Who Bears More Burdens of Carbon Taxes? Heterogeneous Employment Effects within Manufacturing Plants*

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Abstract

This paper investigates the employment impact of British Columbia's carbon tax implemented in 2008. Particularly, I explore the differential impacts among different workers within manufacturing plants. By using confidential plant-level data, I find that the policy negatively affected manufacturing employment; however, this is only true for production workers. Their number of jobs and wages are both decreased in response to the policy. On the other hand, non-production workers, such as executives and scientists, were unaffected by the policy. These results help us understand the incidence of carbon pricing policies among different workers.

Key Words: Carbon tax; manufacturing employment

JEL Codes: H23, Q52, Q58

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1. Introduction

In the wake of the Paris Agreement, many jurisdictions are implementing a climate policy to reduce emission and meet their target. One of the difficulties is that many stakeholders worry that such a policy would disproportionately harm low-income households and small businesses. For this reason, carbon tax has been a popular policy as its tax revenue can be recycled back to the economy to compensate for those who might be disproportionately affected. Yet, its distributional concern has been the crux of the public debates.

This paper extends the research of Yamazaki (2017) by asking "who bears more burdens of carbon taxes?" Yamazaki (2017) finds that British Columbia's revenue-neutral carbon tax negatively affected manufacturing workers. To explore the distributional concerns among these workers, this paper uses confidential detailed plant-level data, the Annual Survey of Manufacturers (ASM), to investigate the heterogeneous employment effects of carbon taxes. Specifically, I examine whether the employment impacts differ between production (wage-paid) workers and non-production (salary-paid) workers.

British Columbia implemented a carbon tax on July 1st, 2008, applying it to the purchase of all fossil fuels.[1]It is the first and most comprehensive carbon pricing policy in North America. This policy offers a unique opportunity because it was implemented as revenue-neutral. All the tax revenue raised were used to reduce personal and corporate income taxes and provide lump-sum transfers to low-income households. This revenue-recycling adds an extra reason why the employment effect of carbon taxes would be heterogeneous. Recent studies have shown that the effects of carbon taxes are heterogeneous across different groups (Rivers and Schaufele, 2014; Yamazaki, 2017; Azevedo et al., 2018; Yip, 2018). For example, Yip (2018) has shown that the BC carbon tax disproportionately increased the unemployment rate for the less-educated workers.

My results suggest that the BC carbon tax had the negative employment effect only on production workers. Their employment level and wages are both decreased in response to the policy. On

[1] See Yamazaki (2017) for more detail description of this policy.

the other hand, non-production workers are unaffected by the policy. These findings are consistent with Yip (2018) if one is to assume that the production-workers tend to be less-educated. One may also interpret this finding as a negative effect on the unskilled-labor although manufacturing workers are becoming more skilled in recent years. The findings contribute to our understanding of the incidence of carbon taxes among different workers, which is important for both the public policy and literature.

2. Data and Method

I use the plant-level data on manufacturing activities. The ASM is an annual survey that contains industrial statistics and commodity data for all manufacturing locations in Canada.[2] What is unique about this data is that a number of total employment is further broken down to that of production workers and non-production workers. It also includes data on wages for each worker type. A production worker is a wage-paid employee involved in manufacturing operations while a non-production worker is an executive, administrative, or sales and research worker who is paid in salary.

Using this data, I employ a semiparametric difference-in-difference (DID) matching estimator. This method compares changes in outcomes of interest for plants in BC with changes in outcomes for plants in the rest of Canada (ROC) before and after the implementation of the carbon tax. Unlike the conventional parametric DID estimator, this method better identifies the effect by constructing the estimates for the counterfactual from the ROC plants that resemble the BC plants. I match BC plants with ROC plants using a rich set of observable pre-treatment characteristics from the ASM, such as energy expenditures by various fuel types. Exploiting the panel structure of the data together with the matching method allows me to rule out potential biases and unobserved factors that would otherwise confound identification of the causal effect. Formally, I estimate the following equation, introduced by Heckman et al. (1997):

[2] Although the ASM is a survey data, over the sample period it was essentially a census with data on smaller firms being filled with administrative records.

$$\widehat{\alpha} = \frac{1}{N_1} \sum_{i \in I_1} \left\{ \Big(Y_{it'}(1) - Y_{it}(0) \Big) - \sum_{k \in I_0} W_{N_1,N_0}(i,k) \Big(Y_{kt'}(0) - Y_{kt}(0) \Big) \right\} \tag{1}$$

where I_1 denotes the set of plants that are subject to the carbon tax (BC plants), I_0 denotes the set of plants that are not subject to the tax (ROC plants), N_1 denotes the number of plants in the treated group, and N_0 denotes the number of plants in the control group. The weight $W_{N_1,N_0}(i,k)$ with $\sum_{k \in I_0} W_{N_1,N_0}(i,k) = 1$ is assigned to control plant k when constructing the counterfactual estimate for treated plant i. Plants in the control group are weighted more heavily if they are more similar to treated plants based on the estimated propensity scores. Matching estimator reduces the bias by estimating the treatment effect only among plants that are similar in observable characteristics. Furthermore, it needs not to specify a functional form. These ensure that the counterfactual outcomes are imputed correctly for the treated plants.

3. Results and Conclusion

I employ the DID nearest neighbor (NN) matching estimator. The treated plant is matched with m nearest neighbors from the control plants. In the case of a one-to-one NN matching (i.e., $m = 1$), $W_{N_1,N_0}(i,k) = 1$ for the matched control plant and 0 for all other plants. When $m > 1$, $W_{N_1,N_0}(i,k) = 1/m$ for all matched control plants. Austin (2010) recommends that an optimal number of m is either 1 or 2 when the NN matching is used. There is a trade-off between the size of bias and precision when choosing m. The precision of the estimate improves at the cost of increasing the bias when m is increased, and vice versa. For this reason, I will present results using one-to-one, one-to-five, and one-to-twenty NN matching.

The results of three specifications based on Eq.(1) are reported in Table 1. Standard errors for the matching estimator are calculated based on Abadie and Imbens (2016) to take into account that the propensity scores are estimated.[3] Regardless of the choice of m, these results show a robust

[3] Often the bootstrap method is used to calculate the standard errors for the matching estimations. However, Abadie and Imbens (2008) demonstrated that the bootstrap is not valid for matching estimators.

Table 1: Effects of the BC Carbon Tax by Different Job Types

	NN (1:1)	NN (1:5)	NN (1:20)
Production workers			
# of Employees	-0.057**	-0.078***	-0.081***
	(0.027)	(0.021)	(0.019)
Wages	-0.067	-0.083**	-0.085***
	(0.044)	(0.034)	(0.032)
Non-production workers			
# of Employees	0.024	-0.0088	-0.014
	(0.026)	(0.02)	(0.019)
Wages	0.11	0.017	0.019
	(0.089)	(0.07)	(0.065)

Notes: For all the outcome variables, there are 10,813 plants (1,298 plants in BC and 9,515 plants in ROC). Standard errors are in parentheses. These standards error are calculated based on Abadie and Imbens (2016). All variables are inverse hyperbolic sine transformed, instead of log, to account for zeros.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

finding that the carbon tax negatively affects manufacturing jobs, but only production workers. The estimates for non-production workers are much smaller than production workers and statistically insignificant. At the average tax rate ($20/t), the number of production workers is reduced by approximately 6∼8 percent and their wages are also reduced by approximately 8 percent.

To make the case more concrete, I allowed the employment effects to vary over time. Not only does this allow me to see the time-varying employment effect, but also allows me to check the pre-treatment trends. Fig.1 rules out the concern that the differences in the pre-treatment trends are driving the results shown in Table1 as the point estimates during the pre-treatment periods are all zero.[4] This results further show robust evidence that production workers are reduced immediately after the implementation of the policy, but there are absolutely no effects on non-production workers.

Anecdotal evidence suggests that production workers face an ever-increasing risk of being replaced by the adoption of new technologies. Environmental policy, especially carbon pricing policy, provides incentives for firms and plants to invest in new "green" technologies. Not only do

[4]More pre-treatment trends checks and robustness checks are presented in Online Appendix.

such technologies help them become more environmentally responsible, but also they may make their operations more efficient. This may be a reason why the burden of carbon taxes fall only on production workers. Therefore, moving to a lower carbon society may also require careful consideration of differential impacts on different workers.

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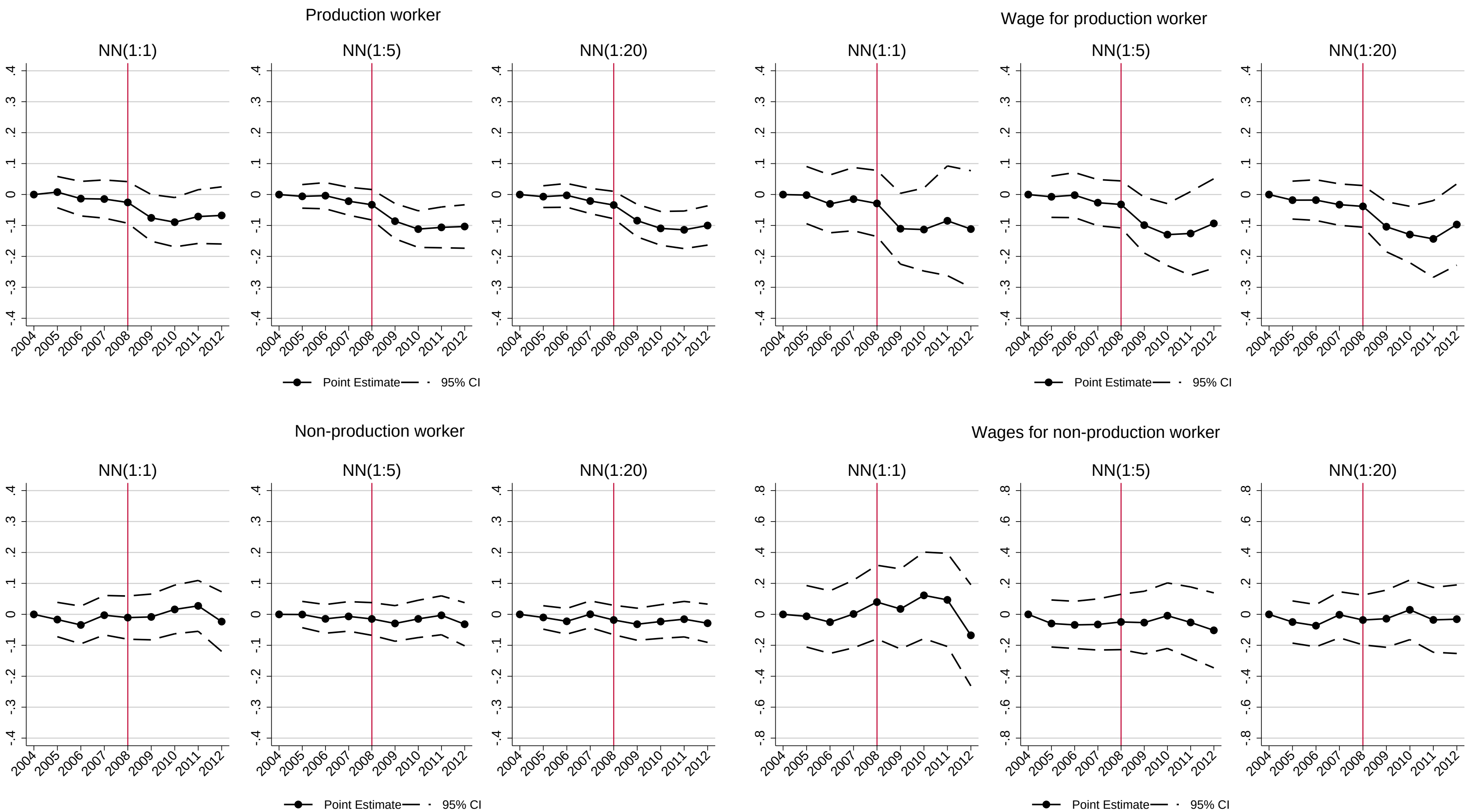

Figure 1: Indirect Test of Parallel Trends & Dynamic Effects

Source: Author's calculation.