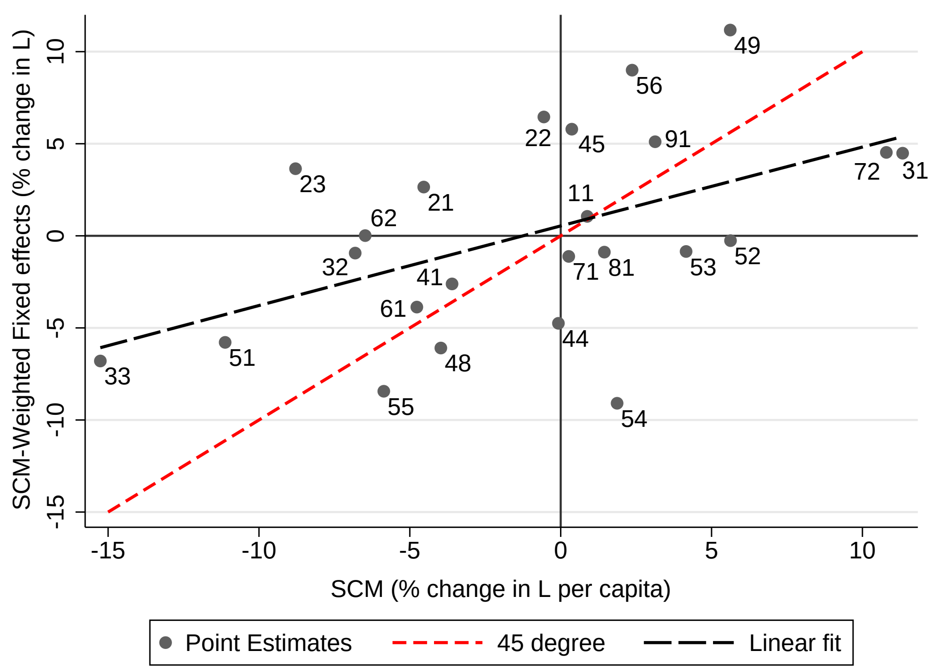

Figure 8: Comparison of estimates between our SCM approach and SCM-weighted FE model

Note: This figure plots point estimates from our SCM approach and SCM-weighted fixed effect model. The red dash line is a 45 degree line, i.e., if point estimates are on this line, estimates perfectly matches. Black dash line is a linear-fitted line.
Source: Author's calculation.

To visually compare the employment effects between our SCM approach and fixed effect model, we plot one against another, presented in Fig.8. If the results perfectly match between our two approaches, the point estimates would be on the 45-degree dash line. Several estimates are closely on the 45-degree line. Although the match is not perfect, we do see a strong positive correlation between these approaches.

II. Small vs. Large Firms

Fig.9 and 10 present the employment effects on the smallest 33$^{\text{rd}}$ percentile and largest 33$^{\text{rd}}$ percentile of firms, respectively.[35] A subtle, but clear difference is seen between the two figures, and is highlighted by the fact that the aggregate estimate generated by the bottom 33$^{\text{rd}}$ percentile of firms is above zero while the aggregate estimate generated by the top 33$^{\text{rd}}$ percentile is negative. This implies that the carbon tax appears to affect employment in the smallest 33$^{\text{rd}}$ percentile of firms more positively than employment in the largest 33$^{\text{rd}}$ percentile of firms.

In particular, employment in small businesses in the service industries such as healthcare and social assistance and retail trade (online, department stores, hobby) are significantly positively impacted by the policy. Small businesses in the healthcare and social assistance industry see a significant 24% increase in employment per capita, while retail and trade (online, department stores, hobby) industries see a significant 11% increase in employment per capita due to the carbon tax. Additionally, employment per capita among small firms in the manufacturing (food + clothing) industry increases significantly, by 27%.

On the other hand, employment per capita in the transportation and warehousing (air, rail, truck, pipeline) industry falls by 33% due to the policy. Fig.11 illustrates the difference between the estimates from the bottom 33$^{\text{rd}}$ percentile and top 33$^{\text{rd}}$ percentile of firms. Here we see that the negative result for the manufacturing (metal) industry in our estimations using all firms appears to be driven entirely by job losses in the sector's largest firms. Interestingly, we also see that while employment in small firms is significantly positively impacted

[35] The corresponding tables (Table C.4 and C.5) are presented in Appendix C.

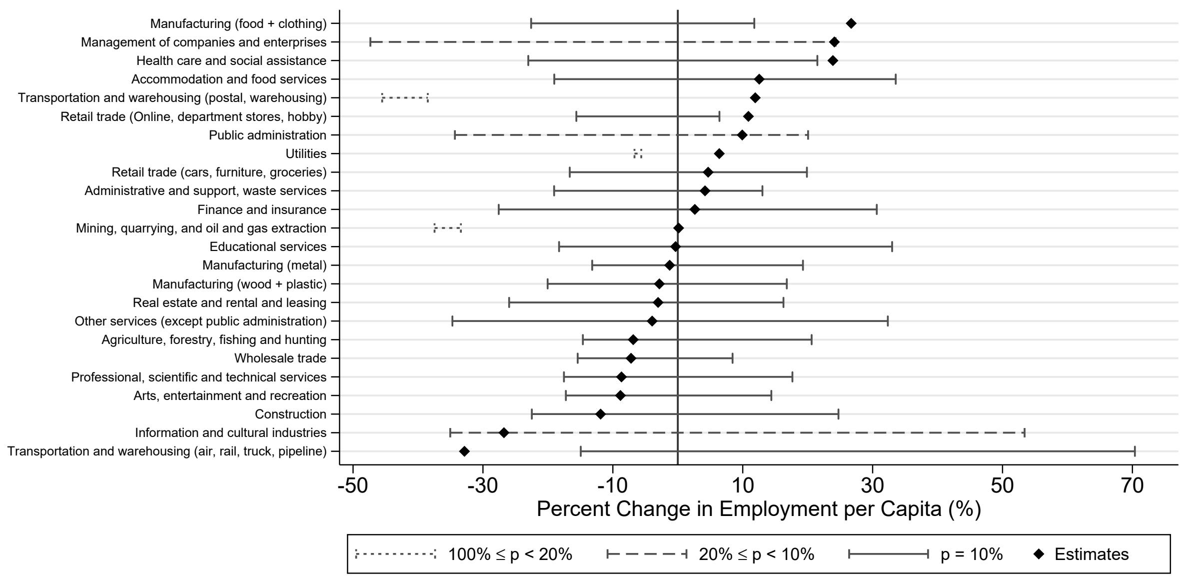

Figure 9: Percentage change in employment per capita, bottom 33rd percentile of firms

Note: This figure shows the estimated percent change in employment per capita for all industries. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. In order to apply the SCM to this firm-level dataset, firms are aggregated into "representative firms" which are then used as donor controls in the SCM. The results in this figure were produced using the smallest 33rd percentile of firms in our cleaned dataset. The range presented (by a solid, dash, or dotted line) for each industry is the pseudo confidence interval (pseudo-CI). If the estimate lies outside this pseudo-CI, then the estimate is significant at the corresponding significance level. If the estimate lies within the pseudo-CI, then the estimate is insignificant at the corresponding significance level.
Source: Author's calculation.

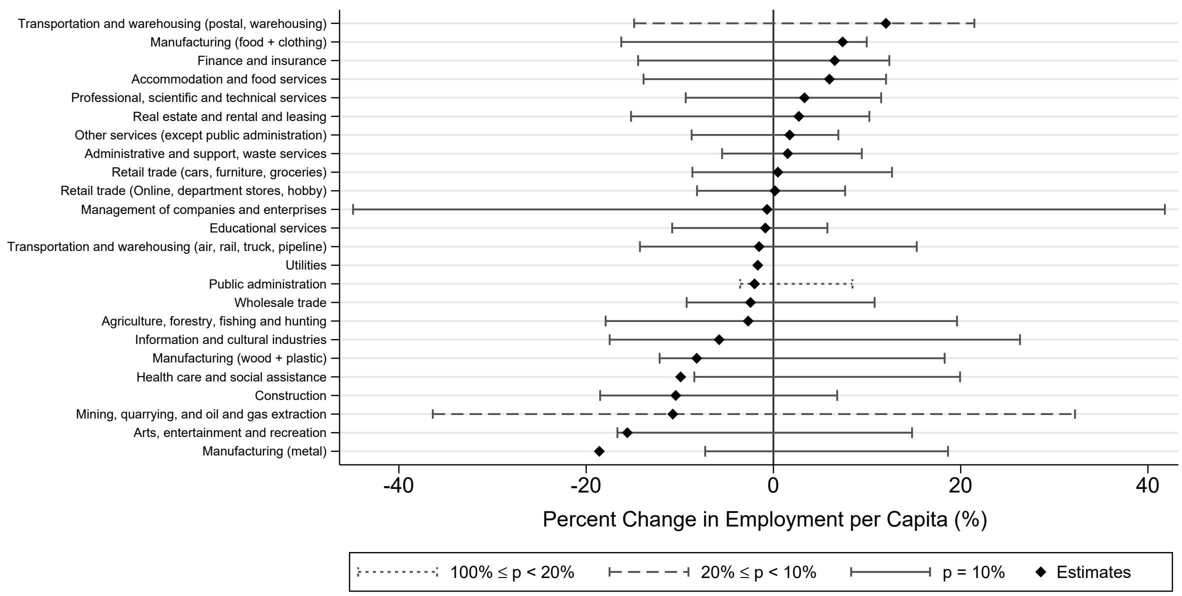

Figure 10: Percentage change in employment per capita, top 33rd percentile of firms

Note: This figure shows the estimated percent change in employment per capita for all industries. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. In order to apply the SCM to this firm-level dataset, firms are aggregated into "representative firms" which are then used as donor controls in the SCM. The results in this figure were produced using the largest 33rd percentile of firms in our cleaned dataset. The range presented (by a solid, dash, or dotted line) for each industry is the pseudo confidence interval (pseudo-CI). If the estimate lies outside this pseudo-CI, then the estimate is significant at the corresponding significance level. If the estimate lies within the pseudo-CI, then the estimate is insignificant at the corresponding significance level.
Source: Author's calculation.

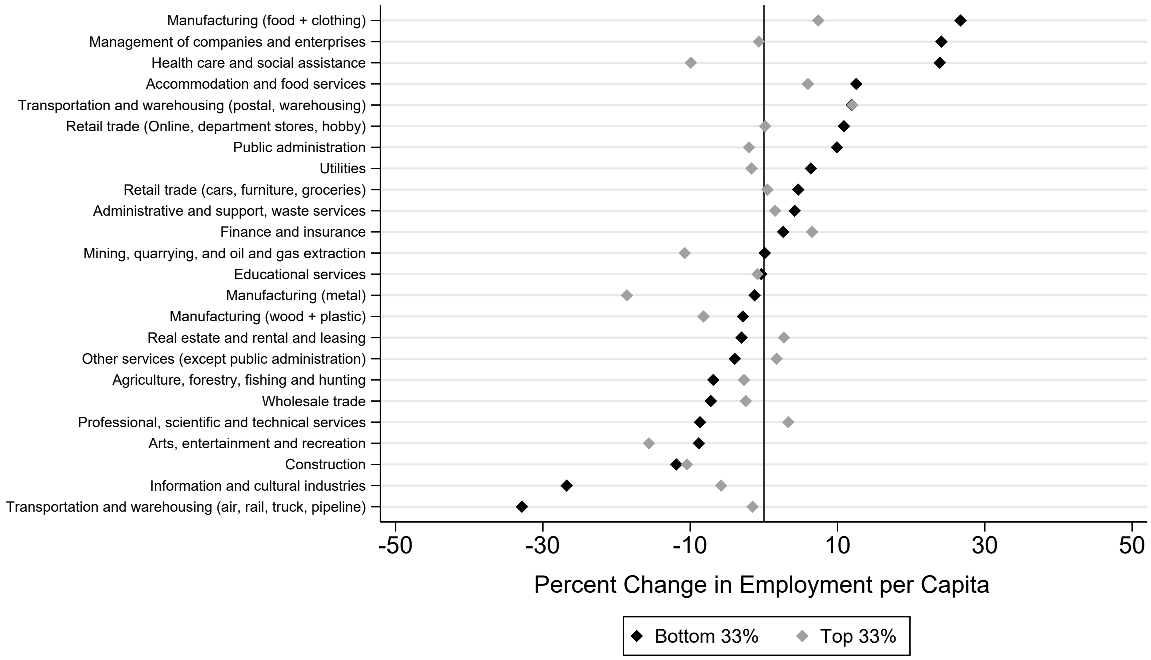

Figure 11: Comparison of results for top and bottom 33rd percentiles

Note: This figure presents the point estimates from figures 9 and 10 in one graph. This is done to illustrate the differential impact the carbon tax had on the largest 33rd percentile of firms compared to its effect on employment in the smallest 33rd percentile of firms.
Source: Author's calculation.

by the policy, employment in large businesses in the healthcare and social assistance industry is significantly negatively impacted.

III. Sub-industries (3-digit NAICS Industries)

Fig.12 and 13 present the percent change in employment per capita estimates for the manufacturing industries and selected other industries at the 3-digit level NAICS, respectively.[36] This gives us insight into which sub-industries are driving the results seen in Fig.5.

In Fig.12, we see that while the point estimate for the primary metal manufacturing industry is not statistically significant, it is large and negative. This suggests that this sub-industry likely drives a large portion of the statistically significant and negative result seen in Fig.5 for the manufacturing (metal) industry. Further, we see that this overall result for the manufacturing (metal) sector is also largely contributed to by the transportation

[36]The corresponding tables (Table C.6 and C.7) are presented in Appendix C.

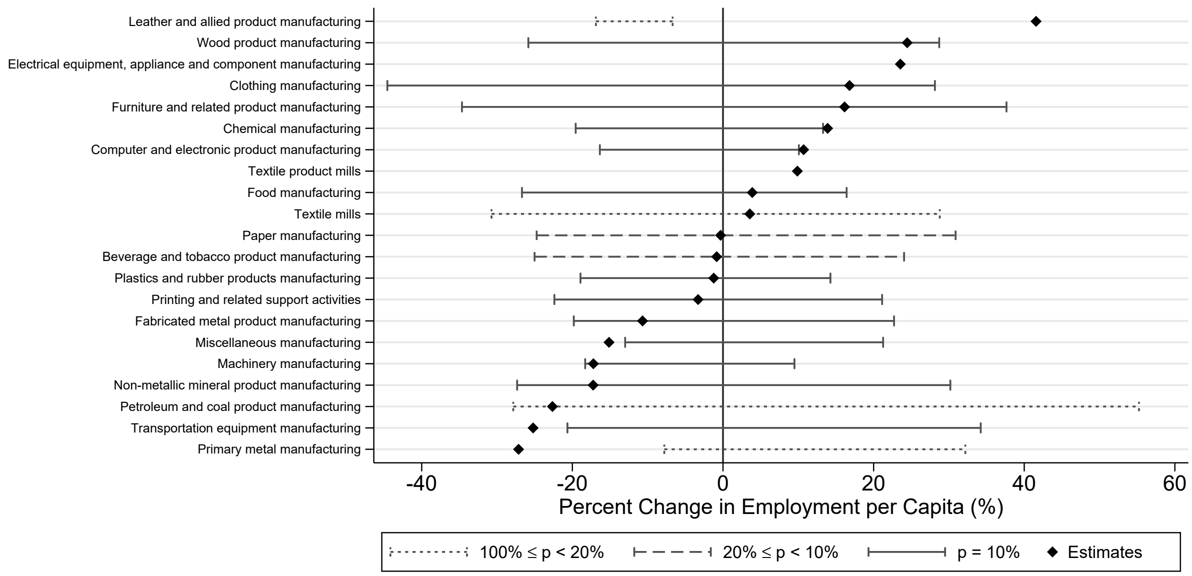

Figure 12: Percentage change in employment per capita for manufacturing sub-industries (3-digit NAICS)

Note: This figure shows the estimated percent change in employment per capita for manufacturing 3-digit subsectors. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. In order to apply the SCM to this firm-level dataset, firms are aggregated into "representative firms" which are then used as donor controls in the SCM. The range presented (by a solid, dash, or dotted line) for each industry is the pseudo confidence interval (pseudo-CI). If the estimate lies outside this pseudo-CI, then the estimate is significant at the corresponding significance level. If the estimate lies within the pseudo-CI, then the estimate is insignificant at the corresponding significance level.
Source: Author's calculation.

equipment manufacturing sub-industries, which see a statistically significant -25% change in employment per capita, and the miscellaneous manufacturing sub-industries, which see a significant -15% change in employment per capita. Together, the changes across these three sub-industries account for a total job loss of 10,800 jobs.

However, we also see that the overall result in the manufacturing (metal) industry is attenuated by statistically significant increases in the computer and electronic product manufacturing sub-industry and a large, but statistically insignificant, increase in employment per capita in the electrical equipment, appliance and component manufacturing sub-industry. We also see that the positive result in the manufacturing (food + clothing) industry is largely driven by positive changes in the leather and allied product manufacturing and clothing manufacturing sub-industries. Interestingly, employment per capita in chemical manufacturing

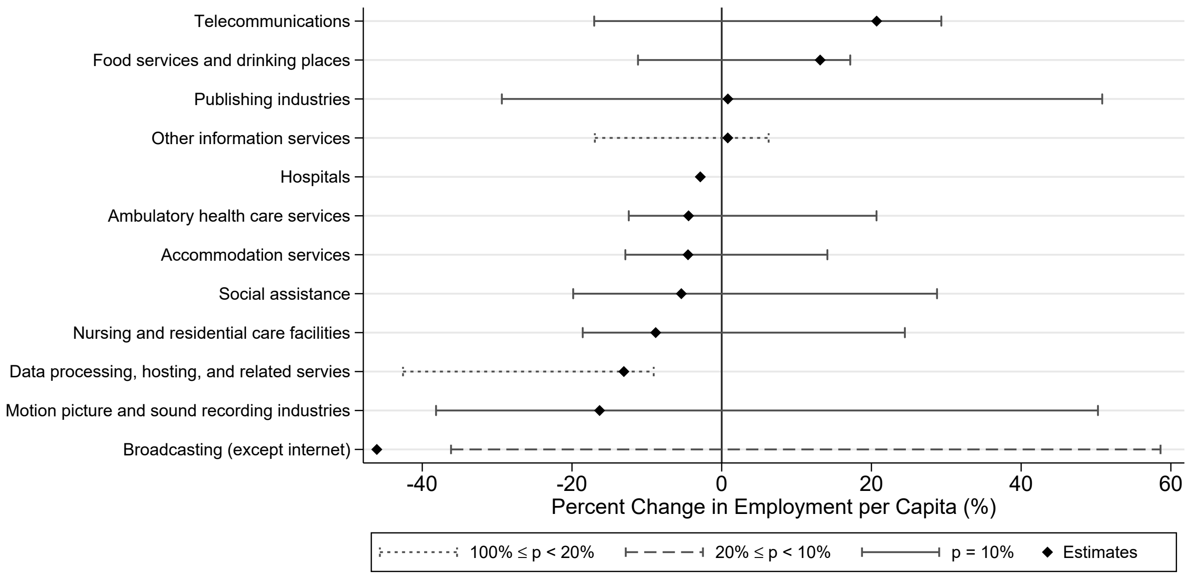

Figure 13: Percentage change in employment per capita for selected other sub-industries (3-digit NAICS)

Note: This figure shows the estimated percent change in employment per capita for 3-digit subsectors of the accommodation and food services sector, the healthcare and social assistance sector, and the information and cultural services sector. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. In order to apply the SCM to this firm-level dataset, firms are aggregated into "representative firms" which are then used as donor controls in the SCM. The range presented (by a solid, dash, or dotted line) for each industry is the pseudo confidence interval (pseudo-CI). If the estimate lies outside this pseudo-CI, then the estimate is significant at the corresponding significance level. If the estimate lies within the pseudo-CI, then the estimate is insignificant at the corresponding significance level. Source: Author's calculation.

increases by a significant 14%.

In Fig.13, we see which sub-industries are driving the results in the healthcare and social assistance, accommodation and food services, and information and cultural services sectors. While no particular sub-industry seems to dominate the result of the healthcare and social assistance sector, in the accommodation and food services industry, we see that, while not statistically significant, the estimate for the food services and drinking places sub-industry, which accounts for a gain of 10,000 jobs, drives the positive point estimate for its parent industry in Fig.5. Fig.13 also illustrates that the large negative result seen in the information and cultural services sector is driven by a large negative employment effect seen in the broadcasting (except internet) sub-industry and the motion picture and sound recording industries.

IV. Correlation Between Employment Effect and GHG and Trade Intensity

Here we explore the question: are the changes in employment per capita related to the emissions and trade intensity of the industry? Fig.14 illustrates the relationship between the industry point estimates of the employment effect from our SCM analysis and the greenhouse gas (GHG) intensity of the industry.[37] As seen in the figure, there is a weak negative relationship between the two variables. The slope of the line is -1.04% per kilotonne (kt) CO_2e/\$1,000,000, with a standard error of 1.97% per kt CO_2e/\$1,000,000, making the relationship insignificant.

However, it must be noted that because our analysis is conducted at the 2-digit NAICS code industry level, many high-emitting industries, such as the primary metal manufacturing industry, are combined with low-emitting industries such as the computer and electronics

[37] GHG intensity is defined here as the GHGs emitted by an industry in a given year divided by the GDP produced by that industry in the same year. Emissions intensity is calculated using GHG data from CANSIM Table 153-0034 and GDP data from CANSIM Table 379-0029. Both of these datasets only include data for Canada. Hence, an assumption implicit in this part of the analysis is that industries in BC have a similar GHG intensity as the Canadian average.

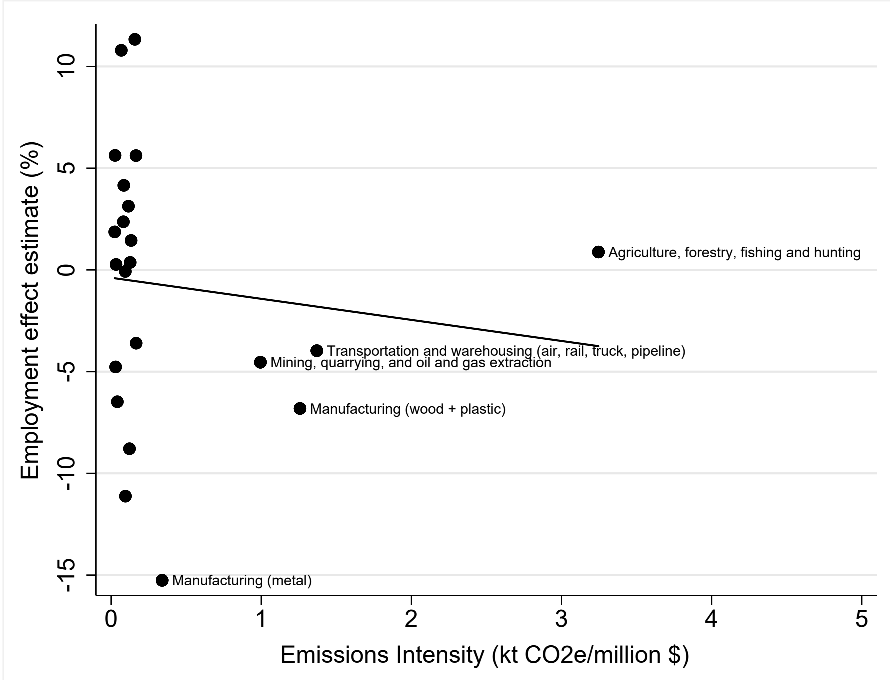

Figure 14: Correlation of employment effects with emission intensity at 2-digit NAICS industries

Note: This plot illustrates how the industry point estimates are correlated with emissions intensity. Due to the high level of aggregation used in this study, many high emitting subindustries (e.g., the primary metal manufacturing industry) are combined with low-emitting subindustries (e.g., computer manufacturing), resulting in small variations in emission intensity amongst the 24 industries. The utilities industry is not included in this graph as the GHG data used here are Canada-wide data, and since BC's electricity is primarily generated from hydroelectricity, while most other provinces rely much more heavily on fossil fuels, the emissions intensity data for the utilities industry was misleading. The fitted line has a slope of -1.04% per kilotonne (kt) CO_2e/\$1,000,000, with a standard error of 1.97% per kt CO_2e/\$1,000,000. Hence, the relationship is negative but insignificant.
Source: Author's calculation.

manufacturing industry, leading to little variation in the GHG intensity amongst the industries and potentially masking a stronger relationship at the 3-digit NAICS code level. Hence, we re-run this correlation on the estimates for the manufacturing industry at the 3-digit NAICS code level and present this regression in Fig.15. In this figure, we clearly see that the negative relationship is stronger and, indeed, the regression results confirm this with a coefficient of -7.71% per kt CO2e/\$1,000,000 with a standard error of 3.73% per kt CO_2e/\$1,000,000. Hence, this correlation is statistically significant at the 5% level.

Fig.16 shows a weak negative correlation between the employment effect estimates and

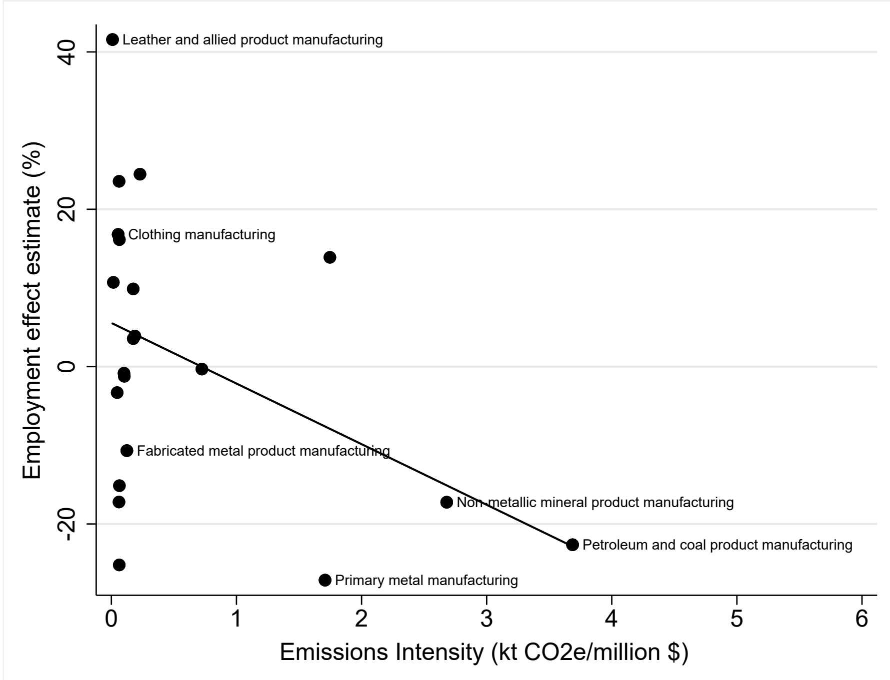

Figure 15: Correlation of employment effects with emission intensity at 3-digit NAICS manufacturing industries

Note: This plot illustrates how the industry point estimates, generated from the 3-digit NAICS industry level analysis presented in Fig.12 and 13, are correlated with emissions intensity. The fitted line has a slope of -7.71% per kilotonne (kt) CO_2e/\$1,000,000 with a standard error of 3.73% per kt CO_2e/\$1,000,000. Hence, the relationship is negative and significant at the 5% level.
Source: Author's calculation.

the trade intensity of the industry.[38] As the policy also lowered the two lowest tax brackets and gave carbon dividends of \$500 per year to the lowest income households, these revenue-recycling features of the policy increased the purchasing power of low income households benefiting locally operating businesses (e.g., grocery stores, clothing stores, and dental clinics), but at the expense of more internationally-exposed manufacturing firms.[39] Therefore, the employment effects are more likely to be negative for highly trade-exposed firms.

[38] Trade intensity is defined as: (Import + Export)/(Total demand + Import) as in Yamazaki (2017).

[39] The hypothesis that additional cash in the hands of low-income households will largely be spent on food, clothing, and healthcare is supported by Jones and Milligan (2019) and Statistics Canada data: https://proof.utoronto.ca/wp-content/uploads/2018/05/spending-patterns.pdf.

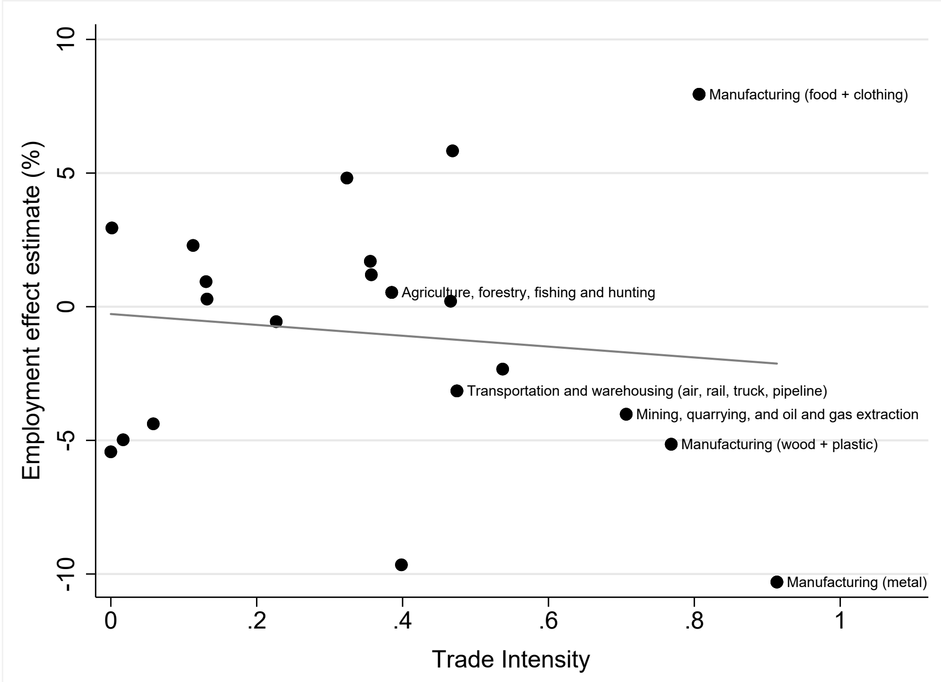

Figure 16: Correlation of employment effects with trade intensity at 2-digit NAICS industries

Note: This plot illustrates how the industry point estimates, generated from the 2-digit NAICS industry level analysis presented in Fig.5, are correlated with trade intensity. The fitted line has a slope of -2.03% change in employment per unit change in trade intensity with a standard error of 3.93% change in employment per unit change in trade intensity. Hence, the relationship is negative and insignificant at the 5% level.
Source: Author's calculation.

6. Discussion

Our analysis shows that the BC carbon tax led the emission-intensive manufacturing sectors, particularly these sectors' large companies, to contract while it boosted employment in small businesses in the service sectors and the manufacturing (food + clothing) sector (a non-emission-intensive manufacturing sector). These "job shifts" were due to the differing impact of each of the four components of the overall BC carbon tax policy. The carbon tax itself caused reductions in employment in emission-intensive industries; income tax reductions and low carbon credits put more money into the pockets of poorer households which was spent on small day-to-day purchases, such as massage services, chiropractors, and restaurants which disproportionately benefitted the service sector; and the reduction in the small business tax, funded by the carbon tax, led to the positive employment effect we find in the small business sector.

Yamazaki (2022) and Ahmadi, Yamazaki and Kabore (2022) both theoretically argue that recycling the carbon tax revenues via reductions of corporate income taxes can positively affect manufacturing output and productivity. These papers show that the positive impacts on output and productivity are bigger when firms are less emission-intensive because they benefit largely from their corporate income tax reductions. Although these papers focus only on the manufacturing sectors, the findings from these papers can also explain the results of this paper because more productive firms tend to hire more workers (Lentz and Mortensen, 2015; Kaas and Kircher, 2015). Productivity gains from the corporate income tax reductions through the carbon tax revenues may also allow firms to hire more workers, especially in the clean service sectors.

When the combined effect of this boost to employment in small firms and contraction in large firms is considered, the results presented here suggest that the BC carbon tax had only a modest effect on employment in the provincial economy. For 20 out of 24 industries, placebo tests show that larger employment changes occurred in other provinces absent from the carbon tax, and so the null hypothesis of no employment effect cannot be rejected for most industries, nor on the aggregate. This may be an indication that most industries are able to switch to using lower carbon-emitting processes, the substitutability between labour and energy is high for many industries, and/or the reduction in corporate and income taxes increased the demand for and supply of labour to the point that it offset the negative employment effects of the BC carbon tax. Alternately, this result could suggest that there was an employment effect of the BC carbon tax, but there were other economic factors following the implementation of the carbon tax, which caused employment effects that were cumulatively larger than the employment effect from the carbon tax policy.[40]

We note that other economic events occurred following the implementation of the car-

[40] For example, consider the accommodations and food services industry. The $\alpha_{j,\mathrm{BC},2013}$ estimate measured in percent change in employment for this industry is large, at an increase of 11%. However, the span of placebo estimates is much larger, ranging from -8% to 18%. Hence, this suggests that at the same time as the carbon tax was implemented in BC, employment in the accommodations and food services industry was also affected by other important factors.

bon tax that may bias the estimator in certain industries. In the case of the Information and Cultural industry, which our results suggest was one of the sectors with large employment declines, the estimate is likely biased by tax credits introduced in two other Canadian provinces, Ontario and Québec, which helped boost their film and, potentially, broadcasting industries. According to a BC film association report, these tax credits drew a significant amount of production away from BC and into Ontario and Québec, particularly in 2009 and 2010.[41] The report further states that action taken by the BC government in 2011 and 2012 helped stem the flow of production to Ontario and Québec but did not regain the productions that had initially left. Additionally, the construction industry is likely biased downwards by the high price of oil following 2008. This is because high oil prices led to an oil boom in the Alberta oil sands, which increased construction activity in Alberta.[42]

Since British Columbia's oil industry is much smaller than Alberta's, the effect of high oil prices on construction is likely much larger in Alberta than in BC. Therefore, since the SCM gave Alberta a positive weighting, high oil prices would disproportionately affect employment in Alberta's construction industry, biasing the synthetic control upwards and consequently biasing the employment effect estimate downwards.[43] In short, future research needs to investigate the employment effect in these particular sectors to obtain a clearer picture of

[41] See Creative BC, 2011. https://www.creativebc.com/database/files/library/BCFM_ActivityReport_1011.pdf

[42] See Economic Commentary: Alberta's Oil and Gas Supply Chain Industry. Alberta Government. https://www.albertacanada.com/files/albertacanada/SP-Commentary_12-11-13.pdf

[43] Two other major policy changes which occurred around the same time as the implementation of the BC carbon tax were the creation (and destruction) of the Harmonized Sales Tax (HST) system in BC and changes to the minimum wage (in control provinces as well). In 2010, the BC government combined the Provincial and Goods and Services Tax into an HST; however, due to strong opposition, a referendum led to the repeal of the HST legislation on April 1st, 2013. According to a 2012 manufacturing industry association report, the HST saved the manufacturing industry $140 million annually. Since the HST was in place for four months of the year in which we measured the effect of the carbon tax, it is possible that our manufacturing estimates were biased upwards, as the synthetic control was matched to BC during a period without the HST. However, the manufacturing industry report also estimated that the carbon tax had cost the industry over one billion dollars since being implemented, so if there is a bias, it is likely small in comparison to the effect of the carbon tax. BC and a number of the control provinces changed the level of their minimum wage during the period of analysis (for historic minimum wage rates across Canada, see: https://open.canada.ca/data/en/dataset/390ee890-59bb-4f34-a37c-9732781ef8a0). If changes in minimum wages affect employment or cause large differences in earnings across provinces, this could bias our results. However, Dickens, Machin and Manning (1999) find that minimum wages do not have a negative impact on employment, and the minimum wage reforms implemented during this time were not large (e.g., Ontario and BC increased their minimum wage by a maximum of $0.75 in any given year)

the impact of the policy in these industries.

It should also be noted that while the BC carbon tax applies to the burning of all fossil fuels, a number of industries emit large amounts of GHGs not related to fossil combustion. For example, Picard (2000) estimates that gas extraction leads to the creation of 3.1 tonnes of fugitive methane emissions per 106 m^3 gas production. Using this estimate, and given that BC produces approximately 44 billion cubic metres of gas annually, we calculate that approximately 138,000 tonnes of methane are produced each year which are not captured by the BC carbon tax due to fugitive emissions being exempted from the tax.[44] Hence, the employment impact on the mining, quarrying, oil and gas extraction industry might have been notably different if the carbon tax did not exempt fugitive emissions. In addition, the air transportation industry does not have to pay the tax on any emissions outside of BC. For example, while an airplane from Vancouver, BC to Prince George, BC would pay the full tax, a plane from Vancouver to Calgary would only pay for the portion of emissions released in BC airspace. Thus, if the carbon tax policy were to be expanded to include these emissions, the impact on employment in the airline industry may be substantially different than found here.[45]

Another important factor that may limit the generalizability of these findings is that BC's electricity grid is unique in that 95% of its power is generated by renewables, such as (mostly) hydro, wind, and biomass.[46] Hence, in other regions where fossil fuels are used to generate electricity, the magnitudes of the employment effects and job-shifting may be different.

[44] See Government of British Columbia. https://www2.gov.bc.ca/gov/content/industry/natural-gas-oil/statistics

[45] Yet another example of how exemptions may play a notable role in our results stems from the fact that the BC carbon tax does not cover emissions created from chemical processes. Hence, the non-metallic mineral manufacturing industry, which contains the large amounts of CO_2 emissions created as a by-product of the cement-making process, is not taxed on a large proportion of its emissions, and so, if the carbon tax were expanded to cover all GHGs, the employment effect estimate may be even more negative.

[46] See Canada Energy Regulator https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/provincial-territorial-energy-profiles/provincial-territorial-energy-profiles-british-columbia.html

7. Conclusion

Our study re-examines the question of whether the BC carbon tax has had an effect on employment at the provincial and industry level. We investigate this question using the most confidential firm-level data available in Canada. To overcome the challenge of insufficient donor pool size for the SCM inference, we aggregate our data to construct representative firms and test this aggregation in a Monte Carlo simulation. Our results show considerable heterogeneity in employment responses to the BC carbon tax across industries, yet the policy did not adversely affect provincial employment. We further find that the policy had significant negative impacts on large metal manufacturing firms while, in general, boosting employment in small firms in the health, retail, and food and clothing manufacturing business sectors. By recycling the tax revenues from the carbon tax, jobs are likely to "shift" from emission-intensive industries to clean service industries, particularly from large firms to small firms.

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Appendices

Appendix A Estimation Recipe

This appendix provides a step-by-step guide for our new approach to implement the SCM with firm-level data.

Stage one: Construct representative firms

1. Calculate the pre-treatment average of employment for all firms.
2. For each province-industry (2-digit NAICS) pair, we group firms by their firm size (i.e., we use the pre-treatment average employment calculated above to determine the quintile, quartile, etc.). Depending on the number of firms in each province-industry pair, we adjust the number of groups, i.e.,
   - if there are 500 or more firms in a given province-industry pair, a representative firm is created for each quintile (5 rep. firms)
   - if there are 400 to 499 firms in a given province-industry pair, a representative firm is created for each quartile (4 rep. firms)
   - if there are 300 to 399 firms in a given province-industry pair, a representative firm is created for each 33 percentile (3 rep. firms)
   - if there are 200 to 299 firms in a given province-industry pair, a representative firm is created for each 50 percentile (2 rep firms)
   - if there are 100 to 199 firms in a given province-industry pair, one representative firm is created
   - if there are less than 100 firms in a given province-industry pair, no representative firm is created

   This is to ensure that we have at least 100 firms for each representative firm.
3. Generate a new employment variable for representative firms by summing employment across all firms within province-industry-firm size triplet.

In our paper, we construct a representative firm for each of the firm size groups in province-industry pairs. One can use other firm characteristics to construct representative firms.

Stage two: Employ the SCM with representative firms

1. Run the SCM for each treated firm to obtain the employment effect. Except for two industries (utilities and public administration), we have five treated representative firms in BC, resulting in 5 employment effects. This allows each treated representative firm to be compared with a different synthetic firm. As each province-industry pair in

the non-BC groups (control group) also has multiple representative firms, a synthetic firm for the largest treated representative firm in BC can be constructed with large representative firms from the donor pool. The same logic is applied to the rest of the treated representative firms with different sizes.

2. Take the average of the employment effects weighted by the number of employees with each estimate's associated representative firms.

3. Conduct placebo tests by running the SCM for each representative firm in the donor pool.

This approach can be used for various micro-level data as long as the variable of the main interest varies in three dimensions. In our paper, employment varies by province, industry, and firm size.

Appendix B Calibration Exercise

This appendix presents a calibration exercise to illustrate that the employment effects differ substantially across industries, and both positive and negative effects are possible. We calibrate an analytical model adopted from Yamazaki (2017). Yamazaki analyzes a partial equilibrium model to express changes in labour as a function of the "factor", "output" and "income" effects, summarized in the following equation (Eq.(1.24) of Online Appendix of Yamazaki (2017)):

$$\widehat{l^d} = \underbrace{\sigma\phi\,\widehat{\tau}}_{\text{Factor effect}} - \underbrace{(\varepsilon_{\text{DP}}\phi)\,\widehat{\tau}}_{\text{Output effect}} + \underbrace{\varepsilon_{\text{DT}}(1-\varepsilon_{e\tau}-\varepsilon_{\text{DP}}\phi)\,\widehat{\tau}}_{\text{Income effect}} \tag{B.1}$$

where l^d denotes a labour demand while τ denotes a carbon tax ("$\widehat{\ }$" denotes a percentage change). $\varepsilon_{\text{DP}} \leq 0$ is the price elasticity of demand. ϕ is the cost share of a carbon tax. $\sigma \geq 0$ is elasticity of substitution between labour and fossil fuels. $\varepsilon_{DT} \geq 0$ is income elasticity of demand, particularly changes in demand in response to changes in the lump-sum transfer. $\varepsilon_{e\tau} > 0$ is price elasticity of input demand for fossil fuels, i.e., changes in demand for fossil fuels as inputs in response to a carbon tax.

Table B.1: Calibration results

	Clean industry (Food & clothing manuf.)	Dirty industry (Metal & electrical manuf.)
ε_{DT}	0.42	0.8
σ	0.07	0.07
ϕ	0.05%	3.1%
ε_{DP}	0.55	0.27
τ	30	30
$\varepsilon_{e\tau}$	0.02	0.02
Change in L		
excluding income effect	-0.72%	-18.6%
including income effect	11.28%	-15.17%

Notes: ε_{DT} income elasticity of demand, σ is elasticity of substitution between labour and fossil fuels, ϕ is cost share of carbon tax, ε_{DP} is price elasticity of demand, τ is carbon tax rate, and $\varepsilon_{e\tau}$ is price elasticity of input demand for fossil fuels.

To illustrate the importance of our paper, we present results for two distinct industries, one clean industry (the food and clothing manufacturing) and one dirty industry (the metal and electrical manufacturing). We carefully reviewed the literature to parametrize the equation numerically (see footnote for details).[1]

Table B.1 shows that sizeable employment effects are possible for these parameter values, and the employment effects are calibrated well within the results of our paper. Moreover, it shows that both positive and negative impacts are possible in theory, highlighting the need for careful empirical analysis.

Appendix C Additional Figure & Tables

[1] The parameter values for income elasticity of demand come from Fouquet (2012) and Euromonitor International (2013). We use Statistics Canada's Tables (36-10-0217-01 and 38-10-0097-01) to calculate the cost shares of carbon. The parameter values for price elasticity of demand comes from Anderson et al. (1997) and Tiffin et al. (2011). The parameter values for price elasticity of input demand for fossil fuels are taken from IMF (2011).

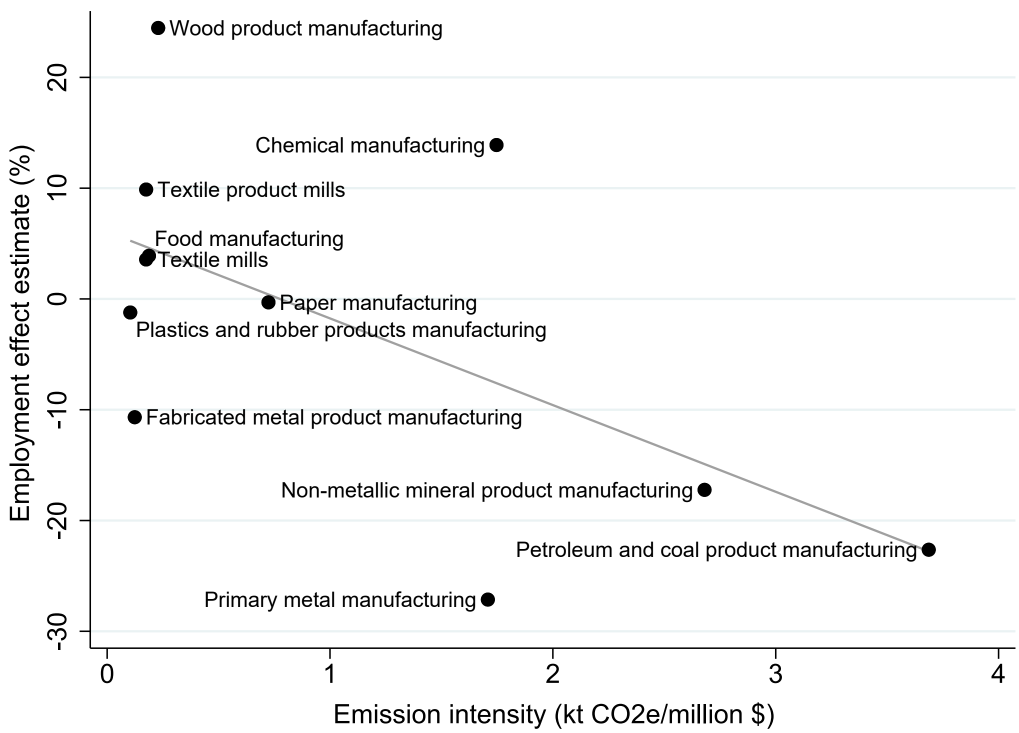

Figure C.1: Correlation of employment effects with emission intensity at 3-digit NAICS manufacturing industries (only high emission-intensive industries)

Note: This plot illustrates how the industry point estimates, generated from the 3-digit NAICS industry level analysis presented in Fig.12. This presents the same data as Fig.15 but only those with emission intensity above the median within the manufacturing industries.
Source: Author's calculation.

Table C.1: Test of parallel pre-treatment trends by firm size

NAICS	Size 1		Size 2		Size 3		Size 4		Size 5	
	ROC	SC	ROC	SC	ROC	SC	ROC	SC	ROC	SC
Agriculture, forestry, fishing and hunting (11)	0.76	0.90	0.45	0.98	0.10*	0.99	0.00	0.99	0.25	0.91
Mining, quarrying, and oil and gas extraction (21)	0.79	0.98	0.03**	0.87	0.02**	0.84	0.01**	0.83	0.20	0.92
Utilities (22)	0.51	0.71								
Construction(23)	0.09*	0.97	0.00***	0.91	0.00***	0.86	0.00***	0.86	0.01***	0.92
Manufacturing										
food + clothing (31)	0.03**	0.95	0.01***	0.98	0.00***	0.99	0.00***	0.94	0.02**	0.93
wood + plastic (32)	0.03**	0.98	0.08*	1.00	0.01**	0.96	0.00***	0.94	0.71	0.98
metal (33)	0.12	0.95	0.23	0.98	0.00***	0.98	0.04**	0.98	0.00***	0.97
Wholesale trade (41)	0.42	0.94	0.01***	0.95	0.00***	0.94	0.00***	0.94	0.00***	0.91
Retail trade										
cars, furniture, groceries (44)	0.13	0.94	0.06*	0.99	0.00***	0.97	0.42	0.98	0.01***	0.92
online, department stores, hobby (45)	0.52	0.92	0.02**	0.97	0.04**	0.99	0.71	0.98	0.10	0.90
Transportation and warehousing										
air, rail, truck, pipeline (48)	0.36	0.98	0.01**	0.99	0.85	0.98	0.01***	0.98	0.05*	0.99
postal, warehousing (49)	0.05*	0.97	0.60	0.99	0.70	0.98	0.91	0.99	0.96	1.00
Information and cultural industries (51)	0.51	0.97	0.20	0.98	0.04**	0.95	0.23	0.95	0.60	0.98
Finance and insurance (52)	0.71	0.93	0.36	0.96	0.91	0.96	0.83	0.97	0.04**	0.97
Real estate and rental and leasing (53)	0.43	0.92	0.24	1.00	0.50	0.99	0.09*	1.00	0.36	0.96
Professional, scientific and technical services (54)	0.69	0.91	0.12	0.95	0.16	0.97	0.18	0.95	0.49	0.94
Management of companies and enterprises (55)	0.60	0.89	0.51	0.99	0.22	0.93	0.49	0.92	0.23	0.99
Administrative and support, waste services (56)	0.90	0.89	0.20	0.98	0.10*	0.99	0.03**	0.96	0.01***	0.88
Educational services (61)	0.03**	0.99	0.01***	0.96	0.00***	0.93	0.00***	0.93	0.13	0.96
Healthcare and social assistance (62)	0.00***	0.90	0.00***	0.96	0.01**	0.90	0.47	0.92	0.34	0.93
Arts, entertainment and recreation (71)	0.02**	1.00	0.09*	0.99	0.36	0.98	0.02**	0.92	0.01***	0.93
Accommodation and food services (72)	0.41	0.90	0.61	0.97	0.01**	0.99	0.26	0.96	0.02**	0.86
Other services (except public administration) (81)	0.01***	0.87	0.76	0.95	0.10	0.96	0.28	0.96	0.74	0.99
Public administration (91)	0.93	1.00	0.06*	0.96	0.53	0.99	0.00***	0.99		

Note: This table presents the p-values generated by the Wald test between α and β in Eq.(4.2) for each representative firm in each industry. Notice that for many industries the p-value for the rest of Canada (ROC) representative firms is less than 0.05, indicating that the pre-treatment trends are not parallel, whereas the p-value for the synthetic control (SC) is always greater than 0.7, indicating that the pre-treatment trend for the SC representative firms is not statistically different from that of the BC representative firm. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table C.2: Percentage change in employment per capita, all firms

NAICS	Industry name	Estimate (%)	Pseudo-CI Lower	Pseudo-CI Upper	# of rep. SC firms
11	Agriculture, forestry, fishing and hunting	0.88	-17.68	11.18	29
21	Mining, quarrying, and oil and gas extraction	-4.54	-9.03	26.76	14
22	Utilities	-0.56	-6.67	-5.63	3
23	Construction	-8.79	-14.57	20.74	31
31	Manufacturing (food + clothing)	11.33*	-14.76	2.08	15
32	Manufacturing (paper + chemicals)	-6.81	-7.73	8.90	17
33	Manufacturing (metal + electrical)	-15.26*	-7.14	15.52	17
41	Wholesale trade	-3.60	-5.64	13.69	27
44	Retail trade (cars, furniture, groceries)	-0.08	-8.82	7.21	30
45	Retail trade (online, department stores, hobby)	0.37	-12.39	4.19	19
48	Transportation and warehousing (air, rail, truck, pipeline)	-3.97	-15.31	16.20	30
49	Transportation and warehousing (postal, warehousing)	5.62*	-35.93	4.75	15
51	Information and cultural industries	-11.12*	-9.29	19.24	17
52	Finance and insurance	5.63	-7.27	16.54	17
53	Real estate and rental and leasing	4.16	-25.27	17.31	22
54	Professional, scientific and technical services	1.87	-11.71	18.53	27
55	Management of companies and enterprises	-5.86	-32.31	33.13	19
56	Administrative and support, waste services	2.37	-11.58	10.28	25
61	Educational services	-4.77	-5.26	18.89	17
62	Healthcare and social assistance	-6.48	-16.91	21.80	30
71	Arts, entertainment and recreation	0.27	-21.84	19.95	30
72	Accommodation and food services	10.79	-8.01	18.40	30
81	Other services (except public administration)	1.45	-6.57	20.15	30
91	Public administration	3.13	-15.09	9.58	21

Note: This table shows the estimated percent change in employment per capita for all industries, presented in Fig.5. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. The results in this figure were produced using all firms in our dataset. The pseudo-CI is generated by the placebo tests using the representative firms from the donor pool, i.e., SC firms. The number of representative SC firms presented in this table is the final number of firms that makes up the pseudo-CI. If the estimate lies outside this pseudo-CI, it is significant at the corresponding significance level. The corresponding significance level depends on the number of representative SC firms in the donor pool. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table C.3: Percentage change in employment from the SCM-weighted fixed effects

NAICS	Industry name	Estimate	SE
11	Agriculture, forestry, fishing and hunting	0.011	0.024
21	Mining, quarrying, and oil and gas extraction	0.026	0.090
22	Utilities	0.065	0.113
23	Construction	0.036*	0.021
31	Manufacturing (food + clothing)	0.045	0.049
32	Manufacturing (paper + chemicals)	-0.009	0.038
33	Manufacturing (metal + electrical)	-0.068***	0.028
41	Wholesale trade	-0.026	0.048
44	Retail trade (cars, furniture, groceries)	-0.048***	0.016
45	Retail trade (online, department stores, hobby)	0.058***	0.017
48	Transportation and warehousing (air, rail, truck, pipeline)	-0.061	0.052
49	Transportation and warehousing (postal, warehousing)	0.112*	0.067
51	Information and cultural industries	-0.058	0.078
52	Finance and insurance	-0.003	0.032
53	Real estate and rental and leasing	-0.009	0.044
54	Professional, scientific and technical services	-0.091*	0.053
55	Management of companies and enterprises	-0.084**	0.041
56	Administrative and support, waste services	0.090	0.059
61	Educational services	-0.039***	0.008
62	Healthcare and social assistance	0.000	0.021
71	Arts, entertainment and recreation	-0.011	0.044
72	Accommodation and food services	0.045**	0.016
81	Other services (except public administration)	-0.009	0.013
91	Public administration	0.051*	0.027

Note: This table shows the estimated percent change in employment for all industries, presented in Fig.7. These results were produced using the SCM-weighted fixed effects method applied to confidential firm-level data. The results in this figure were produced using all firms in our dataset. The estimation is run industry by industry at the 2-digit NAICS level. All estimations include control variables (population growth, gasoline price index, and healthcare and education per capita spending) as well as firm fixed effects and industry (3-digit NAICS) by year fixed effects. SE indicates a standard error clustered at industry (3-digit NAICS) by province level. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table C.4: Percentage change in employment per capita, bottom 33 % of firms

NAICS	Industry name	Estimate (%)	Pseudo-CI Lower	Pseudo-CI Upper	# of rep. SC firms
11	Agriculture, forestry, fishing and hunting	-6.86	-14.62	20.61	27
21	Mining, quarrying, and oil and gas extraction	0.13	-37.45	-33.40	3
22	Utilities	6.39	-6.67	-5.63	3
23	Construction	-11.88	-22.48	24.74	29
31	Manufacturing (food + clothing)	26.70*	-22.58	11.78	10
32	Manufacturing (paper + chemicals)	-2.84	-20.04	16.79	10
33	Manufacturing (metal + electrical)	-1.25	-13.18	19.27	15
41	Wholesale trade	-7.20	-15.42	8.43	18
44	Retail trade (cars, furniture, groceries)	4.68	-16.64	19.88	29
45	Retail trade (online, department stores, hobby)	10.88**	-15.62	6.41	18
48	Transportation and warehousing (air, rail, truck, pipeline)	-32.85**	-14.94	70.38	23
49	Transportation and warehousing (postal, warehousing)	11.93	-45.52	-38.50	3
51	Information and cultural industries	-26.77	-35.04	53.40	9
52	Finance and insurance	2.62	-27.57	30.64	17
53	Real estate and rental and leasing	-3.03	-25.97	16.27	14
54	Professional, scientific and technical services	-8.67	-17.53	17.65	14
55	Management of companies and enterprises	24.11	-47.33	24.30	9
56	Administrative and support, waste services	4.19	-19.05	13.03	20
61	Educational services	-0.34	-18.28	33.00	14
62	Healthcare and social assistance	23.88**	-23.02	21.49	26
71	Arts, entertainment and recreation	-8.83	-17.24	14.40	15
72	Accommodation and food services	12.55	-19.02	33.56	27
81	Other services (except public administration)	-3.95	-34.71	32.34	30
91	Public administration	9.93	-34.32	20.07	9

Note: This table shows the estimated percent change in employment per capita for all industries, presented in Fig.9. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. The results in this figure were produced using firms that are in the bottom 33 % in our dataset. The pseudo-CI is generated by the placebo tests using the representative firms from the donor pool, i.e., SC firms. The number of representative SC firms presented in this table is the final number of firms that makes up the pseudo-CI. If the estimate lies outside this pseudo-CI, then it is significant at the corresponding significance level. The corresponding significance level depends on the number of representative SC firms in the donor pool. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table C.5: Percentage change in employment per capita, top 33 % of firms

NAICS	Industry name	Estimate (%)	Pseudo-CI Lower	Pseudo-CI Upper	# of rep. SC firms
11	Agriculture, forestry, fishing and hunting	-2.69	-17.92	19.61	28
21	Mining, quarrying, and oil and gas extraction	-10.74	-36.38	32.21	8
22	Utilities	-1.67	-29.58	73.53	2
23	Construction	-10.43	-18.51	6.81	22
31	Manufacturing (food + clothing)	7.39	-16.25	9.97	11
32	Manufacturing (paper + chemicals)	-8.19	-12.15	18.29	16
33	Manufacturing (metal + electrical)	-18.59*	-7.29	18.65	17
41	Wholesale trade	-2.45	-9.27	10.81	28
44	Retail trade (cars, furniture, groceries)	0.48	-8.65	12.67	30
45	Retail trade (online, department stores, hobby)	0.17	-8.16	7.66	22
48	Transportation and warehousing (air, rail, truck, pipeline)	-1.53	-14.25	15.31	17
49	Transportation and warehousing (postal, warehousing)	12.02	-14.87	21.46	5
51	Information and cultural industries	-5.79	-17.49	26.34	16
52	Finance and insurance	6.55	-14.45	12.38	10
53	Real estate and rental and leasing	2.72	-15.21	10.25	16
54	Professional, scientific and technical services	3.32	-9.36	11.51	12
55	Management of companies and enterprises	-0.68	-44.89	41.81	16
56	Administrative and support, waste services	1.53	-5.48	9.44	18
61	Educational services	-0.86	-10.81	5.76	15
62	Healthcare and social assistance	-9.91**	-8.45	19.94	25
71	Arts, entertainment and recreation	-15.60	-16.66	14.81	18
72	Accommodation and food services	5.99	-13.87	12.03	29
81	Other services (except public administration)	1.74	-8.73	6.94	30
91	Public administration	-2.01	-3.55	8.44	3

Note: This table shows the estimated percent change in employment per capita for all industries, presented in Fig.10. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. The results in this figure were produced using firms that are in the top 33 % in our dataset. The pseudo-CI is generated by the placebo tests using the representative firms from the donor pool, i.e., SC firms. The number of representative SC firms presented in this table is the final number of firms that makes up the pseudo-CI. If the estimate lies outside this pseudo-CI, then it is significant at the corresponding significance level. The corresponding significance level depends on the number of representative SC firms in the donor pool. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table C.6: Percentage change in employment per capita, manufacturing firms (3-digit NAICS)

NAICS	Industry name	Estimate (%)	Pseudo-CI Lower	Pseudo-CI Upper	# of rep. SC firms
311	Food manufacturing	3.89	-26.69	16.42	16
312	Beverage and tobacco product manufacturing	-0.83	-25.02	24.04	6
313	Textile mills	3.56	-30.73	28.78	3
314	Textile product mills	9.88	-3.36	37.89	6
315	Clothing manufacturing	16.80	-44.56	28.14	11
316	Leather and allied product manufacturing	41.57	-16.88	-6.68	3
321	Wood product manufacturing	24.46	-25.84	28.71	15
322	Paper manufacturing	-0.31	-24.74	30.89	5
323	Printing and related support activities	-3.30	-22.39	21.13	16
324	Petroleum and coal product manufacturing	-22.64	-27.85	55.24	4
325	Chemical manufacturing	13.89*	-19.56	13.29	15
326	Plastics and rubber products manufacturing	-1.23	-18.92	14.27	12
327	Non-metallic mineral product manufacturing	-17.23	-27.33	30.19	12
331	Primary metal manufacturing	-27.14	-7.80	32.18	4
332	Fabricated metal product manufacturing	-10.68	-19.81	22.72	17
333	Machinery manufacturing	-17.21	-18.30	9.49	16
334	Computer and electronic product manufacturing	10.71*	-16.35	10.08	10
335	Electrical equipment, appliance and component manufacturing	23.56	-12.23	56.29	10
336	Transportation equipment manufacturing	-25.21*	-20.65	34.22	13
337	Furniture and related product manufacturing	16.15	-34.65	37.64	15
339	Miscellaneous manufacturing	-15.13*	-12.99	21.26	16

Note: This table shows the estimated percent change in employment per capita for all industries, presented in Fig.12. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. The results in this figure were produced using manufacturing firms in our dataset. The pseudo-CI is generated by the placebo tests using the representative firms from the donor pool, i.e., SC firms. The number of representative SC firms presented in this table is the final number of firms that makes up the pseudo-CI. If the estimate lies outside this pseudo-CI, then it is significant at the corresponding significance level. The corresponding significance level depends on the number of representative SC firms in the donor pool. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table C.7: Percentage change in employment per capita, firms in selected sub-industries (3-digit NAICS)

NAICS	Industry name	Estimate (%)	Pseudo-CI Lower	Pseudo-CI Upper	# of rep. SC firms
511	Publishing industries (except Internet)	0.83	-29.37	50.83	16
512	Motion picture and sound recording industries	-16.31	-38.16	50.26	15
515	Broadcasting (except Internet)	-46.07	-36.16	58.62	6
517	Telecommunications	20.70	-17.03	29.34	11
518	Data processing, hosting, and related services	-13.07	-42.57	-9.08	4
519	Other information services	0.81	-16.95	6.27	4
621	Ambulatory healthcare services	-4.42	-12.41	20.68	32
622	Hospitals	-2.86			4
623	Nursing and residential care facilities	-8.82	-18.57	24.47	18
624	Social assistance	-5.39	-19.84	28.77	31
721	Accommodation services	-4.50	-12.87	14.12	29
722	Food services and drinking places	13.16	-11.18	17.17	32

Note: This table shows the estimated percent change in employment per capita for all industries, presented in Fig.13. These results were produced using the synthetic control method (SCM) applied to confidential firm-level data. The results in this figure were produced using firms that are in the selected sub-industries in our dataset. The pseudo-CI is generated by the placebo tests using the representative firms from the donor pool, i.e., SC firms. The number of representative SC firms presented in this table is the final number of firms that makes up of the pseudo-CI. If the estimate lies outside this pseudo-CI then it is significant at the corresponding significance level. The corresponding significance level depends on the number of representative SC firms in the donor pool. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.