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CARBON PRICING WITH REGRESSIVE CO-BENEFITS: EVIDENCE FROM BRITISH COLUMBIA'S CARBON TAX

Abstract. This paper examines the impacts of carbon taxation on air quality co-benefits and environmental justice. Using high-resolution data and a synthetic difference-in-differences strategy, I find that the 2008 carbon tax in British Columbia has reduced $PM_{2.5}$ emissions by 5.2-10.9%. The flow of monetised co-benefits from climate policy is large, corresponding to 40-81% of annual carbon tax revenues. While pollution reductions arise for all citizens, the tax widens pre-existing disparities in pollution exposure across income and racial diversity categories. The distribution of co-benefits from market-based climate mitigation instruments may be regressive, requiring additional policies targeting environmental inequalities.

Keywords. Carbon tax, air pollution, co-benefits, environmental justice

1. INTRODUCTION

The major sources of CO_2 emissions are the fossil fuel combustion processes which also release toxic air pollutants, making climate change and air pollution complementary externalities. Policy efforts to control CO_2 emissions by internalising the social cost of carbon are thus bound to give rise to significant health "co-benefits" associated with air quality improvements, with climate mitigation hailed as "the greatest global health opportunity of the 21st century" (Watts *et al.*, 2015). Moreover, a substantial body of research has documented severe historical inequities in air pollution exposure across income and racial groups (Colmer *et al.*, 2020; Jbaily *et al.*, 2022), and recent work has reported the ambiguous impacts of market-based climate policy in closing these "environmental justice gaps" (Cain *et al.*, 2024). In this paper, I jointly assess the air quality co-benefits and environmental justice implications of carbon taxation, leveraging as a case study the experience of the 2008 carbon tax in British Columbia, Canada.

Given the relative scarcity of long-tenured carbon pricing schemes, it is unsurprising that empirical evidence of their causal impact on local air pollution co-benefits is sporadic, and mostly limited to cap-and-trade schemes (Deschenes *et al.*, 2017; Hernandez-Cortes and Meng, 2023) with fewer studies focusing on fuel taxes (Basaglia *et al.*, 2023). On the contrary, there is a large and growing literature which, using theoretical insights (Parry *et al.*, 2015) and simulation models (Knittel and Sandler, 2011; Zhang *et al.*, 2021), has attempted to calculate the monetary value of air pollution improvements due to carbon taxation and compare them with the cost of mitigation policies. In particular, net health co-benefits arising from carbon taxation are theorised to reach a high enough magnitude to partially or fully offset the mitigation costs for households at a national (Li *et al.*, 2018; Shindell *et al.*, 2016) and global (West *et al.*, 2013; Vandyck *et al.*, 2018) level, and may provide strong additional incentives for a swift transition to a low-carbon economy[1].

In light of the considerable size of projected air pollution co-benefits, it is fundamental to examine how carbon pricing policies may impact the spatial distribution of pollutants over affected populations, a theme also referred to as the "environmental justice question" (Banzhaf *et al.*, 2019; Currie *et al.*, 2023). While carbon taxation is expected to produce higher pollution reductions in areas with lower marginal abatement costs, this efficiency criterion is blind to equity considerations, and CO_2 abatement is not necessarily perfectly correlated with the dispersion of air pollutants (Hernandez-Cortes and Meng, 2023; Cain *et al.*, 2024). It is thus paramount to inspect whether carbon taxation presents efficiency-equity trade-offs in the distribution of realised co-benefits, evidence of which is not unidirectional in the environmental economics literature (Fowlie *et al.*, 2012; Boyce and Pastor, 2013; Grainger and Ruangmas, 2018; Shapiro and Walker, 2021; Currie *et al.*, 2023; Sheriff, 2024).

The 2008 British Columbian carbon tax, covering approximately 75% of the Canadian province's CO_2 emissions, was initially introduced at a rate of \$10/tCO_2, and sequentially ramped up by \$5 per year until 2012, when it was frozen at \$30/tCO_2 until 2018. Importantly, no other Canadian Province introduced carbon pricing schemes between 2008 and 2018, when the tax was rolled out on a federal basis. I acquire high-resolution data on $PM_{2.5}$, based on a combination of satellite observations, geo-chemical models and ground-based monitoring stations, from Meng *et al.* (2019) and van Donkelaar *et al.* (2019), and combine them with granular socio-economic data at the Dissemination Area level[2], retrieved from the Canadian Census at 5-year intervals between 2001 and 2016. I exploit this highly disaggregated dataset to assess the effect of the carbon tax on air pollution co-benefits and the dynamics of the environmental justice gap.

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[1] Reductions in morbidity and mortality due to improvements in air quality are likely not to capture the full extent of the local pollution externality: a large body of research has linked air pollution to non-health outcomes (see Aguilar-Gomez *et al.*, 2022, for a review). Studies have linked air pollution to negative educational outcomes (Ebenstein *et al.*, 2016; Wen and Burke, 2022), increase in crime rates (Bondy *et al.*, 2020) and suicides (Persico and Marcotte, 2022), reductions in labour productivity (Graff Zivin and Neidell, 2012), and in housing prices (Sager and Singer, 2024; Freeman *et al.*, 2019), suggesting that any attempt at quantifying the monetary impact of co-benefits based on health outcomes alone would, at best, provide a lower bound of the beneficial consequences of air quality improvements.

[2] Corresponding roughly to US Census tracts.

The central result of the paper is that the carbon tax has resulted in statistically significant reductions in $PM_{2.5}$ concentrations, with a lower bound average estimate of -0.36 $\mu g/m^3$ and an upper bound average estimate of -0.89 $\mu g/m^3$, corresponding to a 5.2-10.9% reduction in particulate matter concentrations with respect to pre-treatment average levels. Importantly, this result is obtained by moving away from traditional difference-in-differences estimation, in light of a violation of the foundational parallel trends assumption: particulate matter trends between British Columbian and control Dissemination Areas diverge prior to the implementation of the carbon tax, thereby potentially biasing DID estimates. I rely on a family of estimators related to the synthetic control method (SCM) for comparative case studies (Abadie and Gardeazabal, 2003; Abadie, 2021), employing in particular the synthetic difference-in-differences (SDID) estimator by Arkhangelsky *et al.* (2021) as my preferred methodology.

I subsequently inspect the efficiency-equity trade off, examining whether air pollution reductions arise heterogeneously within British Columbian metropolitan areas. I split the pool of treated units in quintiles of pre-existing pollution, population density, median income levels and racial diversity, and estimate the impact of the tax on $PM_{2.5}$ reductions for each quintile of these characteristics. While Pareto-optimal in the welfare dimension, with reductions in pollution across the board, the carbon tax is regressive in the environmental justice dimension: reductions are 1.6-2.2 times higher in the bottom quintile of pre-treatment air pollution, population density and racial diversity compared to the top quintile, and 1.7 times higher in the top median income quintile compared to the bottom quintile.

Finally, I convert my estimates of particle pollution reductions into mortality reductions[3] and associated monetary gains, relying on the concept of the Value of a Statistical Life[4]. The median monetary health gains appear to be large, in the order of $88-402/year per capita. The central estimate of $198 is almost double the $115.50 per capita Low-Income Climate Action Tax Credit, the carbon tax governmental rebate accruing to low-income individuals to mitigate the cost of carbon pricing. The total annual health gains are comparable to annual carbon tax revenues at its inception (Ministry of Finance, 2009) and amount to 40-81% of annual tax revenues at maturity (Ministry of Finance, 2013). Health gains exhibit a positive spatial correlation with income, corroborating the evidence on the increase in the environmental justice gap.

This paper contributes to the literature on three main fronts. First, I extend the recent evidence on the impact of carbon pricing on air pollution co-benefits, by providing the first study with

[3] Exploiting hazard rates adapted from the environmental health and epidemiology literature (Lepeule *et al.*, 2012; Krewski *et al.*, 2009).
[4] Following Fowlie *et al.* (2019) and Carozzi and Roth (2023).

an explicit empirical focus on carbon taxation instead of the frequently examined cap-and-trade schemes and fuel tax increases (Hernandez-Cortes and Meng, 2023; Basaglia *et al.*, 2023). I overcome known spatial and temporal selection problems connected with the use of sparse air quality monitors (Grainger and Schreiber, 2019) by relying on two sets of remotely sensed $PM_{2.5}$ data (Meng *et al.*, 2019; van Donkelaar *et al.*, 2019) which provide full coverage of the spatial and temporal extent of my dataset. Further, I dispel the notion that the carbon tax has resulted in gasoline to diesel fuel substitution (Saberian, 2017), instead highlighting expected reductions in both fuels' total demand after the tax (Rivers and Schaufele, 2015; Bernard and Kichian, 2019). Moreover, by exploiting highly disaggregated census information on commute mode, I provide evidence on additional mechanisms underlying the air quality improvements: BC residents substitute high emissions trips with public transport and active commute modes following the implementation of the tax. My results are thus also consistent with the findings of Pretis (2022), who found that the 2008 carbon tax reduced CO_2 emissions in the transportation sector alone.

The second contribution regards the growing literature on the relationship between environmental policies and equity. I present the first ex post analysis of the effects of a carbon tax on the environmental justice (EJ) gap. I find that pricing carbon, while giving rise to widespread air quality co-benefits, may do so disproportionately with respect to pre-existing levels of air pollution, income, population density and racial diversity. My estimates thus add a data point to the nascent literature on ex post empirical evaluation of EJ effects from climate policy, which has so far reported mixed evidence (Cain *et al.*, 2024). This result counterbalances some of the recent evidence of EJ implications of market-based instruments (Hernandez-Cortes and Meng, 2023), and highlights the potential for coupling climate mitigation policy with instruments targeting air pollution specifically, which have been shown to be effective in closing EJ gaps (Currie *et al.*, 2023; Sager and Singer, 2024). While it is noteworthy that climate policy can give rise to significant air pollution and associated health co-benefits due to complementarities alone, improvements along the equity axis are not a necessary implication of efficiency-focussed instruments. In order to obtain the greatest gains across multiple independent policy targets, multiple policy instruments may be needed, a notion that economists have considered since the 1950s (Tinbergen, 1952).

Lastly, I contribute to the environmental policy evaluation literature by showing how the traditional DID estimator is susceptible of producing biased estimates, due to substantially diverging pre-treatment trends across treatment and control units. I solve this concern by exploiting SCM and the newly introduced SDID estimator (Arkhangelsky *et al.*, 2021) and exploiting, unlike recent studies in environmental policy evaluation (e.g. Andersson, 2019; Leroutier, 2022; Basaglia *et al.*, 2023) a subnational level treatment and a highly granular framework. In my setting, with multiple treated units and a large number of control units to draw synthetic counterfactuals from, both the SCM and SDID perform well in addressing concerns about diverging pre-treatment trends and identify robust estimates of the impact of the carbon tax on $PM_{2.5}$ levels, improving substantially upon traditional estimators and aggregate policy settings.

The remainder of the paper begins with a description of the carbon tax and the data sources in Section 2. In Section 3, I present the identification strategy, followed by the main results in Section 4. Section 5 shows the consistency of the main analyses to alternative specifications and mechanisms underlying the results are presented in Section 6. I examine environmental justice dynamics in Section 7, and estimate mortality reductions and associated monetary health gains in Section 8. Section 9 concludes the paper.

2. POLICY CONTEXT, DATA AND DESCRIPTIVE STATISTICS

2.1. The 2008 British Columbian Carbon Tax

The introduction of the British Columbia (BC) carbon tax was formally announced in the provincial budget plan in February 2008, catching the public off guard due to the unexpected nature of this move by the Liberal government (Harrison, 2012; Ahmadi *et al.*, 2022). The policy aimed to reduce emissions by a minimum of 33% below 2007 levels by 2020 (Azevedo *et al.*, 2023). Implemented on July 1, 2008, the initial tax rate was set at \$10/tonne CO_2eq and increased by \$5/tonne CO_2eq annually until it reached \$30 in 2012, establishing one of the highest carbon prices globally at the time (Murray and Rivers, 2015; Azevedo *et al.*, 2023). The carbon tax rate remained at \$30 until 2018, when it increased to \$35, with a subsequent annual increment of \$5 anticipated until it reached \$50/tonne in 2022. The tax, applicable to all fossil fuel purchases in BC, accounts for approximately 77% of the province's total greenhouse gas (GHG) emissions, underscoring the comprehensive scope of the policy (Murray and Rivers, 2015; Rivers and Schaufele, 2015; Ahmadi *et al.*, 2022; Azevedo *et al.*, 2023). Notably, the most affected sector is transportation, which contributed to 43.9% of the province's total CO_2 levels in 2007; exemptions cover exported fuels, non-combustion GHGs (e.g. landfill methane), and emissions generated outside BC[5].

A key aspect of implementing the BC carbon tax is its commitment to revenue neutrality, serving as a crucial mechanism to secure public support and mitigate resistance to additional taxation, a notable challenge in the execution of carbon pricing schemes (Carattini *et al.*,

[5] This excludes a significant portion of air transportation and non-metallic mineral manufacturing emissions. Additionally, non-fossil fuel sources like fugitive emissions and chemical processes are exempted, broadening the range of exclusions (Azevedo *et al.*, 2023).

2017; Carattini *et al.*, 2019)[6]. The revenue-neutral design of the tax involved returning funds to consumers and businesses through various means, including direct transfers to low-income individuals, income tax reductions, and corporate tax cuts (Murray and Rivers, 2015; Ahmadi *et al.*, 2022). In particular, the achievement of revenue neutrality in BC involves two primary mechanisms. Firstly, by initiating a 5% reduction in the bottom two income tax brackets, BC secured the lowest income tax rate in Canada for individuals earning up to $122,000. This reduction was complemented by additional measures such as the "low income climate action" tax credit and the Northern and Rural Homeowner benefit (Azevedo *et al.*, 2023)[7]. Secondly, a series of reductions were applied to the general corporate tax rate, starting at 12% in 2008 and gradually decreasing to 11%, 10.5%, and 10% in 2010 and 2011, before returning to 11% in 2014. Simultaneously, the small business corporate income tax rate decreased from 4.5% to 2.5 % in 2008 (Azevedo *et al.*, 2023)[8]. According to the Budget and Fiscal Plan, the carbon tax generated approximately $1.2 billion in annual revenue since 2012 when the rate stabilized at $30/tonne CO_2eq, with around $1.4 billion returned to consumers (Ahmadi *et al.*, 2022; Azevedo *et al.*, 2023).

Given the popularity of the carbon tax, it is unsurprising that economists have conducted several analyses of its effectiveness across a range of measures. Focussing on the transport fuel market, Rivers and Schaufele (2015) and Lawley and Thivierge (2018) find 5-8% reductions in gasoline demand due to the tax implementation. Azevedo *et al.* (2023) investigate the employment response to the tax: the absence of aggregate effects masks heterogeneous impacts, with large emission-intensive firms negatively affected and small businesses benefitting from the policy. In terms of global pollutants, Ahmadi *et al.* (2022) detect emissions reductions in the manufacturing sector, while the multisectoral analysis of Pretis (2022) identifies significant reductions in transportation emissions with negligible effects on the remaining sectors of the economy.

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[6] Subsequent to the initial "Axe the tax" campaigns leading up to the 2009 provincial elections, polling data indicated a sustained increase in public approval of the tax until 2015 (Murray and Rivers, 2015). However, after 2012, there was a shift towards earmarking some revenues for specific sectors, creating a mixed system of redistribution (Murray and Rivers, 2015). Public opinion on the carbon tax was initially volatile, with campaigns against it leading up to the 2009 provincial elections, but sustained approval was observed until 2015 (Murray and Rivers, 2015). Recent studies, though, suggest that attitudes towards carbon pricing may be more influenced by partisan identities than updated information about potential rebates (Mildenberger *et al.*, 2022).

[7] The low income climate action tax credit was initially set as $100 per adult plus $30 per child, and subsequently raised to $115.50 per adult and $34.50 per child (Ministry of Finance, 2009; Ministry of Finance, 2013). The Northern and Rural Homeowner Benefit amounts to $200 but only applies to howeowners in areas outside the Capital (Victoria CMA), Greater Vancouver (Vancouver CMA) and Fraser Valley (Abbotsford CMA) regional districts. The appropriate rebate to compare to health gains is thus the low income climate action tax credit.

[8] Since 2008, various tax credits, ranging from the BC Seniors Home Renovation Tax Credit to the Film Incentive BC tax credit, have been implemented, contributing to the revenue redistribution.

2.2. Data and descriptive statistics

In order to analyse the effect of British Columbia's 2008 carbon tax on air quality, I assemble and process information on local pollutants' concentrations, geographic characteristics, and socio-economic dynamics from multiple sources. The observational units used in the analysis are Dissemination Areas (DAs), the smallest standard geographic areas for which Canadian census data are disseminated. Since the paper is concerned with analysing the effect of carbon pricing on air quality in cities, I restrict the geographic scope of the dataset to 26 Canadian Census Metropolitan Areas (CMAs), thereby excluding rural areas and smaller towns[9]. Canadian census data is obtained from von Bergmann *et al.* (2022), while DA census boundaries are converted to common geographies based on von Bergmann (2021), and using DA administrative boundaries from the 2016 Canadian census as the target geography. My final dataset is thus comprised of 25,479 DAs observed over 19 years, from 2000 to 2018, across 26 CMAs. The main outcome variable employed in the paper is yearly average $PM_{2.5}$ concentration from Meng *et al.* (2019), which combine information from satellite-retrieved Aerosol Optical Depth with simulations and ground-based observations obtained from monitoring stations readings. I extract the mean value of yearly $PM_{2.5}$, weighted by grid-cell level population counts obtained from Rose *et al.* (2020), onto the 25,479 DAs which constitute my dataset for every year between 2000 and 2018[10].

The main advantage of this source compared to data obtained from monitoring stations is its much wider spatial and temporal coverage, which also allows me to overcome the selection problem mentioned in Grainger and Schreiber (2019) relative to the location of monitoring stations within urban areas[11]. The entity of data loss when using ground-based data is considerable: $PM_{2.5}$ data from the National Atmospheric Surveillance Program (NAPS) is only available for 61 DAs in 2000, growing to 230 in 2018 as new monitoring stations get added every year (see Figure A.1). Nonetheless, the satellite-retrieved measurements from Meng *et al.* (2019), when restricted to the DAs with at least one $PM_{2.5}$

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[9] The CMAs in the dataset are: St. John's, Halifax, Saint John, Quebec, Trois Rivieres, Sherbrooke, Montreal, Ottawa, Saguenay, Kingston, Toronto, Hamilton, St. Catharine's, Kitchener, London, Windsor, Sudbury, Thunder Bay, Winnipeg, Regina, Saskatoon, Calgary, Edmonton, Abbotsford, Vancouver, and Victoria. While the number of Canadian CMAs is 35 in the latest available census wave (2016), I only keep in the dataset those CMAs which were designated as such in the 2001 Census, in order to ensure compatibility across all waves.

[10] The resolution of the $PM_{2.5}$ raster data is 0.01°x 0.01°, while population data is available for grid cells of dimension 0.0083° x 0.0083°, implying that the population raster had to be resampled at the resolution of the $PM_{2.5}$ raster in order to be viable for use in the weighted mean calculation.

[11] Monitoring stations are likely to be located where air pollution is lower due to strategic behaviour and discrimination by local regulators, thereby introducing measurement error in an eventual empirical analysis.

ground monitoring station, correlate well with the NAPS readings, as shown in Figure A.2 and Figure A.3.

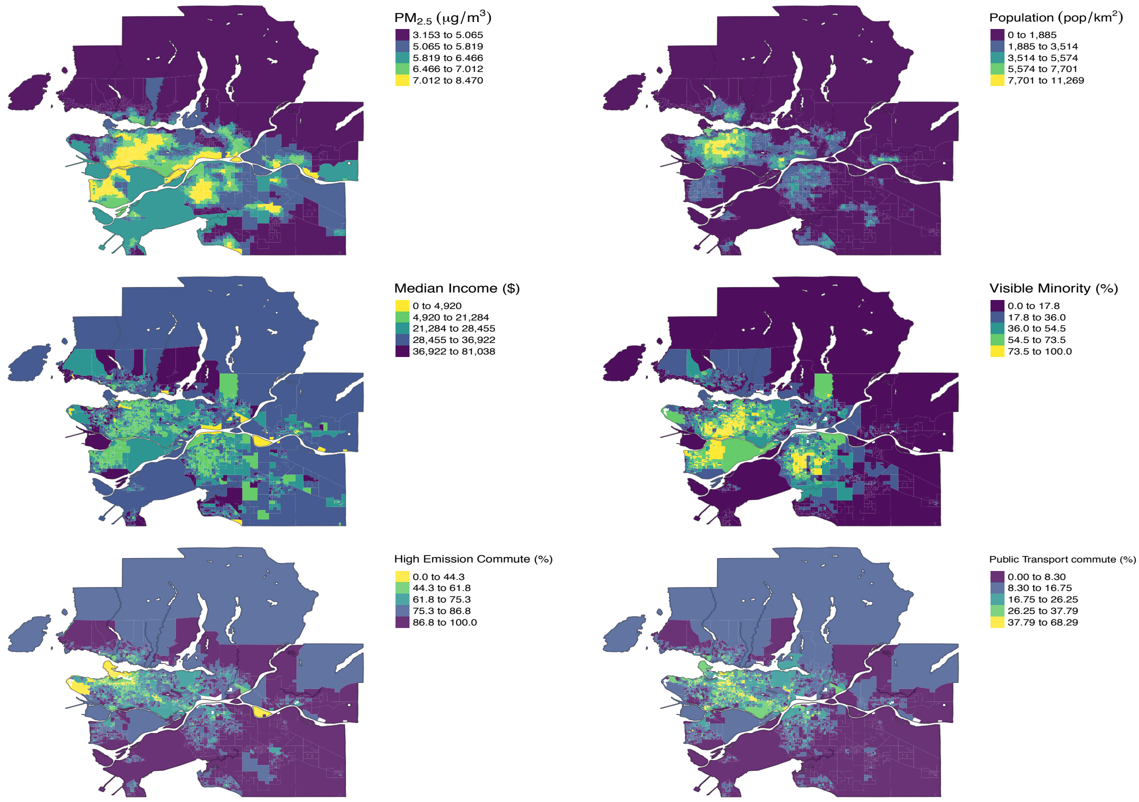
I rely on the Meng *et al.* (2019) $PM_{2.5}$ estimates in order to produce my main results. However, I also run the main analysis using $PM_{2.5}$ concentration data from van Donkelaar *et al.* (2019). While the two estimates are highly related, with a Pearson correlation coefficient of 0.795 (see Figure A.4 and Figure A.5), the concentrations from Meng *et al.* (2019) are generally lower throughout the sample[12]. In terms of relevant covariates and environmental justice dimensions, I first obtain population counts at the DA level from Rose *et al.* (2020), which are available for all years between 2000-2018[13]. Further, I employ four waves of the Canadian census (2001-2016 at 5-year intervals) to retrieve information on median income at the DA level, and on the racial composition of the DA population, calculating the share of population belonging to a visible minority and the Theil's Entropy Index (Iceland, 2004) for racial diversity. I also extract the 2006 Material Deprivation Index from Pampalon *et al.* (2012) for all DAs in my sample. If the carbon tax was successful in producing a behavioural adjustment in BC residents, an expected result would be higher take up of alternative means of transport within metropolitan areas. Therefore, I leverage the detailed information contained in the four waves of Canadian census data to retrieve DA-level data on commute mode shares. I divide commute modes in two different categories: high emissions (cars, taxis, and motorcycles), and low emissions (public transport, bicycles, and walking)[14].

Figure 1 plots the baseline spatial distribution of the dependent variable and the main covariates over the Vancouver CMA, the most populated metropolitan area in the treated province of British Columbia. Time-varying variables are averaged over 2005-2007, the three years preceding the implementation of the carbon tax, while all variables retrieved from the Canadian Census are taken at their 2006 values, the last observation before the tax was instituted. The distibution of $PM_{2.5}$ concentrations is highly spatially correlated with population density, as found e.g. in the US by Carozzi and Roth (2023) or Germany by Borck and Schrauth (2021). Confirming the insights of the enviromental justice literature (Cain *et al.*, 2024) racial diversity and the inverse of median income are also highly spatially correlated with air pollution at the baseline. Baseline commute mode seems to be inversely related with the spatial distribution of $PM_{2.5}$: areas whose inhabitants are less reliant on cars,

[12] The choice of employing data from Meng *et al.* (2019) is conservative, as results using the van Donkelaar *et al.* (2019) dataset are generally higher in magnitude.
[13] The dataset also contains population counts for all DAs extrapolated from Canadian censuses; however, this data is only available in 5-years intervals between 2001 and 2016.
[14] I further decompose the low emissions category into public transport only and zero emissions commutes (cycling and walking).

taxis and motorbikes seem to be more polluted on average, a result probably due to their centrality with respect to the road networks and urban form[15].

FIGURE 1 • DESCRIPTIVE STATISTICS AT THE BASELINE



Notes: Spatial distribution of $PM_{2.5}$ and relevant covariates within the Vancouver CMA. Top row: $PM_{2.5}$ and population density; Middle row: median income and visible minority population share; Bottom row: high emission and public transport commute mode shares.

Lastly, I obtain monthly information on the BC gasoline and diesel fuel markets, at the province level, for January 1991-December 2016. In particular, I extract the annual sales of transportation fuels (motor gasoline and diesel), from Statistics Canada (2021b), gasoline and diesel price data from Kalibrate (formerly Kent Group Ltd.) at the monthly level for the city of Vancouver, which I consider representative of the entire province, monthly after tax income and unemployment rate data from Statistics Canada (2021c), and the CAD-USD monthly exchange rate, retrieved from the Pacific Exchange Rate Service at University of British Columbia's Sauder School of Business.

[15] Summary statistics for the whole sample, split across treatment and control CMAs, are presented in Table A.1 and Table A.2 for the pre-treatment and post-treatment periods, respectively.

3. EMPIRICAL STRATEGY

3.1. Simple and matched difference-in-differences

The core aim of my empirical strategy is to estimate the treatment effect of the 2008 British Columbian carbon tax on local air pollution, measured in terms of $PM_{2.5}$ concentrations at the DA level. A traditional methodology for this estimation is a two-way fixed effects difference-in-differences (TWFE-DID) regression. The estimating equation takes the form:

$$PM_{2.5it} = \tau^{did} D_{it} + \theta_t + \eta_i + \varepsilon_{it} \quad (1)$$

Where D_{it} is the DID binary indicator, taking value 1 for all treated units after the implementation of the carbon tax in 2008, and 0 for all other observations; θ_t and η_i are respectively time and unit specific fixed effects, ε_{it} is a time-varying idiosyncratic error term, and τ^{did} is the coefficient of interest, capturing the average effect of being exposed to the carbon tax.

In order for τ^{did} to be equal to the average treatment effect on the treated cohort (ATT), the identifying assumption is that parallel outcome trends between the treated and the control units hold, i.e. if the 2008 carbon tax had not been implemented in British Columbia, $PM_{2.5}$ levels in British Columbian DAs would have followed the same trajectory as $PM_{2.5}$ levels in DAs located in other Canadian provinces. Figure A.6 and Figure A.7 report the average $PM_{2.5}$ trends for 2000-2016 and 2000-2018, respectively, for British Columbian and control DAs, together with the universe of $PM_{2.5}$ observations. The parallel trends assumption is untestable by definition, but it is essential to inspect the pre-treatment outcome paths and the distribution of treatment and control observations around their mean pre-intervention trends. In both cases, there is reason to suspect that the DID estimator would fail to identify the correct ATT. A visual inspection pre-treatment trends suggests a violation of the parallel trends condition (more evidently in the case of Figure A.7), while a more formal placebo DID regression of $PM_{2.5}$ on treatment status with data limited to 2000-2007 and treatment assigned in 2004 identifies a significant placebo divergence in trends in both cases (Table A.3). Moreover, the dispersion of control observations around their mean trends is much higher than for treatment units, revealing substantial heterogeneity: by giving equal weight to all control observations, DID will include units whose pre and post-treatment outcome paths fundamentally differ from those of DAs in British Columbia, likely introducing an upward bias in the coefficient.

A potential solution to the pre-treatment heterogeneity in levels and trends is matching treatment and control groups on the basis of baseline pollution levels and on covariates which influence air quality. Restricting the analysis to DAs which experience similar outcomes and are exposed to similar pollution stressors can attenuate the pre-treatment dispersion in $PM_{2.5}$ levels and divergence in trends, and ensure the sample is more balanced before performing the DID regression (Imbens, 2015). I use one-to-one matching, moving away from the traditionally employed propensity score algorithm and instead preferring Coarsened Exact Matching (CEM) (Iacus *et al.*, 2012). I perform two versions of this procedure: in the first one (MDID1), I match treatment and control units on the baseline (2005-2007) average level of $PM_{2.5}$. In the second one (MDID2), I add baseline averages of population density, median income, high emission commute mode share, and road density. I exploit CEM to pre-process and trim the sample before running a weighted TWFE-DID regression using the CEM matching weights $\widehat{\omega^{cem}}$ in the following form:

$$PM_{2.5it}\sqrt{\omega_i} = \tau^{did} D_{it}\sqrt{\omega_i} + \theta_t\sqrt{\omega_i} + \eta_i\sqrt{\omega_i} + \varepsilon_{it}\sqrt{\omega_i} \qquad (2)$$

3.2. Synthetic control method and synthetic difference-in-differences

The problem of diverging pre-treatment trends in empirical applications is often addressed through the SCM (Abadie and Gardeazabal, 2003; Abadie, 2021)[16]. In the BC carbon tax case, the SCM constructs a set of synthetic DAs as a weighted combination of control DAs by finding, for each treated unit i, a non-negative vector of weights ω^{sc} summing to one, which ensures that each convex combination of the i outcome variable for control units matches each outcome variable for the treated units for all periods up to the intervention date.

In order to combine the attractive features of both TWFE-DID (the inclusion of additive unit-specific and time-specific fixed effects), and SCM (reducing the reliance on the parallel trends assumption by weighting observations in order to ensure closely matched pre-intervention trends), Arkhangelsky *et al.* (2021) have introduced a new method, synthetic difference-in-differences (SDID), which employs time and unit (two-way) fixed effects in the regression function (as in TWFE-DID), together with unit-specific weights (as in SCM) and time-specific weights which lessen the role of time periods that are largely divergent from post-treatment time periods. In a nutshell, for each treated unit SDID estimates: (1) unit weights ${\omega_i}^{sdid}$ which underpin a synthetic control whose outcome is approximately parallel to the outcome for the treated unit; (2) time weights λ_t^{sdid} which ensure that the average post-treatment outcome for control units only differs by a constant from the weighted average of pre-treatment outcome for each of the control units – a synthetic pre-

[16] Usually with a unique treated unit, but extensible to the case of multiple treated units.

treatment period using controls. Once unit and time weights are calculated, SDID estimates a TWFE regression on the resulting panel, identifying the SDID ATT τ^{sdid} by solving the minimisation problem[17]:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\eta}, \hat{\theta}\right) = \underset{\tau,\mu,\eta,\theta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (PM_{2.5it} - \mu - \eta_i - \theta_t - \tau D_{it})^2 \widehat{\omega_i}^{sdid} \hat{\lambda}_t^{sdid} \right\} \quad (3)$$

In the remainder of the paper, I regard SDID as my preferred method in order to estimate the effect of the 2008 BC carbon tax on air pollution co-benefits, as the methodology allows me to overcome the apparent violation of the parallel trends assumption and pre-treatment outcome heterogeneity problems in conventional DID; nonetheless, I estimate my main regression and robustness checks using DID, MDID, SCM and SDID, in order to assess the direction of the potential bias. I calculate standard errors for SCM and SDID using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021, p. 4109), with 200 replications. The procedure constructs a bootstrap dataset by sampling a portion of the original dataset with replacement, and computes the estimator $\tau^{(b)}$ on this subset for each iteration b. The variance is then defined as:

$$\hat{V}_{\tau}^{\,b} = \frac{1}{b} \sum_{b=1}^{B} (\hat{\tau}^{(b)} - \frac{1}{B} \sum_{b=1}^{B} \hat{\tau}^{(b)})^2 \quad (4)$$

4. Results

In Table 1, I report the results of the DID, MDID, SCM and SDID regressions, using the Meng *et al.* (2019) $PM_{2.5}$ dataset. The simple DID regression is also reported graphically, alongside the outcome path plots for SCM and SDID, in Figure 2. It is immediate to note how the violation of the parallel trends assumption examined in Table A.3 and Figure A.6 results in a likely case of upward bias for the simple DID, confirmed by the positive and significant coefficient, $\hat{\tau}^{did}$ = 0.39μg/m³, reported in column (1) of Table 1 and in the leftmost panel of Figure 2. This result would indicate that the carbon tax has resulted in an increase of $PM_{2.5}$ emissions, which would contradict the findings by Rivers and Schaufele (2015) and Pretis (2022) on fuel consumption and CO_2 emissions. MDID1 and MDID2 results are instead obtained by pre-processing the sample using the CEM procedure

[17] Section A2 presents a detailed formal comparison between TWFE-DID, SCM, and SDID, drawing on the seminal work of Arkhangelsky *et al.* (2021).

described in Section III, matching on baseline $PM_{2.5}$ levels in column (2) and on baseline $PM_{2.5}$, population density, median income, high emission commute mode share and road density in column (3). The matching procedure produces estimation samples which are much more closely aligned (Figure A.8 and A.9), and reverses the sign on the simple DID estimates, with negative and significant results contained in the $\hat{\tau}^{mdid} = [-0.27, -0.35]$ $\mu g/m^3$ range that are a first indication of the incidence of carbon pricing on air quality co-benefits. Moving away from simple DID estimation seems to be an effective strategy in minimising the impact of diverging trends and unbalanced pre-treatment characteristics.

Columns (4) and (5) confirm this insight by relying on the SCM and SDID methods, which also identify negative and statistically significant effects of the tax in reducing $PM_{2.5}$ emissions. In the centre panel of Figure 2, I plot the average outcome path for the treated units and the traditional synthetic control. The improvement in pre-treatment fit is dramatic, with a minimal average deviation between British Columbian DAs and their controls, implying that the SCM performs well in giving positive weights to control units which best approximate treated DAs' outcome paths and zero weight to control units which exhibit different trends. Consistently with the hypothesised bias of the simple DID estimator, SCM indeed agrees with MDID in identifying an effect of opposite sign to DID, $\hat{\tau}^{sc} = -0.14$ $\mu g/m^3$. Results for the SDID estimator are graphically shown in the right-most panel of Figure 2. At the bottom of the panel, pre-treatment time-weights are represented in pink. Pre-treatment periods are weighted to match post-treatment levels (plus a constant) in the outcome variable for the control units. The SDID estimator does a particularly good job in imposing pre-treatment parallel trends in the years preceding the tax, even if weights λ_t are unevenly distributed over the pre-intervention period. However, negligible weights in 2007-2008 are reassuring, given that a standard caveat in event-study methodologies is the excessive reliance on the single period immediately preceding the intervention (Heckman and Smith, 1999). The SDID procedure is able to select control units which exhibit pre-treatment trends that are almost perfectly parallel to BC's outcome path, especially in the four-year window preceding the intervention. The estimated ATT is $\hat{\tau}^{sdid} = -0.36$ $\mu g/m^3$, corresponding to a 5.2% reduction with respect to pre-intervention mean pollution levels. I regard SDID as the preferred methodology due to its greater flexibility and to the selection of a sparser set of control DAs[18]. While SCM obtains a near-perfect fit pre-treatment, the outcome path of its synthetic unit

[18] SDID selects indeed 6,258 control units among the untreated DAs and then performs DID on the matched sample with the inclusion of unit and time fixed effects to aid the estimation.

heavily depends on the particular set of units receiving positive weights, which in my highly disaggregated setting is not ideal[19].

TABLE 1 • THE 2008 CARBON TAX AND CHANGES IN $PM_{2.5}$

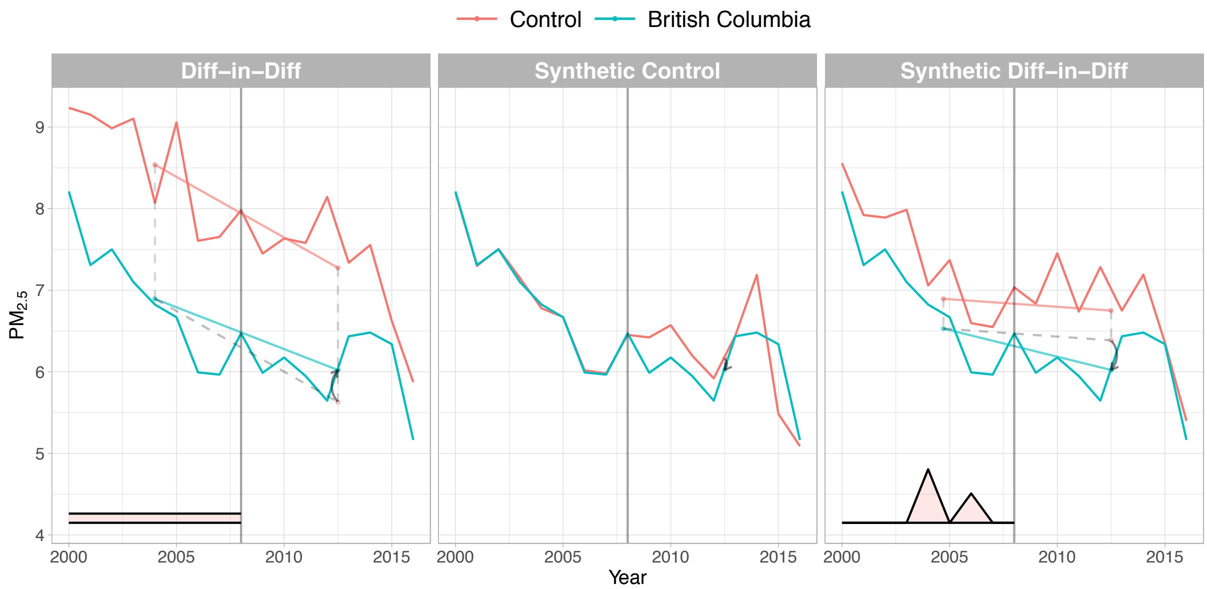
	(1) ***DID***	(2) ***MDID1***	(3) ***MDID2***	(4) ***SCM***	(5) ***SDID***
$\hat{\tau}$	0.3925 (0.074)	-0.2750 (0.1495)	-0.3504 (0.1676)	-0.1421 (0.0809)	-0.3633 (0.0219)
Unit FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
ω_i		$\sqrt{\omega_i}$	$\sqrt{\omega_i}$	Yes	Yes
λ_t					Yes
N_{obs}	432939	305320	132430	432939	432939

Notes: All point estimates represent the average impact of the 2008 carbon tax during the 2009-2016 post-treatment period. Standard errors in parentheses are calculated using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021) with 200 replications for columns (1), (4) and (5), and are clustered at the CMA level for columns (2) and (3). In Column (2) the data is pre-processed by matching on coarsened bins of baseline $PM_{2.5}$ levels. Column (3) additionally matches on population density, median income, high emissions commute mode share and road density at the DA level. All regressions use 2000-2016 data.

Notably, MDID, SCM and SDID all agree in identifying a negative and statistically significant effect of the 2008 carbon tax on $PM_{2.5}$ emissions, contradicting "naive" DID estimates. The potential bias arising in the simple DID regression could be due to the diverging secular trends between treatment and control units, with treatment units on steeper declining trends prior to the implementation of the tax vis-à-vis control units. It is thus essential to address this concern in order to obtain a "clean identification" of the policy impact (Sager and Singer, 2024). Failing to do so would introduce a source of bias which could go as far as reversing the correct estimates. Finally, while I regard SDID as the preferred methodology over SCM due to its flexibility and its reliance on a larger portion of the control pool, it is crucial to note that the MDID in this instance obtains results which are similar in magnitude.

[19] In Figure A.10, I aggregate all 6,258 DAs which receive positive weights to the CMA level, in order to obtain the composition of synthetic BC in terms of percentages of other Canadian CMAs, in a similar vein to the traditional SCM methodology of Abadie (2021).

FIGURE 2 • THE IMPACT OF THE 2008 CARBON TAX ON CHANGES IN $PM_{2.5}$



Notes: Graphical results from DID, SCM and SDID for $PM_{2.5}$ concentrations, with Meng *et al.* (2019) data. The 2008 carbon tax is denoted by a black vertical line. Pre-treatment time weights λ_t are denoted in pink.

5. Robustness checks

5.1. Main results with van Donkelaar et al. (2019) $PM_{2.5}$ data

I repeat the DID, SCM and SDID estimation using the van Donkelaar *et al.* (2019) $PM_{2.5}$ dataset, which is available between 2000 and 2018. Notwithstanding the high correlation between the two outcome variables, as outlined in Figure A.4, both the treatment and control pre-intervention trends exhibit some differences with respect to the Meng *et al.* (2019) dataset[20]. The violation of the parallel trends assumption is once again highlighted in a placebo DID regression (Table A.3), as well as in the graphical representation of the DID regression in Figure A.12 which, differently from the previous estimation, identifies a negative effect of the 2008 carbon tax on emissions of $\hat{\tau}^{did} = -0.5\mu g/m^3$ (see Table A.4).

The SCM, represented graphically in the middle panel of Figure A.12, again obtains a good pre-treatment fit, signalling that each British Columbian DA's outcome path is best approximated by a convex combination of control DAs rather than equally weighted

[20] However, the temporal location of peaks and troughs is generally respected, as is the relationship between the BC and control units outcome path. Indeed, DAs located in British Columbia always exhibit lower average annual concentrations of particulate pollution, and their $PM_{2.5}$ trend prior to 2008 appears to decline at an even faster pace than for control observations, barring some peaks in concentrations typical of the control provinces.

control units. Furthermore, as evidenced in Table A.4, the potential direction of the TWFE-DID bias is consistent with the main result: the SCM estimates a negative ATT of $\hat{\tau}^{sc} = -0.71\mu g/m^3$, therefore qualitatively reinforcing the SCM result of Table 1. A similar conclusion can be drawn from the results of the SDID estimation, presented in the right-most panel of Figure A.12. The SDID procedure is able to select control units[21] which exhibit pre-treatment trends that are almost perfectly parallel to BC's outcome path, with the exception of outlying time periods which receive zero-weights in the estimation. The estimated ATT of $\hat{\tau}^{sdid} = -0.89\mu g/m^3$ is slightly lower, but qualitatively similar to the SCM ATT. In terms of magnitude, both the SCM and SDID regressions identify a substantial drop in $PM_{2.5}$ concentrations with respect to 2000-2007 levels, corresponding to a reduction of 10.9% from the pre-intervention $PM_{2.5}$ mean for British Columbia.

2.2. Accounting for measurement error in satellite-based estimates

The remotely sensed $PM_{2.5}$ datasets which I employ are gridded estimates of concentrations and may contain prediction error, which could substantially alter regression results (Fowlie *et al.*, 2019). I assess the robustness of my estimates to this type of non-classical measurement error, by exploiting the geographic correspondence between gridded $PM_{2.5}$ data and DAs which contain at least one NAPS monitoring station, in order to construct a spatially matched dataset containing predicted and observed $PM_{2.5}$. I first calculate prediction error as the difference between satellite-derived $PM_{2.5}$ and monitor readings for the 1501 DA-year pairs which contain at least one NAPS monitoring station. As in Fowlie *et al.* (2019), I then regress prediction error $\Delta PM_{2.5}$ on a set of covariates at the DA level[22] and I predict out of sample $\Delta PM_{2.5}$ for the entire dataset.

I adjust remotely sensed $PM_{2.5}$ data by accounting for prediction error, and use the quantity $\widehat{PM_{2.5it}} = PM_{2.5it} + \Delta\widehat{PM_{2.5it}}$ to run SDID regressions using Meng *et al.* (2019) and van Donkelaar *et al.* (2019) data, respectively. The results, reported in Table A.5, are slightly lower though qualitatively similar to the main specifications, with $\hat{\tau}^{sdid} = -0.26\mu g/m^3$ using the Meng *et al.* (2019) dataset and $\hat{\tau}^{sdid} = -0.85\mu g/m^3$ using corrected van Donkelaar *et al.* (2019) data. The SDID estimator adequately identifies treatment effects by obtaining pre-treatment parallel trends in both instances (Figure A.13). The adherence between these results and the main specifications reinforces confidence about correctly measuring the policy effects. While the substantial difference between estimated treatment effects using the two gridded $PM_{2.5}$ datasets remains, this is likely due to their calibration and prediction

[21] The composition of the donor pool, aggregated to the CMA level, is reported in Figure A.11.
[22] Namely, satellite-based $PM_{2.5}$, population density, nighttime lights, maximum and minimum temperature, and wind speed.

procedures rather than prediction error. I conservatively adopt lower bound estimates using the Meng *et al.* (2019) as the main result, and regard all estimates using the van Donkelaar *et al.* (2019) product as the upper bound on my results.

5.3. Narrower temporal and spatial scope

Effect Dynamics: I restrict the estimation window to 2000-2013, in order to check whether the carbon tax ramp-up is the main mechanism behind the continuous reductions, and to what extent does the post-2013 tax rate freeze reverse the improvements[23]. The results, presented in Figure A.14 and Table A.6 identify a higher ATT of $\hat{\tau}^{sdid} = -0.67$ μg/m^3, which corroborates the hypothesis. The dynamics of the carbon tax phase-in are thus an important component of observed reductions: the effect is almost double in size in the first 5 years of the tax scheme, when tax rates increase step-wise every year. Air pollution improvements slightly reverse and stabilise at a lower level once the tax signal is kept constant.

Main CMA: I confine the treated pool to DAs within the Vancouver metropolitan area, excluding all DAs in the Abbotsford and Victoria CMAs. The resulting treatment cohort is comprised of 2874 DAs, vis-à-vis the 3490 DAs constituting the entire treatment unit pool; the control pool is kept the same, with 21989 control DAs. Perhaps unsurprisingly, given the relatively small number of DAs pertaining to the Abbotsford and Victoria CMAs, the results (reported in Figure A.15 and Table A.7) are qualitatively unchanged from the main regressions using the Meng *et al.* (2019) dataset.

NAPS Locations: I select DAs corresponding to the location of NAPS monitoring stations (see Figure A.1)[24]. I thus consider just those locations in which pollution monitors have been established, thereby restricting the analysis to areas in which pollution is likely to be a greater concern. Here, the size of the dataset is considerably restricted: the cross-section of DAs kept in the treated pool counts just 25 observations, while 106 DAs are kept in the control pool. Once again, the results (presented in Figure A.16 and Table A.8), are qualitatively similar to the main specifications. Notably, the performance of the SDID estimator is not considerably worsened on this much smaller sample, achieving a reasonable pre-treatment fit, and therefore identifying a credible ATT.

[23] In 2012, the carbon tax was frozen at \$30/tCO_2 as reported in Section 2.

[24] I match DAs with all monitoring stations in the dataset, regardless of the date of establishment of each monitoring station, in order to maximise observations.

6. MECHANISMS

6.1. Reductions in transport fuel demand

The first candidate explanation for the observed reductions in particulate matter concentrations is a change in consumer behaviour regarding transportation fuel. Some evidence supporting this explanation is found in early analyses of the BC carbon tax (e.g. Rivers and Schaufele, 2015; Lawley and Thivierge, 2018), which use a limited post-intervention time period and only focus on gasoline consumption[25]. On the contrary, fuel substitution away from gasoline and towards diesel is claimed to be a potential mechanism behind the $PM_{2.5}$ increases found in Saberian (2017), notwithstanding the negative impacts found by the time series analysis of Bernard and Kichian (2019) and the strong prevalence of gasoline vehicles among BC car sales (see Figure A.19 and A.20).

I reconcile the evidence on the aggregate level effects of the carbon tax on transportation fuel demand by introducing a recently developed method for high-frequency time series analysis: the Causal-ARIMA (C-ARIMA) estimator of Menchetti *et al.* (2022). By exploiting features of ARIMA models, the method is especially appropriate to analyse complex seasonal, nonstationary processes such as gasoline and diesel sales observed monthly (see Figure A.17, panels A and B). C-ARIMA combines attractive features from the DID and SCM estimator for the case in which no suitable control unit is available[26] and when the number of pre-intervention time periods is large[27]. Under standard assumptions[28], C-ARIMA is able to learn the treated unit's time series dynamics and forecast it after the shock takes place. By using the forecasted series as the treated unit's counterfactual outcome, the method identifies two main sets of causal effects: the temporal average causal effect and the cumulative treatment effect.

I run C-ARIMA separately for per capita monthly gasoline and diesel sales at the aggregate BC level between January 1991 and December 2016. The intervention date is July 2008, i.e. the specific month in which the BC carbon tax came into effect. In Table 2, I report the

[25] Which accounts for most of the residential vehicle fleet (see Figure A.19) but does not include heavy duty vehicles used in commercial and industrial operations (Bernard and Kichian, 2019).
[26] In my context, a pool of eligible control units is represented by other Canadian provinces. However, other provinces exhibit diverging pre-intervention trends in gasoline sales (see Figure A.18) when aggregating the TWFE-DID coefficients into an event study plot.
[27] As is the case in the monthly analysis of BC fuel consumption between January 1991 and December 2016, with 210 pre-intervention time periods.
[28] No temporal interference (i.e. absence of anticipation effects), covariates-treatment independence and conditional stationarity (Menchetti *et al.*, 2022).

results from estimations with and without a matrix of business cycle controls[29]. Both the temporal average causal effect $\widehat{\tau_t}$ and the cumulative causal effect $\sum_{t=t_{int}}^{T} \widehat{\tau_t}$ are negative and statistically significant across all specifications, highlighting a successful impact of the BC carbon tax in decreasing fuel demand, consistently with Rivers and Schaufele (2015) and Bernard and Kichian (2019). In Figure A.17, the results from the estimation are reported graphically.

TABLE 2 • C-ARIMA: MONTHLY GASOLINE AND DIESEL DEMAND

	Gasoline Sales		**Diesel Sales**	
	(1)	(2)	(3)	(4)
$\hat{\tau}_t$	-3.883 (0.553)	-4.675 (0.506)	-1.756 (0.412)	-0.912 (0.236)
$\sum_{t=t_{int}}^{T} \widehat{\tau_t}$	-396.052 (56.453)	-818.405 (14.962)	-179.089 (42.066)	-92.983 (24.093)
Controls	-	Yes	-	Yes
N_{obs}	312	312	312	312

Notes: The dependent variable is total monthly gasoline (diesel) sales per capita (in litres) recorded in British Columbia benween January 1991 and December 2016. Columns (2) and (4) include a matrix of monthly province-level covariates, namely consumer price index, gasoline (diesel) crude cost, population, unemployment rate, after tax income and the US-CAD exchange rate. Standard errors in parentheses are computed through 1000 bootstrap runs.

6.2. Commute mode switching

I analyse commute mode choices at the DA level as an additional mechanism driving the main results. While commute mode is an imperfect measure of the number and type of trips made by British Columbians, I can rely on the same administrative level to the one used in the main analysis by retrieving information from the 2001, 2006, 2011, and 2016 Canadian censuses, thereby preserving granularity. In Table 3 and Table 4, I report TWFE-

[29] Namely, provincial population, unemployment, after tax income, exchange rate and the cost of crude gasoline and diesel, respectively.

DID regression results[30] employing the share of commuters using high-emissions and public transport commute modes, respectively[31].

In all tables, column (1) is the baseline specification, a simple DID regression with DA and year fixed effects and no controls, employing the full panel of DAs across census years. In column (4), I add weather controls for precipitation, maximum and minimum temperature, and wind speed, plus the natural logarithm of population and median income. When employing the full pool of control DAs, the first result of note is that British Columbian DAs experience an average 4.2% reduction in the use of cars, taxis, and motorcycles, which rises to 4.7% when adding controls. This reduction is almost specular to the increase in the share of commuters using public transport, biking and walking to reach their workplace (Table A.9). Moreover, as evidenced in Table 4 and Table A.10, most of this increase (3.5-3.9%) is due to a higher reliance on public transport, while a residual share of 0.5-0.7% is due to a switch to active commuting.

All results are confirmed and stronger in magnitude when considering more restrictive specifications: columns (2) and (5) restrict the specifications in (1) and (4) to the DAs which receive positive weights in the main SDID regressions, in order to establish whether the mechanisms are effectively retrieved when employing the same set of observations on which the main ATT is estimated. Results are higher in magnitude by about 1%, jumping to a 5.3% reduction in high-emission commute modes in the case without controls. Here, the inclusion of control variables slightly dampens the impact to 5.2%; nonetheless, the specularity with the increase in low-emission commute modes is preserved. Finally, in columns (3) and (6) I augment the DID regressions by retrieving an including the weights from the main SDID regressions. I weigh all treatment observations equally and all control observations according to the value of ω_i they receive after the data-driven SDID procedure. The magnitude of the increase in public transport commute share increases further, to 4.2% in the case without covariates and is again dampened to 4.1% in the case with covariates. The hypothesis of a behavioural adjustment by BC citizens in response to the carbon tax is thus confirmed; residents of BC's DAs switch away from high-emissions

30 Due to the structure of the data, collected at 5-year intervals, I am prevented from using the SCM and SDID methodology in this exercise; I thus resort to traditional TWFE-DID estimation of commute mode switching, analysing the data separately for each category of commute mode. Details on this estimation strategy are reported in Section B.

31 As the low-emissions transport mode is the sum of public transport and zero-emissions modes, I only report the results for public transport in the main text and present the aggregate low emissions and the sub-split for zero-emissions in Table A.9, and Table A.10.

commute modes towards low-emissions ones, with public transport as the main container for these substitutions.

TABLE 3 • DID RESULTS FOR HIGH EMISSIONS COMMUTE MODE

	High Emissions Commute Mode					
	(1)	(2)	(3)	(4)	(5)	(6)
DID	-0.0417	-0.0527	-0.0549	-0.0466	-0.0519	-0.0516
	(0.0105)	(0.0095)	(0.0103)	(0.0102)	(0.0106)	(0.0109)
DA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls				Yes	Yes	Yes
SDID control pool		Yes	Yes		Yes	Yes
SDID weights			Yes			Yes
R^2	0.87184	0.83989	0.84360	0.87595	0.84508	0.84847
Adj. R^2	0.82896	0.78629	0.79124	0.83400	0.79267	0.79721
N_{obs}	101358	38769	38769	100244	38348	38348

Notes: The dependent variable is the dissemination area level share of high emissions commutes. All regressions include dissemination area and year fixed effects. Columns (4)-(6) include controls for precipitation, maximum and minimum temperature, and wind speed, plus the natural logarithm of population and median income. Columns (2), (3), (5) and (6) restrict the control unit pool to DAs which receive positive weights in the main SDID regression. Columns (3) and (6) additionally include the estimated SDID unit weights ωi as regression weights. Standard errors in parentheses are clustered at the CMA level.

TABLE 4 • DID RESULTS FOR PUBLIC TRANSPORT

	Public Transport Commute Mode					
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.0352	0.0410	0.0417	0.0391	0.0422	0.0414
	(0.0107)	(0.0107)	(0.0112)	(0.0115)	(0.0115)	(0.0111)
DA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls				Yes	Yes	Yes
SDID control pool		Yes	Yes		Yes	Yes
SDID weights			Yes			Yes
R^2	0.83768	0.78668	0.78011	0.84196	0.79197	0.78571
Adj. R^2	0.78336	0.71526	0.70650	0.78851	0.72160	0.71322
N_{obs}	101358	38769	38769	100244	38348	38348

Notes: The dependent variable is the dissemination area level share of public transport commutes. All regressions include dissemination area and year fixed effects. Columns (4)-(6) include controls for precipitation, maximum and minimum temperature, and wind speed, plus the natural logarithm of population and median income. Columns (2), (3), (5) and (6) restrict the control unit pool to DAs which receive positive weights in the main SDID regression. Columns (3) and (6) additionally include the estimated SDID unit weights ωi as regression weights. Standard errors in parentheses are clustered at the CMA level.

7. ENVIRONMENTAL JUSTICE DYNAMICS

In light of a growing literature in environmental justice (see Banzhaf *et al.*, 2019; Cain *et al.*, 2024), I examine efficiency-equity trade-offs in the realisation of co-benefits, inspecting whether the estimated air pollution reductions arise heterogeneously over metropolitan areas. In the main analysis, the parameter identifying the effect of the 2008 BC carbon tax on $PM_{2.5}$ emissions has always been assumed as constant across treated units. Nonetheless, when dealing with disaggregated data within Census Metropolitan Areas, a homogeneously estimated ATT is likely to mask substantial heterogeneities across DAs which could be highly informative about the performance of different locations within metropolitan areas.

A first channel to explore is certainly that of pre-existing pollution levels: standard economic theory would in fact predict that emission abatement would happen first where the marginal cost of reducing emissions is lower, i.e. where pre-existing pollution is higher (that is, lower-hanging fruits would be picked earlier). This avenue is explored by Auffhammer *et al.* (2009) and Sager and Singer (2024), who find substantially higher reductions in $PM_{2.5}$ and PM_{10} due to the Clean Air Act in non-attainment US census tracts that are more polluted in the three years preceding the implementation of the policy. Nonetheless, the opposite result may also arise if the rate of vehicle replacement is higher in less polluted areas or if more polluted areas substitute more strongly towards less CO_2-intensive, but more $PM_{2.5}$ -intensive vehicles such as diesel automobiles or, crucially, diesel-powered public transport[32].

In light of the results of Borck and Schrauth (2021) and Carozzi and Roth (2023), it is also worth exploring whether heterogeneity in air pollution reductions arises at different levels of the population density distribution: indeed, while densely populated areas have been shown to experience higher concentrations of $PM_{2.5}$ particulate, usually population density is higher in city centres, where greater opportunities for substitution away from cars may arise. Again, the nature of the eventual substitution plays a crucial role in determining the direction of the realised effect[33].

The most investigated avenue in studies focussing on air quality and environmental justice dynamics is certainly that of racial disparities (e.g. Colmer *et al.*, 2020; Jbaily *et al.*, 2022; Currie *et al.*, 2023; Sheriff, 2024; Sager and Singer, 2024). This is possibly due to a relatively higher weight of US-centric studies in the literature, with much fewer evidence on extra-

[32] That is, if the implicit assumption of homogeneous abatement technology across locations is removed.
[33] To the point of determining detrimental impacts in case the substitute transport mode is more CO_2 efficient but emits greater $PM_{2.5}$ concentrations than the original one – such as the case of diesel-powered engines substituting for gasoline ones.

US contexts. Nonetheless, as shown in Figure 1, there is a high spatial correlation between the location of DAs with higher shares of visible minority population and the pre-intervention $PM_{2.5}$ distribution. It is thus extremely important to (1) assess whether there is an ex ante racial disparity in $PM_{2.5}$ exposure in British Columbian metropolitan areas, (2) examine whether ex post air quality racial EJ gaps fall or widen as a result of a market-based intervention such as a carbon tax.

Lastly, a large body of research has shown that carbon pricing is regressive along income and wealth dimensions (Poterba, 1991; Grainger and Kolstad, 2010; Sager, 2023), but its incidence depends on the destination of tax revenues (Metcalf, 2009; Davis and Knittel, 2019). While this insight is well understood, constituting for instance the basis for the BC low income climate action tax credit, there is much less certainty about the role of realised air quality co-benefits in mitigating or exacerbating income regressiveness. Indeed, if a disproportionately large share of co-benefits accrue to population in higher income brackets, there is an additional dimension of carbon tax inequality that is not factored in projected governmental revenue rebates.

In Figure 3, the long term changes in $PM_{2.5}$ concentrations are mapped out for the three BC CMAs in my sample, to individuate areas which have withstood more pronounced improvements. Confirming the traditional insights of the EJ literature (Colmer *et al.*, 2020; Jbaily *et al.*, 2022) there appears to be a secular convergence in air pollution concentrations: dense, central areas with higher initial $PM_{2.5}$ concentrations and higher levels of socioeconomic deprivation see greater absolute improvements in air quality.

These insights are only descriptive, as they do not take into account the potential for similar secular trends in control areas, nor the impact of the BC carbon tax on air pollution concentrations within a potential outcomes framework. Table A.11 and Table A.12 report ex ante and ex post gaps in observed $PM_{2.5}$ in British Columbia and control CMAs along the top and bottom quintiles of three covariates describing environmental justice dimensions: (1) baseline population density, (2) baseline share of population belonging to a visible minority (as a measure of racial disparity), (3) baseline median income[34]. It is straightforward to assess how, before the implementation of the carbon tax, EJ gaps manifest along every dimension in both subsamples. Denser, more racially diverse, and poorer areas of BC CMAs are comparatively more polluted at the start of the sample, by 1.9-2.2 3 $\mu g/m^3$, or 27-32% of the pre-treatment $PM_{2.5}$ average level in treated units. Similar EJ gaps are observed in control DAs, with generally higher pollution levels across quintiles.

[34] In Figure A.22, I also use Material Deprivation Index and the Theil Entropy Index for racial diversity.

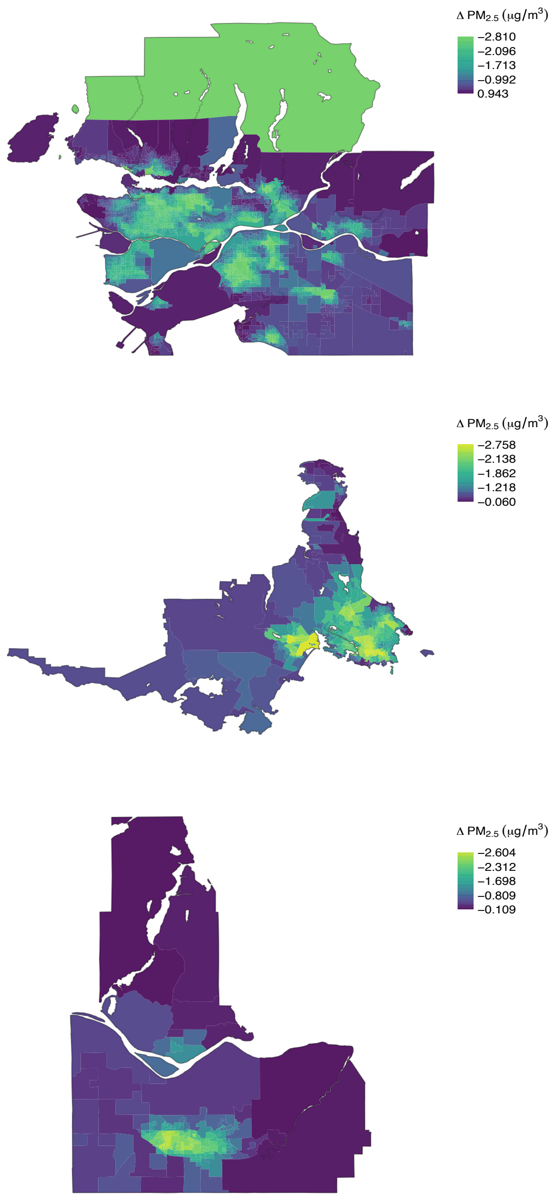
For all DAs in treated and control CMAs, EJ gaps reduce substantially in the last three years of the sample, to 1-1.3 μg/m^3 in BC and 0.5-1.2 3 μg/m^3in control DAs.

Reading the statistics reported in Table A.11 and Table A.12 in conjunction, the pollution convergence hypothesis is not only confirmed for BC, but emerges as a common trend, with EJ gaps shrinking along every dimension across all Canadian DAs in the sample. It is thus important to examine whether the 2008 BC carbon tax has had heterogeneous contributions along these axes in order to determine winners and losers from climate mitigation policy. While the long term air quality improvements illustrated in Figure 3 accrue more strongly to relatively more deprived areas, this consideration is not causally determined in the absence of an appropriate counterfactual for each stratus of the EJ dimension under consideration. To estimate the impact of the carbon tax on $PM_{2.5}$ emissions at different points of the distribution of EJ characteristics, I split the treatment sample into quintiles of baseline[35] $PM_{2.5}$, population density, median income and racial diversity. As the SDID methodology does not allow the inclusion of interaction terms in the estimation procedure, I then run SDID separately for each quintile, allowing the data-driven algorithm to select the combination of control DAs which best approximates the outcome path of each quintile split of the treated units (plus a constant). In Figure 4, I summarise the results graphically, reporting point estimates and 95% confidence intervals at each quintile of the baseline EJ characteristics' distributions.

Quintile-SDID results for baseline $PM_{2.5}$ concentrations are presented in panel (A) of Figure 4. It is immediate to infer that greater reductions arise in DAs with lower pollution levels between 2005 and 2007. The bottom quintile of baseline pollution indeed experience 2.2 times larger reductions with respect to the top quintile. Panel (B), which shows the SDID effects for quintiles of baseline population density, is consistent with the results for baseline pollution levels.

[35] For time-varying covariates I use the average of the three years prior to treatment as the baseline value; for variables retrieved from the Canadian census, I use their 2006 values, i.e. the last observation prior to the implementation of the carbon tax.

FIGURE 3 • SPATIAL DISTRIBUTION OF THE LONG-TERM CHANGE IN $PM_{2.5}$ IN BC CMA



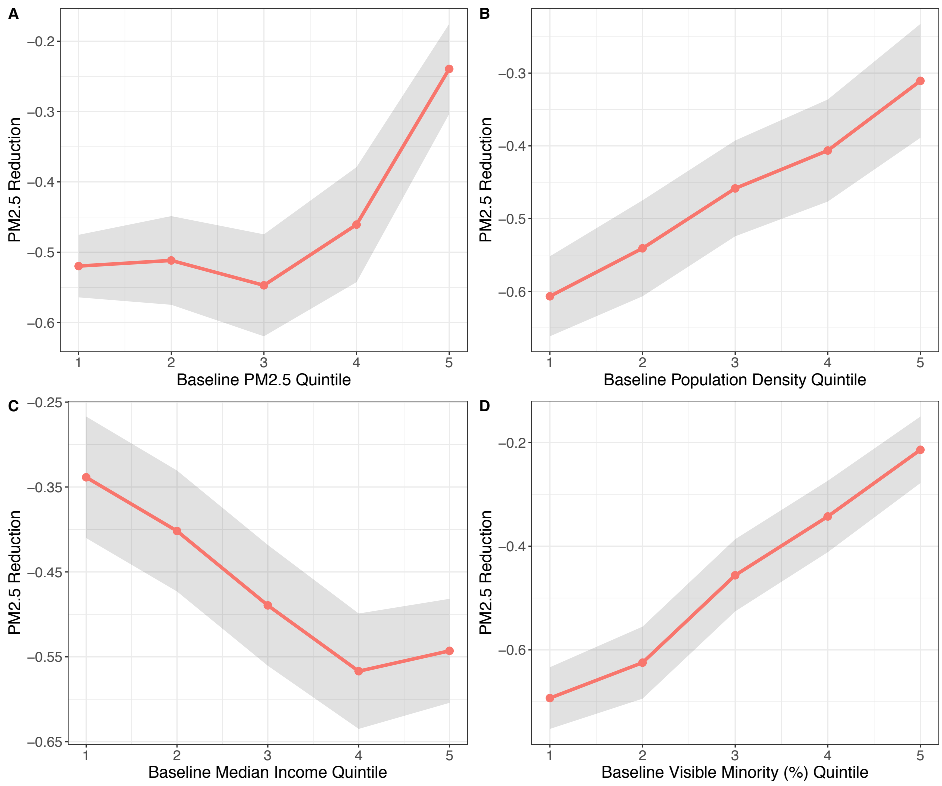
Notes: This figure plots the geographical distribution of changes in $PM_{2.5}$ concentrations for the Vancouver (top panel), Victoria (middle panel) and Abbotsford (bottom panel) CMAs from 2000-2002 to 2014-2016 (three-year averages).

Denser locations within metropolitan areas see lower reductions of particulate matter with respect to less dense DAs, underpinning a worsening of the pollution-density gap. Taken in conjunction, these insights appear to confirm that the 2008 carbon tax was not effective in curtailing traffic in more central areas within British Columbian metropolitan areas, but rather had greater effect in peri-urban locations. More surprising are the results in panel (C), which highlight the fact that relatively better off DAs within metropolitan areas have experienced greater reductions, possibly reflecting an inverse relationship between density and income, but more importantly signalling that the pollution-income gap has increased as a result of the carbon tax. This result is a clear confirmation of the hypothesis of co-benefits regressiveness, highlighting how there is an additional distributional dimension that needs to be considered when designing climate policy. Finally, panel (D) illustrates how metropolitan areas with a lower proportion of visible minorities, i.e. less racially diverse districts, experience greater gains in terms of realised air quality co-benefits, a result that is in agreement with the findings for baseline pollution and income, which exhibit high correlation with racial diversity. The positive findings of a burgeoning EJ literature focussed on the black-white exposure gap in the US and on command-and-control regulations (e.g. Currie *et al.*, 2023; Sager and Singer, 2024) are then not confirmed in the case of British Columbia and a market-based instrument.

It is important to notice how these results highlight pollution reductions that arise at every quintile of the baseline EJ characteristics, compared to a synthetic DID counterfactual of no carbon tax implementation. The carbon tax policy thus produces Pareto-optimal air quality co-benefits, since every group experiences improvements in pollution exposure after its implementation. Compared to a counterfactual scenario of no policy[36], the carbon tax is thus welfare-improving across the board, a result which could be considered beneficial also in terms of environmental justice, with least-advantaged groups observing important reductions in pollution exposure. However, the unequal distribution of realised $PM_{2.5}$ reductions widens the EJ gap along every considered dimension. This confirms mixed evidence from the EJ literature, which claims that while market-based instruments for climate mitigation can give rise to inequality-improving air quality co-benefits (Hernandez-Cortes and Meng, 2023), they can also worsen pre-existing disparities (Grainger and Ruangmas, 2018; Shapiro and Walker, 2021; Cain *et al.*, 2024) or result in no significant distributional changes (Fowlie *et al.*, 2012). Economic instruments which specifically target air pollution, such as command-and-control regulation[37] have been shown to produce sustained EJ gains (Currie *et al.*, 2023), and may thus be coupled with market-based climate mitigation policies[38] in order to reap the full set of benefits from regulation and reduce environmental inequality between groups, in addition to decreasing pollution exposure across groups.

[36] As opposed e.g. to the command-and-control counterfactual of Fowlie *et al.* (2012).
[37] A prime example of which are the National Ambient Air Quality Standards (NAAQS) enforced by the US Clean Air Act.
[38] Additional instruments can be aimed at internalising the congestion externality in urban centres and reducing local pollution (e.g. Gehrsitz, 2017; Pestel and Wozny, 2021; Sarmiento *et al.*, 2023), with a specific focus on policy impacts on disadvantaged communities. Further co-benefits can be generated by public transport electrification and incentives for alternative transport modes, as low-income and disadvantaged households are relatively more cash and credit constrained.

FIGURE 4 • QUINTILE-SDID RESULTS FOR ENVIRONMENTAL JUSTICE GAPS



Notes: Results of SDID regressions by quintile of baseline characteristics. Panel A) Quintiles of baseline $PM_{2.5}$; B) Quintiles of baseline population density; C) Quintiles of baseline median income; D) Quintiles of visible minority share. ATT point estimates reported in red, with 95% confidence intervals calculated with the Arkhangelsky *et al.* (2021) procedure with 200 bootstrap runs in grey shading.

8. HEALTH GAINS

In order to understand the magnitude of the economic co-benefits from air pollution reductions arising due to the 2008 carbon tax, I convert the quintile SDID $PM_{2.5}$ estimates into a monetary quantification of the associated health gains. Notwithstanding the relatively low concentrations of particle pollution in the the British Columbian context, where pre-treatment air quality was of substantial better quality than in other North American locations (e.g. in the USA), it is important to note that the concept of "safe" thresholds for particle pollution concentrations is more normative than positive. Indeed, some studies (e.g. Krewski *et al.*, 2009) have highlighted that the marginal benefits from abatement may be nonlinear in baseline concentrations, with lower gains from abatement at higher levels of baseline air pollution. Hence, any improvement in air quality is likely to carry significant benefits in terms of reductions in mortality rates; moreover, the estimates reported in this section are a lower bound of the gains from local pollution reductions, as $PM_{2.5}$ has been shown to have a multidimensional impact, ranging from health to productivity, to cognition and the formation of human capital (Aguilar-Gomez *et al.*, 2022).

Drawing from Fowlie *et al.* (2019) and Carozzi and Roth (2023), my approach consists of two steps. I first estimate the impact of a reduction in $PM_{2.5}$ concentrations in terms of mortality reductions, using concentration-response ("hazard") functions derived from the environmental health literature. Second, I retrieve the central estimate of the willingness to pay (WTP) to avoid a premature death from Health Canada (2021) and Chestnut and De Civita (2009)[39], and multiply the mortality reductions estimated in the first step by the central estimate of the Value of a Statistical Life (VSL), equal to $6.5 million in 2007 Canadian dollars, for each DA in the census metropolitan areas of Vancouver, Victoria, and Abbotsford.

The traditional form of the Cox proportional hazard model used in the environmental health literature is the log-linear regression reported in Fowlie *et al.* (2019):

$$\ln(\gamma) = \zeta + \alpha PM_{2.5} \tag{5}$$

Where $\ln(\gamma)$ is the natural logarithm of mortality risk, $\zeta = \ln(Z)$, and $PM_{2.5}$ are the

local pollution concentrations. The term Z is a vector of covariates other than $PM_{2.5}$ which impact mortality, and can be rewritten as $Z = Z_0 + \exp(\beta_1 x_1 + \cdots + \beta_n x_n)$, with Z_0 being the mortality risk when all covariates are zero. Indicating γ_{0i} as the baseline mortality risk, and rearranging terms[40], the change in mortality rate $\Delta\gamma i$ can be related to the change in pollution levels $\Delta PM_{2.5i}$ with the following equation:

$$\Delta\gamma_i = \gamma_{0i}\left(1 - \frac{1}{e^{\alpha\Delta PM_{2.5i}}}\right) \tag{6}$$

In order to find the total number of deaths for each DA associated with the above change in mortality rate $\Delta\gamma_i$, this quantity needs to be multiplied by the population of each DA[41]:

$$\Delta Deaths_i = Population_i\left[\gamma_{0i}\left(1 - \frac{1}{e^{\alpha\Delta PM_{2.5i}}}\right)\right] \tag{7}$$

[39] It must be noted that the reported estimate for the Value of a Statistical Life does not reflect directly the economic value of an individually identified person's life, but rather the aggregation of estimates of the WTP for a small reduction in mortality risk. Using the VSL central estimate of $6,500,000, for example, the average Canadian would be willing to pay $65 to reduce the risk of premature death by 1 out of 100,000.

[40] The derivation is as follows (Carozzi and Roth, 2023):

$$\Delta\gamma = Z\left(e^{\alpha PM_{2.5}^0} - e^{\alpha PM_{2.5}^1}\right) \rightarrow \Delta\gamma = Ze^{\alpha PM_{2.5}^0}\left[1 - e^{-\alpha(PM_{2.5}^0 - PM_{2.5}^1)}\right]$$

[41] I use the baseline population level, that is, the population of each DA in the year 2008.

And finally, the monetary health gains in terms of mortality reductions at the DA level, ΔYi, are obtained by multiplying the above estimates by the VSL figure of $6.5 million CAD obtained from Health Canada (2021):

$$\Delta Y_i = VSL * \Delta Deaths_i \tag{8}$$

Hence, in order to estimate the model outlined in Equation 6, and thus obtain mortality rate changes at the DA level, I first need to estimate the baseline mortality rate γ_{0i}. Consistently with the literature, I obtain data for deaths due to lung cancers, all circulatory diseases, and all respiratory diseases from the ICD.10 selected causes of death at the CMA level from Statistics Canada (2021a)[42]. I divide total deaths due to the listed causes by total CMA population, and assign the resulting (baseline) mortality rates to all DAs in a given CMA. The parameter α is usually not directly indicated in epidemiology studies, which instead report the relative risk (RR) increase due to a given increase in $PM_{2.5}$. For instance, Lepeule *et al.* (2012) report an all-cause RR of 1.14 associated with a $\Delta PM_{2.5}$ of 10 μg/m^3, while Krewski *et al.* (2009)'s estimate is 1.06. However, it is straightforward to retrieve α by exploiting the relationship between RR and $\Delta PM_{2.5}$: $\alpha = \ln(RR) / \Delta PM_{2.5}$.

I employ these two estimates, in combination with the estimated $PM_{2.5}$ reductions for each quintile of the pre-intervention $PM_{2.5}$ distribution, in order to calculate the gains from mortality reductions at the DA level for the three CMAs included in the treated sample: Vancouver, Victoria and Abbotsford. In Figure 5, I visually report the results of this exercise for each CMA, using RR = 1.14 as estimated by Lepeule *et al.* (2012)[43].

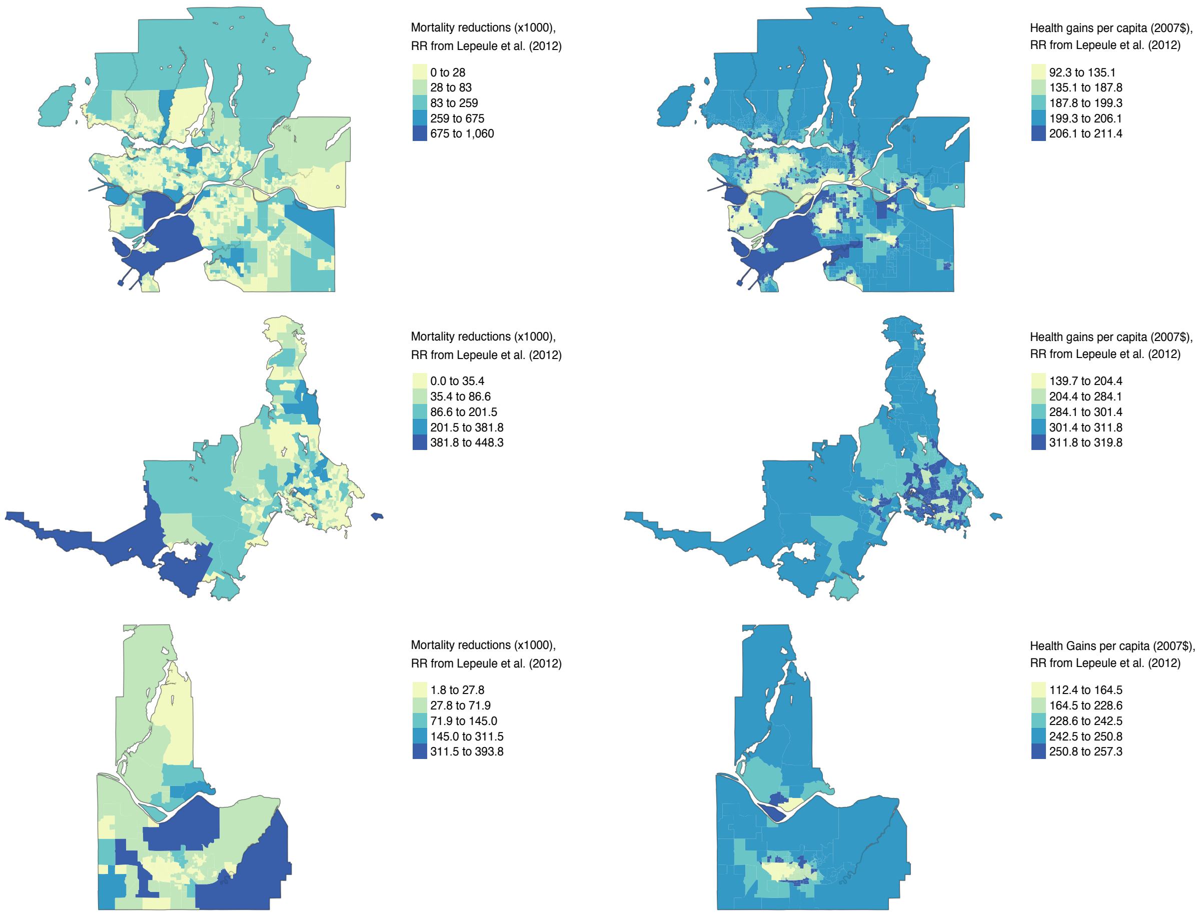
The left panel maps the estimated mortality reductions per 1000 people (estimated according to Equation 7), while the right panel shows the associated per capita health gains, estimated via Equation 8. The median per capita monetary gains due to the estimated reductions in $PM_{2.5}$ are large: $198 when using the Lepeule *et al.* (2012) RR and $88 with the RR from Krewski *et al.* (2009)[44].

The monetary value of per capita air quality co-benefits from the BC carbon tax is 1.7 times of the per capita low income climate action tax credit, i.e. the carbon tax rebate for low-income families[45]. Moreover, the total monetary value of co-benefits ranges between $507.2 million and $1.03 billion annually, or 40-81% of annual carbon tax revenues once

[42] This is the smallest geographic unit for which the data are available.
[43] Visual results using the RR estimate from Krewski *et al.* (2009) are reported in Figure A.23.
[44] The same gains are $402 and $178, respectively, if calculated using the ATT estimated with the van Donkelaar *et al.* (2019) $PM_{2.5}$ dataset instead of Meng *et al.* (2019).
[45] For this comparison, I use the last revision of the low income climate action tax credit, amounting to $115.50 per adult plus $34.50 per child (Ministry of Finance, 2013).

the tax reached its \$30/tCO_2 level in 2012 (Ministry of Finance, 2013). The spatial distribution of these gains shows substantial heterogeneity: in particular, it is once again striking how air pollution co-benefits seem to be concentrated in peri-urban areas and positively correlated with income (see also Figure A.24). The results confirms that co-benefits from carbon taxation appear to be regressively distributed in metropolitan areas, with greater air quality improvements arising in higher income, low pollution DAs, underpinning increasing environmental justice gaps, as also evidenced in Section VII.

FIGURE 5 • MORTALITY REDUCTION AND MONETARY HEALTH GAINS



Notes: Spatial distribution of mortality reductions per 1000 residents (left panel) and health gains per capita (right panel) using the RR estimates from Lepeule *et al.* (2012), for the Vancouver (top row), Victoria (middle row) and Abbotsford (bottom row) CMAs.

9. Conclusions

This paper connects two areas of extreme importance in environmental economics. Air pollution co-benefits from carbon taxation are likely to be as large in magnitude as to partially or fully offset the costs of climate mitigation. Incorporating the monetary value of air quality improvements in cost-benefit analyses of carbon taxes is essential in order to correctly calibrate them and enhance their attractiveness. Conversely, environmental justice implications of market-based instruments are an often overlooked dimension due to the focus on efficiency, rather than equity. Ignoring potentially regressive consequences in terms of the societal distribution of co-benefits could hinder public support towards climate policy.

I show that the introduction of carbon pricing can significantly improve local air quality. After the implementation of the 2008 carbon tax, $PM_{2.5}$ levels dropped by 5.2-10.9% in British Columbian dissemination areas, compared to a no policy counterfactual obtained through the synthetic difference-in-differences estimator. The air quality improvement is driven by reductions in fuel demand and by transport mode switching, mostly in favour of public transport. In terms of environmental justice, alongside evidence of Pareto optimal improvements for all segments of the population, pollution reduction dynamics are significantly regressive, with greater effects found in less polluted, less dense, less racially diverse areas and in richer neighbourhoods. Finally, I convert the improvements in air quality into reductions in mortality rates and monetary health gains from co-benefits of carbon taxation. With a median estimate of $198 per capita, the health gains are large and comparable to the rebates offered to low-income families in British Columbia to mitigate the impact of the tax on their disposable income, as well as to the total annual revenue from the carbon tax at maturity.

These results highlight an equity dimension of the regressive nature of carbon pricing, showing how environmental justice improvements are not a necessary consequence of market-based instruments. While addressing complementary global and local environmental externalities via a carbon tax can yield significant air pollution and health co-benefits in addition to climate mitigation, regressive outcomes ought to be considered. Instruments designed to attenuate inequitable effects may then be designed in advance of the deployment of carbon pricing in order to help closing environmental justice gaps and reap greater policy gains.

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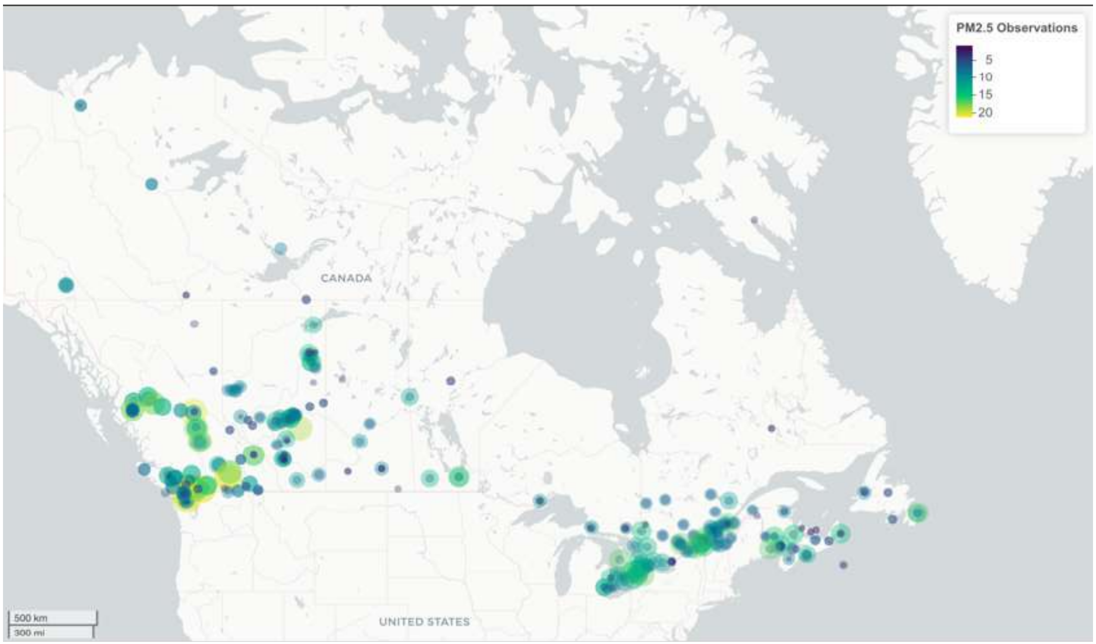
von Bergmann, J., Shkolnik, D., and Jacobs, A. (2022), *cancensus: R Package to Access, Retrieve, and Work with Canadian Census Data and Geography*, R package version 0.5.3

APPENDIX

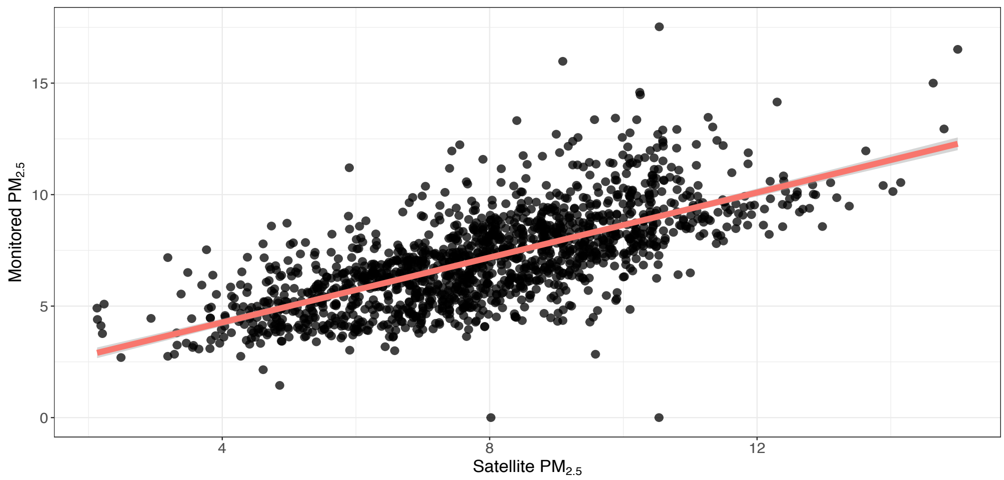
A1. DESCRIPTIVE STATISTICS AND GRAPHS

FIGURE A.1 • SPATIO-TEMPORAL PLACEMENT OF GROUND AIR POLLUTION MONITORS



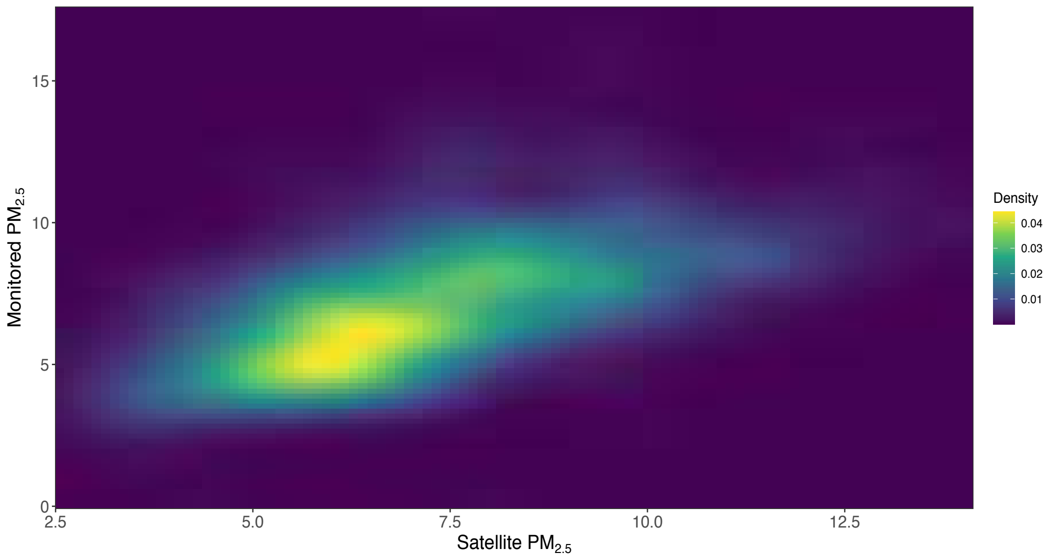
Notes: Availability of $PM_{2.5}$ readings in the National Atmospheric Surveillance Program database between 2000 and 2018. Lighter colours and larger dot sizes indicate higher availability of readings (monitoring stations which were added earlier).

FIGURE A.2 • SATELLITE AND GROUND $PM_{2.5}$ READINGS



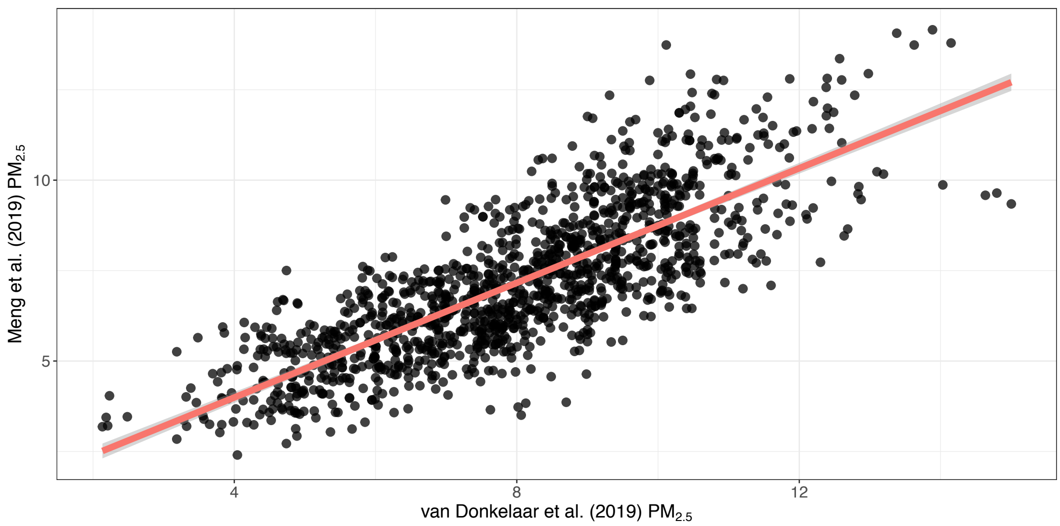
Notes: Scatterplot of satellite $PM_{2.5}$ (Meng *et al.*, 2019) (y-axis) and $PM_{2.5}$ from NAPS monitoring stations (x-axis). Both measures are in µg/m3. The correlation coefficient is 0.597.

FIGURE A.3 • SATELLITE AND GROUND $PM_{2.5}$ READINGS



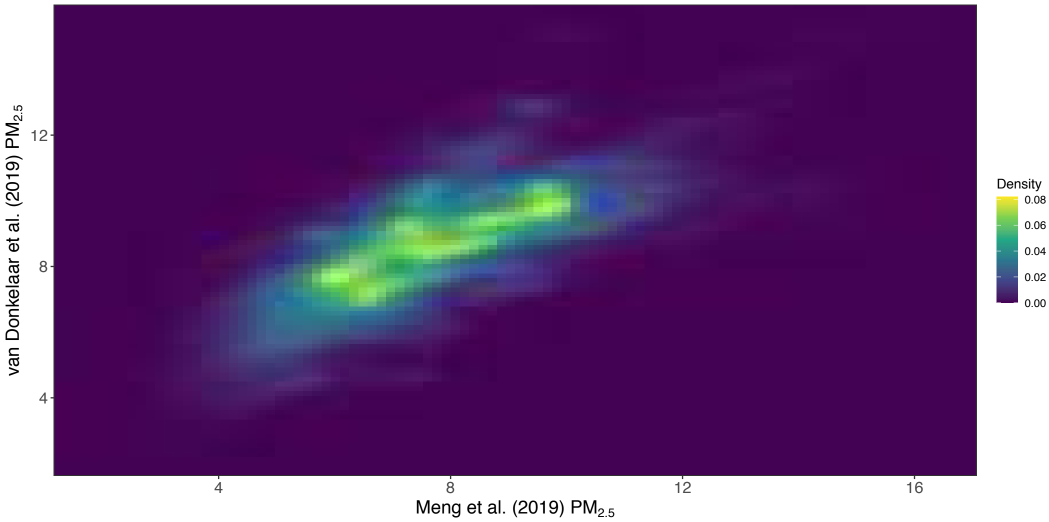
Notes: Density plot of satellite $PM_{2.5}$ (Meng *et al.*, 2019) (y-axis) and $PM_{2.5}$ from NAPS monitoring stations (x-axis). Both measures are in µg/m3.

FIGURE A.4 • TWO REMOTELY SENSED $PM_{2.5}$ MEASURES



Notes: Scatterplot of satellite $PM_{2.5}$ (Meng *et al.*, 2019) (x-axis) vs Satellite $PM_{2.5}$ (van Donkelaar *et al.*, 2019) (y-axis). Both measures are in µg/m3. The correlation coefficient is 0.729.

FIGURE A.5 • TWO REMOTELY SENSED $PM_{2.5}$ MEASURES



Notes: Density plot of satellite $PM_{2.5}$ (Meng *et al.*, 2019) (x-axis) vs Satellite $PM_{2.5}$ (van Donkelaar *et al.*, 2019) (y-axis). Both measures are in µg/m3.

TABLE A.1 • SUMMARY STATISTICS 2000-2007

	Control Provinces			British Columbia		
	N	Mean	SD	N	Mean	SD
$PM_{2.5}$ (van Donkelaar *et al.* 2019)	175870	9.52	1.54	27920	8.06	1.19
$PM_{2.5}$ (Meng *et al.* 2019)	175870	8.61	2.07	27920	6.95	1.39
Pop. Density (Rose *et al.* 2020)	175912	3358.26	3375.33	27920	3169.94	2136.98
Median Income	43978	26341.65	9088.59	6980	25055.65	8090.75
Minority Share	43709	18.07	20.7	6926	34.25	26.22
Theil's Diversity Entropy Index	43978	0.53	0.47	6980	0.79	0.44
Material Deprivation Index	20606	46.48	28.60	3313	43.57	28.12
High Emissions Commute %	43701	74.93	18.33	6926	77.64	16.37
Low Emissions Commute %	43701	24.52	18.26	6926	21.62	16.26
Public Transport Commute %	43701	17.02	14.48	6926	13.06	10.68
Zero Emissions Commute %	43701	7.50	9.43	6926	8.56	10.79
Precipitation (Abatzoglou *et al.* 2018)	175870	74.05	21.74	27920	131.20	37.06
Max Temp. (Abatzoglou *et al.* 2018)	175870	11.93	1.58	27920	14.55	0.66
Min. Temp (Abatzoglou *et al.* 2018)	175870	1.74	2.50	27920	6.46	0.62
Wind Speed (Abatzoglou *et al.* 2018)	175870	3.63	0.49	27920	2.98	0.16

TABLE A.2 • SUMMARY STATISTICS 2008-2018

	Control Provinces			British Columbia		
	N	Mean	SD	N	Mean	SD
$PM_{2.5}$ (van Donkelaar *et al.* 2019)	241865	8.15	1.51	38390	6.09	0.95
$PM_{2.5}$ (Meng *et al.* 2019)	197888	7.35	1.73	31410	6.07	1.10
Pop. Density (Rose *et al.* 2020)	241879	3614.39	3365.36	38390	3478.58	2305.69
Median Income	43978	33324.06	11718.48	6980	31772.63	9765.79
Minority Share	43825	23.84	22.86	6958	40.2	27.15
Theil's Diversity Entropy Index	43978	0.65	0.51	6980	0.89	0.47
High Emissions Commute %	43806	74.39	20.20	6955	72.94	18.75
Low Emissions Commute %	43806	25.06	20.12	6955	26.25	18.61
Public Transport Commute %	43806	18.85	15.89	6955	18.38	13.38
Zero Emissions Commute %	43806	6.21	10.15	6955	7.87	11.32
Precipitation (Abatzoglou *et al.* 2018)	241861	77.57	21.99	38390	134.58	37.33
Max Temp. (Abatzoglou *et al.* 2018)	241861	12.32	1.76	38390	14.58	0.86
Min. Temp (Abatzoglou *et al.* 2018)	241861	2.11	2.59	38390	6.56	0.80
Wind Speed (Abatzoglou *et al.* 2018)	241861	3.64	0.48	38390	3.00	0.19

A2. ADDITIONAL DETAILS ON THE EMPIRICAL STRATEGY

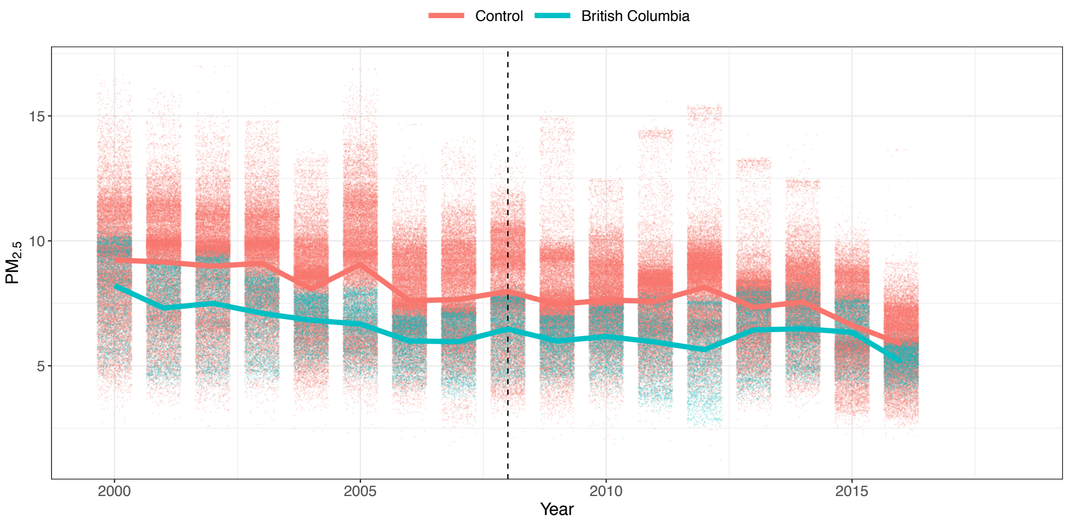
A2.1. The DID parallel trends assumption

TABLE A.3 • PLACEBO DID REGRESSIONS ON 2000-2007 DATA

	(1) DID	(2) DID
$\hat{\tau}$	-0.3754	-1.355
	(0.1362)	(0.2390)
Unit FE	Yes	Yes
Year FE	Yes	Yes
N_{obs}	203736	203736

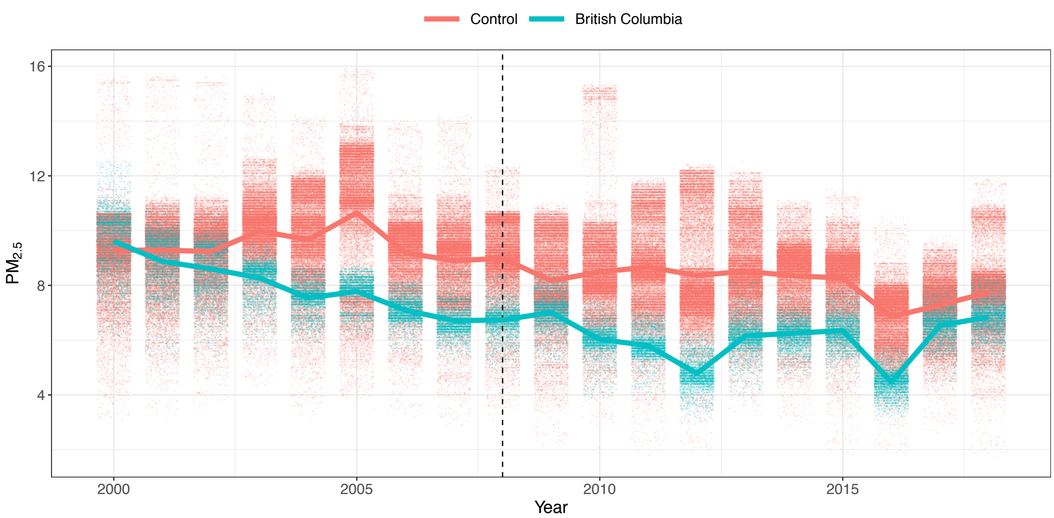
Notes: All point estimates represent the placebo impact of a carbon tax assigned in 2004 during the 2005-2007 placebo post-treatment period. All regressions use 2000-2007 data. Column (1) uses the Meng *et al.* (2019) $PM_{2.5}$ data, and column (2) uses the van Donkelaar *et al.* (2019) $PM_{2.5}$ data. Standard errors in parentheses are clustered at the CMA level.

FIGURE A.6 • $PM_{2.5}$ PRE-TRENDS DIFFERENCES (MENG *ET AL.*, 2019)



Notes: Trends and observations of satellite $PM_{2.5}$ in British Columbia and an average of all control provinces, between 2000 and 2016. The implementation of the carbon tax in 2008 is highlighted by the dashed vertical line. Observed data is jittered around the observation year to enhance legibility. A placebo FE regression of $PM_{2.5}$ on the traditional DID indicator with data limited to 2000-2008 and treatment assigned in 2004 identifies a negative and significant effect, indicating a likely failure of the parallel trends hypothesis.

FIGURE A.7 • $PM_{2.5}$ PRE-TRENDS DIFFERENCES (VAN DONKELAAR *ET AL.*, 2019)



Notes: Trends and observations of satellite PM2.5 in British Columbia and an average of all control provinces, between 2000 and 2018. The implementation of the carbon tax in 2008 is highlighted by the dashed vertical line. Observed data is jittered around the observation year to enhance legibility.

A2.2 Comparison between TWFE-DID, SCM and SDID

In order to formally explain how SDID combines features from TWFE-DID and SCM, let me consider a balanced panel with N observations and T time periods. In the British Columbian case, the outcome variable is $PM_{2.5it}$, and the binary treatment is D_{it}. Let $i = 1, \ldots, N_{tr}$ be the treated DAs in BC, Let $i = N_{tr+1}, \ldots, N_{co}$ be the DAs in control provinces. The baseline TWFE-DID regression problem can be expressed as:

$$\left(\hat{\tau}^{did}, \hat{\mu}, \hat{\eta}, \hat{\theta}\right) = \underset{\tau,\mu,\eta,\theta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(PM_{2.5it} - \mu - \eta_i - \theta_t - \tau D_{it}\right)^2 \right\} \tag{9}$$

Which is solved without the use of unit or time-specific weights, but with the inclusion of unit and time-specific fixed effects ηi and θt as also illustrated in Equation 2. The SCM estimator, instead, does not employ unit fixed effects, but includes time fixed effects and unit-specific weights ω_i^{sc} :

$$\left(\hat{\tau}^{sc}, \hat{\mu}, \hat{\eta}, \hat{\theta}\right) = \underset{\tau,\mu,\eta,\theta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(PM_{2.5it} - \mu - \eta_i - \theta_t - \tau D_{it}\right)^2 \widehat{\omega_i^{sc}} \right\} \tag{10}$$

Finally, the SDID estimator combines features from Equation 9 and Equation 10. Unit weights ω_i^{sdid} are chosen such that the pre-treatment outcome path of control DAs are parallel to those of the treated units[46]:

$$\omega_0 + \sum_{i=N_{tr}+1}^{N_{co}} \widehat{\omega}_i^{sdid} PM_{2.5it} \approx \frac{1}{N_{tr}} \sum_{i=1}^{N_{tr}} PM_{2.5it} \tag{11}$$

Moreover, time weights λˆsdid need to ensure that the pre-treatment levels for the control units differs from the post-treatment levels for the same units only by a constant. Letting $t = 1, \ldots, T$ be the total length of the panel, T_{pre} be the number of pre-intervention periods, and T_{post} be the number of post-intervention periods, the condition can be expressed as:

$$\lambda_0 + \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} PM_{2.5it} \approx \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} PM_{2.5it} \tag{12}$$

[46] When the intercept ω_0 and the regularisation parameter are set to 0, the unit weights ω_i correspond to the SCM weights in Abadie *et al.* (2010). For further details on the procedure used to estimate ζ, please refer to Arkhangelsky *et al.* (2021).

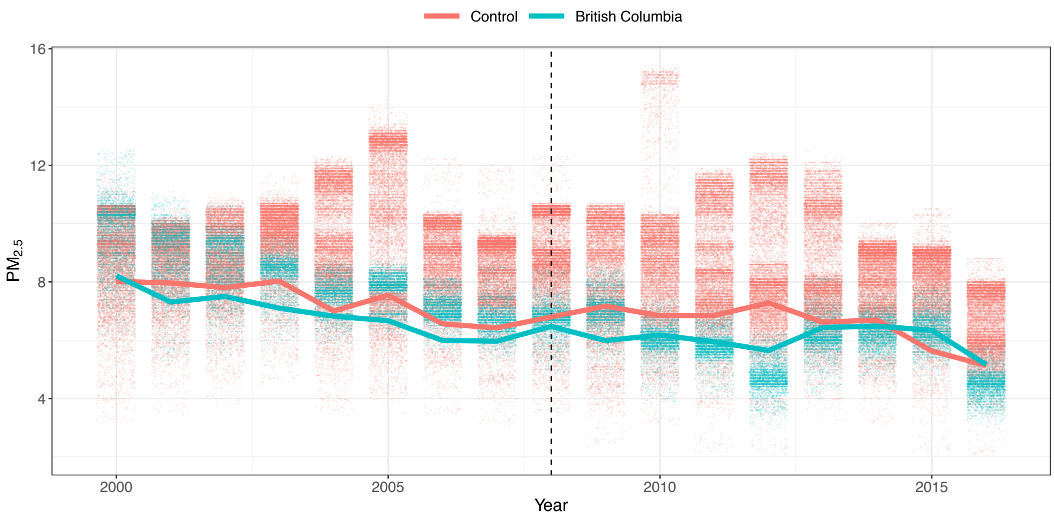
Thus, the regression problem for the SDID estimator can be expressed as a weighted TWFE-DID problem which incorporates unit and time-specific fixed effects η_i and θ_t, plus unit and time-specific weights ω_i and λ_t, as illustrated in Equation 13:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\eta}, \hat{\theta}\right) = \underset{\tau,\mu,\eta,\theta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (PM_{2.5it} - \mu - \eta_i - \theta_t - \tau D_{it})^2 \widehat{\omega_i}^{sdid} \hat{\lambda}_t^{sdid} \right\} \quad (13)$$

A3. Additional results and robustness checks

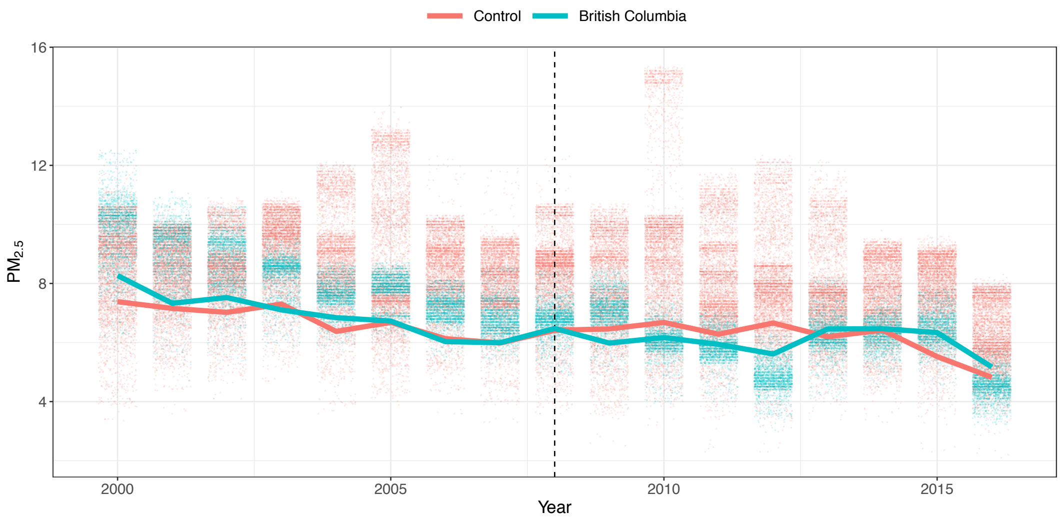
A3.1. Matched Difference-in-Differences Plots

FIGURE A.8 • PRE-TRENDS IN $PM_{2.5}$ AFTER CEM (1)



Notes: Trends and observations of satellite $PM_{2.5}$ (Meng *et al.*, 2019) in British Columbia and an average of all control provinces, between 2000 and 2016. The implementation of the carbon tax in 2008 is highlighted by the dashed vertical line. Observed data is jittered around the observation year to enhance legibility. The data results from a Coarsened Exact Matching procedure on baseline $PM_{2.5}$ levels.

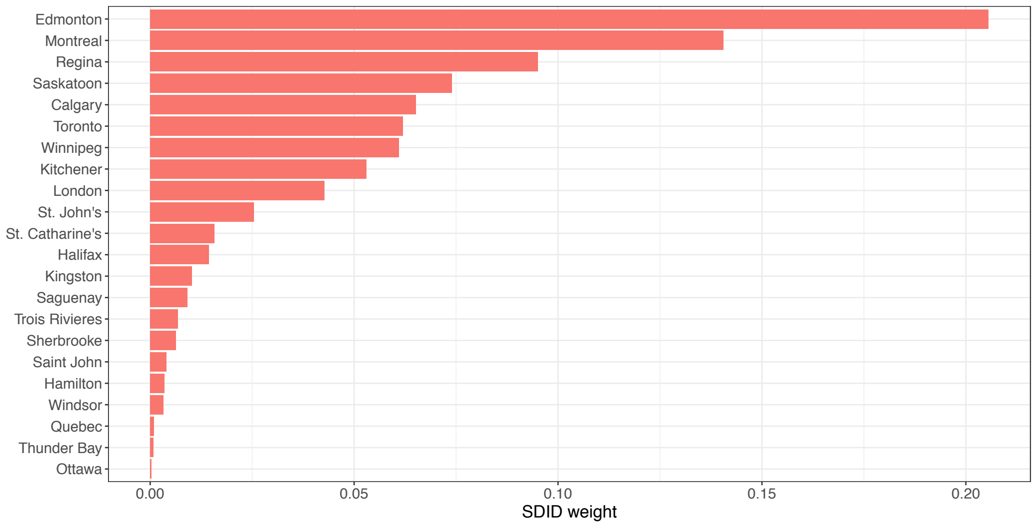
FIGURE A.9 • PRE-TRENDS IN $PM_{2.5}$ AFTER CEM (2)



Notes: Trends and observations of satellite $PM_{2.5}$ (Meng *et al.*, 2019) in British Columbia and an average of all control provinces, between 2000 and 2016. The implementation of the carbon tax in 2008 is highlighted by the dashed vertical line. Observed data is jittered around the observation year to enhance legibility. The data results from a Coarsened Exact Matching procedure on baseline $PM_{2.5}$ levels and baseline levels of population density, median income, high emission commute mode share, and road density.

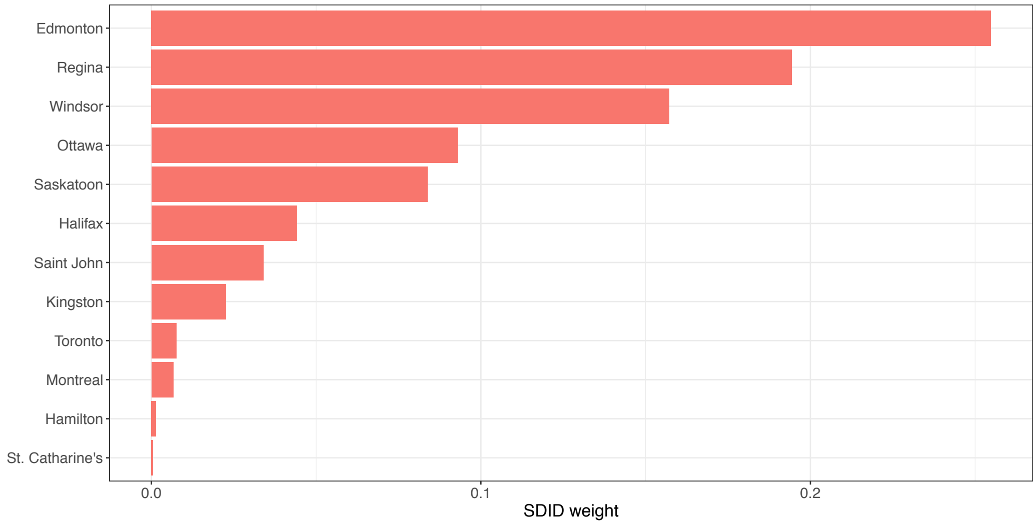
A3.2. Composition of SDID control pools

FIGURE A.10 • SYNTHETIC BC AT THE DA LEVEL (MENG *ET AL.*, 2019)



Notes: Composition of the synthetic DID unit of Figure 2. Individual DA weights are aggregated up to the CMA level.

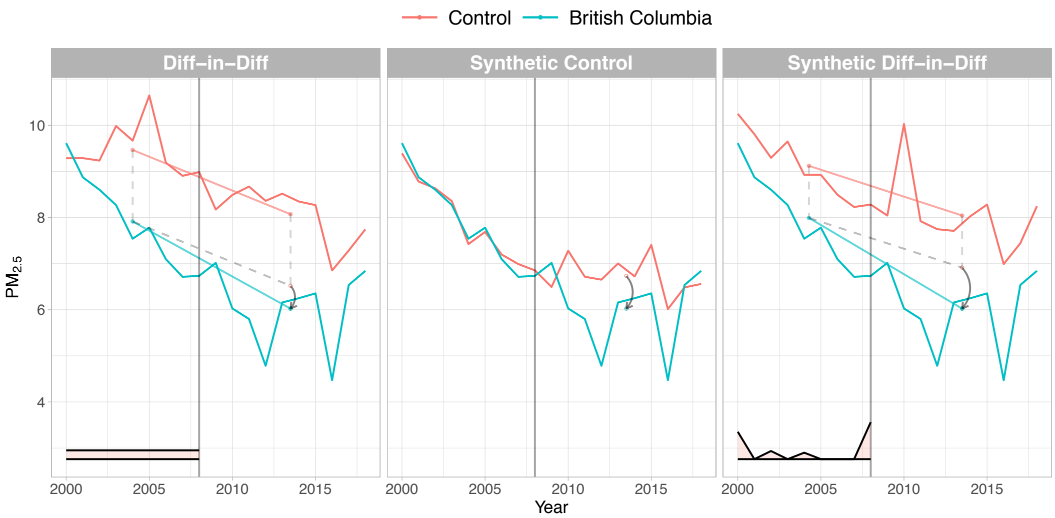
FIGURE A.11 • SYNTHETIC BC AT THE DA LEVEL (VAN DONKELAAR *ET AL.*, 2019)



Notes: Composition of the synthetic DID unit of Figure A.12. Individual DA weights are aggregated up to the CMA level.

A3.3. Main results with van Donkelaar et al. (2019) $PM_{2.5}$ data

FIGURE A.12 • THE IMPACT OF THE 2008 CARBON TAX ON CHANGES IN $PM_{2.5}$, VAN DONKELAAR *ET AL.* (2019) OUTCOME VARIABLE



Notes: Graphical results from DID, SCM and SDID for $PM_{2.5}$ concentrations, with van Donkelaar *et al.* (2019) data. Time weights λ_t are represented in light red at the bottom of the pre-intervention panel. The curved arrows graphically represent the ATT over the post-intervention period.

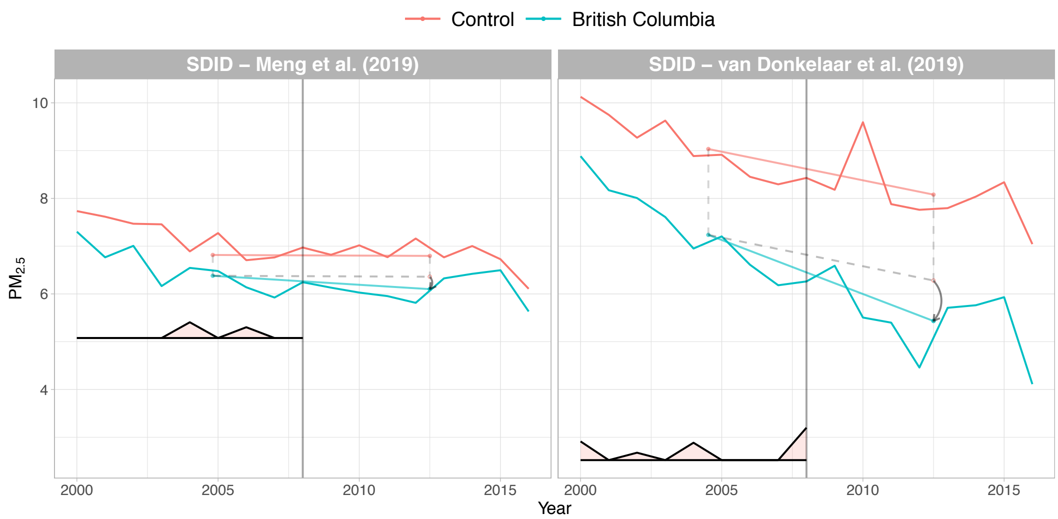
TABLE A.4 • THE 2008 CARBON TAX AND CHANGES IN $PM_{2.5}$

	(1) *DID*	(2) *SCM*	(3) *SDID*
$\hat{\tau}$	-0.4954 (0.0085)	-0.7087 (0.1540)	-0.8896 (0.0300)
Unit FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
ω_i		Yes	Yes
λ_t			Yes
N_{obs}	483873	483873	483873

Notes: All point estimates represent the average impact of the 2008 carbon tax during the 2009-2018 post-treatment period. Standard errors in parentheses are calculated using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021) with 200 replications. All regressions use 2000-2016 data.

A3.4. Accounting for measurement error à la Fowlie et al. (2019)

FIGURE A.13 • THE IMPACT OF 2008 CARBON TAX ON CHANGES IN PREDICTED $PM_{2.5}$ ACCOUNTING FOR MEASUREMENT ERROR



Notes: Graphical results from SDID for $PM_{2.5}$ concentrations, with Meng *et al.* (2019) data (left panel) and van Donkelaar *et al.* (2019) data (right panel). Time weights λ_t are represented in light red at the bottom of the pre-intervention panel. The curved arrows graphically represent the ATT over the post-intervention period.

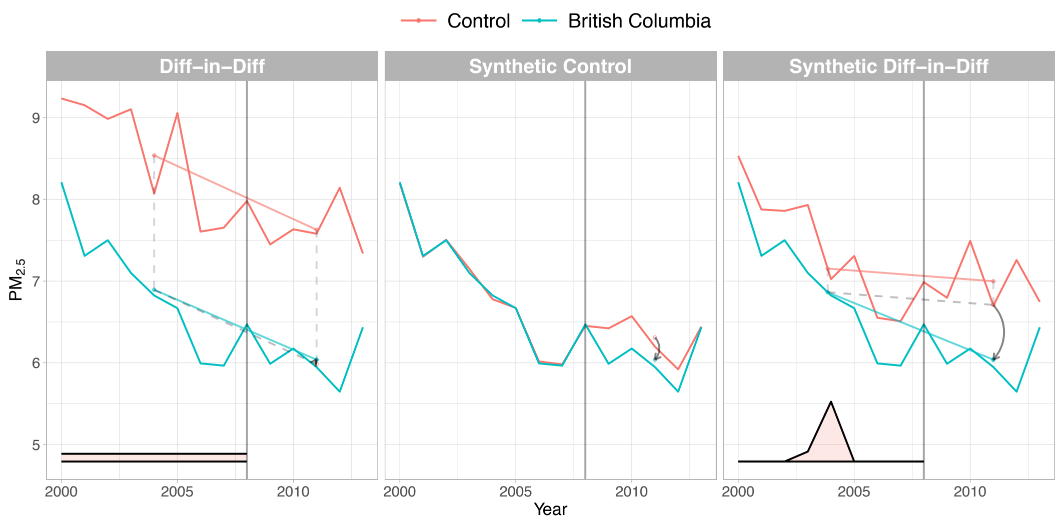
TABLE A.5 • THE 2008 CARBON TAX AND CHANGES IN PM2.5, ACCOUNTING FOR MEASUREMENT ERROR

	(1) ***SDID***	(2) ***SDID***
$\hat{\tau}$	-0.260 (0.010)	-0.847 (0.027)
Unit FE	Yes	Yes
Year FE	Yes	Yes
ω_i	Yes	Yes
λ_t	Yes	Yes
N_{obs}	432939	432939

Notes: Point estimates represent the average impact of the 2008 carbon tax using data from Meng *et al.* (2019) (column 1) and van Donkelaar *et al.* (2019) (column 2) as the outcome, during the 2009-2016 post-treatment period. Standard errors are calculated using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021) with 200 replications. All regressions use 2000-2016 data.

A3.5. Post-treatment period limited to 2013

FIGURE A.14 • THE IMPACT OF THE 2008 CARBON TAX ON CHANGES IN PM2.5, 2000-2013 SAMPLE



Notes: Graphical results from DID, SCM and SDID for $PM_{2.5}$ concentrations, with Meng *et al.* (2019) data, dataset restricted to 2013. Time weights λ_t are represented in light red at the bottom of the pre-intervention panel. The curved arrows graphically represent the ATT over the post-intervention period.

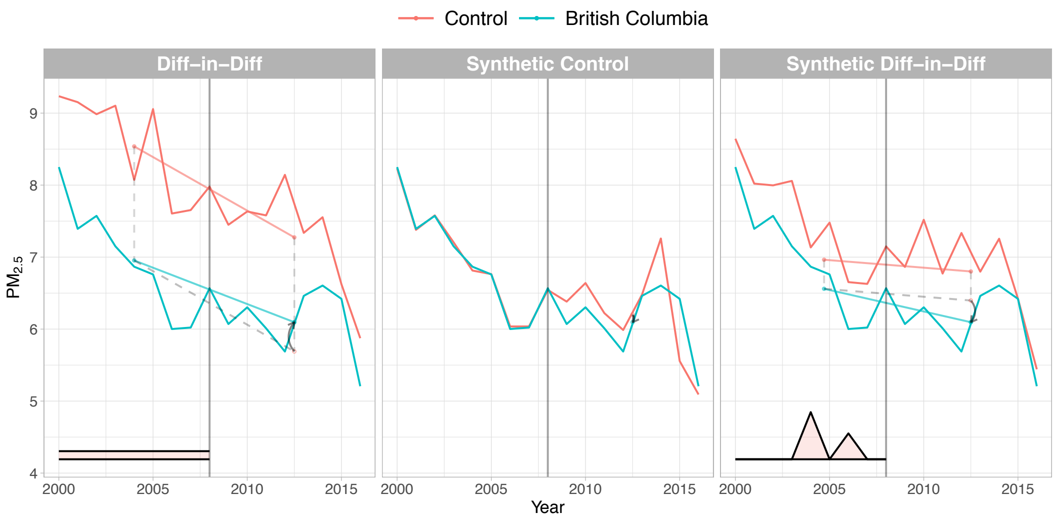
TABLE A.6 • THE 2008 CARBON TAX AND CHANGES IN $PM_{2.5}$, 2000-2013 SAMPLE

	(1) ***DID***	(2) ***SCM***	(3) ***SDID***
$\hat{\tau}$	0.0547 (0.0081)	-0.2723 (0.0803)	-0.6703 (0.0341)
Unit FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
ω_i		Yes	Yes
λ_t			Yes
N_{obs}	432939	432939	432939

Notes: All point estimates represent the average impact of the 2008 carbon tax using data from Meng *et al.* (2019) as the outcome, during the 2009-2013 post-treatment period. Standard errors are calculated using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021) with 200 replications. All regressions use 2000-2013 data.

A3.6. DAs in the Vancouver CMA

FIGURE A.15 • THE IMPACT OF THE 2008 CARBON TAX ON CHANGES IN $PM_{2.5}$ FOR DAS IN THE VANCOUVER CMA



Notes: Graphical results from DID, SCM and SDID for $PM_{2.5}$ concentrations, with Meng *et al.* (2019) data, dataset restricted to DAs in the Vancouver CMA. Time weights λ_t are represented in light red at the bottom of the pre-intervention panel. The curved arrows graphically represent the ATT over the post-intervention period.

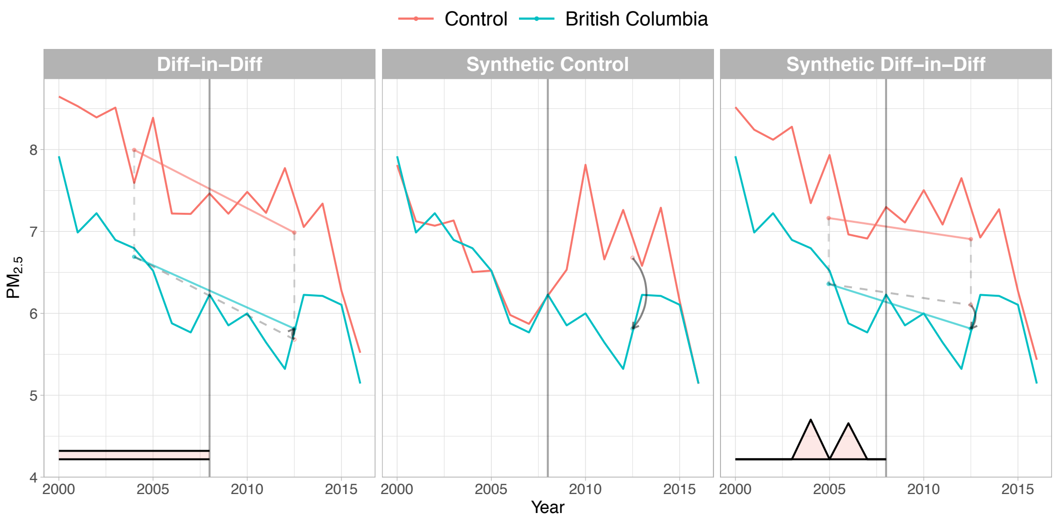
TABLE A.7 • THE 2008 CARBON TAX AND CHANGES IN $PM_{2.5}$, DAS IN THE VANCOUVER CMA

	(1) *DID*	(2) *SCM*	(3) *SDID*
$\hat{\tau}$	0.4061 (0.0071)	-0.1062 (0.0702)	-0.3014 (0.0225)
Unit FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
ω_i		Yes	Yes
λ_t			Yes
N_{obs}	432939	432939	432939

Notes: All point estimates represent the average impact of the 2008 carbon tax during the 2009-2016 post-treatment period, using the outcome variable from Meng *et al.* (2019) and restricting the sample to DAs in the Vancouver CMA. Standard errors are calculated using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021) with 200 replications. All regressions use 2000-2016 data.

A3.7. DAs matching NAPS monitoring stations

FIGURE A.16 • THE IMPACT OF THE 2008 CARBON TAX ON CHANGES IN $PM_{2.5}$ FOR DAS MATCHING NAPS LOCATIONS



Notes: Graphical results from DID, SCM and SDID for $PM_{2.5}$ concentrations, with Meng *et al.* (2019) data, dataset restricted to DAs matching NAPS monitoring stations' locations. Time weights λ_t are represented in light red at the bottom of the pre-intervention panel. The curved arrows graphically represent the ATT over the post-intervention period.

TABLE A.8 • THE 2008 CARBON TAX AND CHANGES IN $PM_{2.5}$,
DAS MATCHING NAPS LOCATIONS

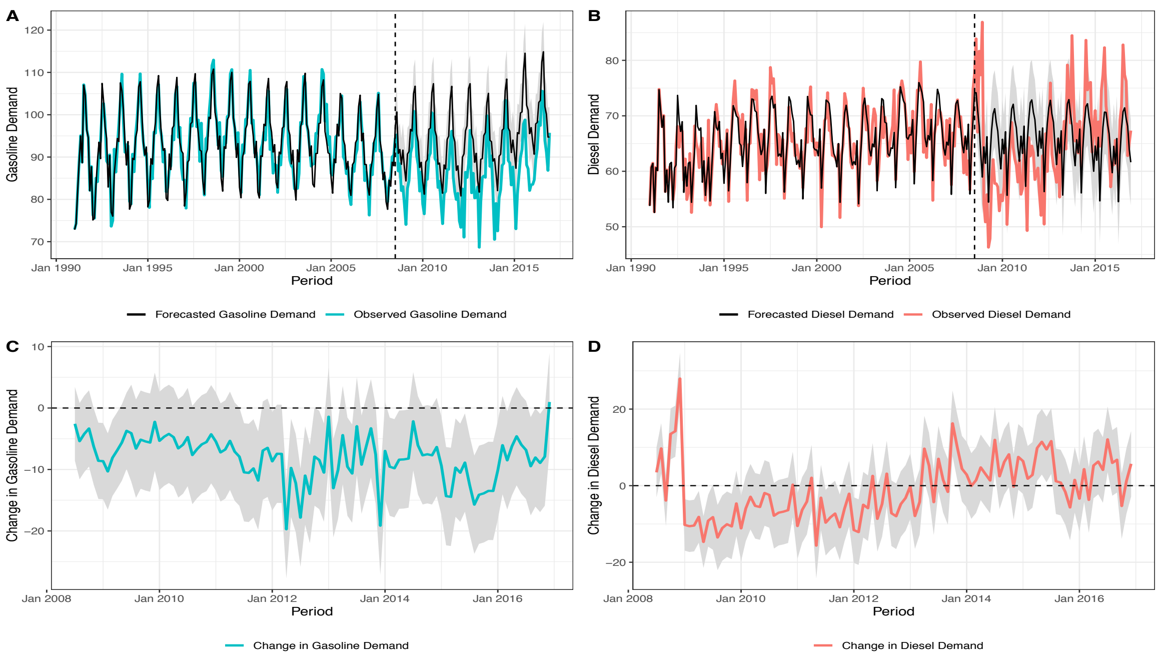
	(1) ***DID***	(2) ***SCM***	(3) ***SDID***
$\hat{\tau}$	0.132 (0.117)	-0.865 (0.128)	-0.288 (0.097)
Unit FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
ω_i		Yes	Yes
λ_t			Yes
N_{obs}	2227	2227	2227

Notes: All point estimates represent the average impact of the 2008 carbon tax during the 2009-2016 post-treatment period, using the outcome variable from Meng *et al.* (2019) and restricting the sample to DAs in the Vancouver CMA. Standard errors are calculated using the bootstrap variance estimation algorithm described in Arkhangelsky *et al.* (2021) with 200 replications. All regressions use 2000-2016 data.

A4. ADDITIONAL DETAILS ON MECHANISMS

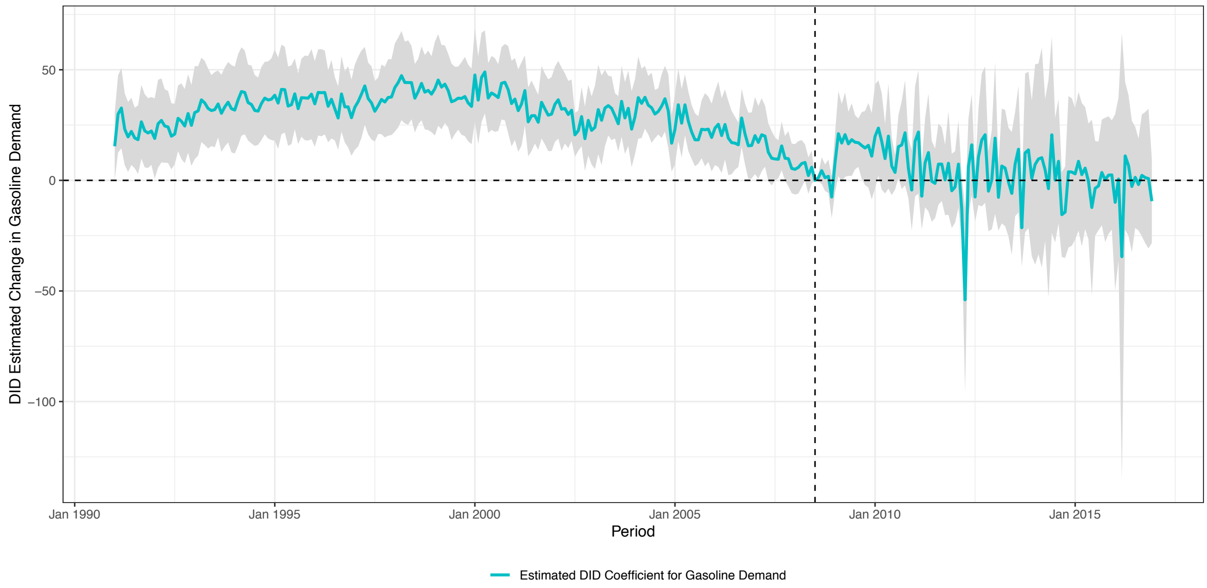
A4.1. Fuel demand

FIGURE A.17 • C-ARIMA RESULTS FOR FUEL SALES



Notes: Graphical results from the C-ARIMA regressions on monthly gasoline and diesel sales. Panel (A) and (B) show the observed and forecasted gasoline and diesel sales time series for the full post-intervention horizon. Panels (C) and (D) represent the gap between observed and forecasted series for gasoline and diesel sales. 95% confidence intervals in grey shading using robust standard errors.

FIGURE A.18 • EVENT STUDY RESULT FOR FUEL SALES



Notes: Event study regression of monthly gasoline sales at the province level, 1990-2016 data. 95% confidence interval in grey shading using standard errors clustered at the province level.

A4.2. Commute mode switching empirical analysis

Ideally, when concerned with the estimation of $PM_{2.5}$ reductions arising from the implementation of carbon pricing, I would look at DA-level reductions in motor fuel sales or in the quantity of vehicle kilometres travelled; however, these data are not available at the desired level of granularity for Canada between 2000 and 2018. Moreover, while Canadian province-level data on vehicle sales disaggregated by type of fuel is only available from 2011 onwards, the post-2011 trends in sales of diesel vehicles are relatively flat (See Figure A.20), and the landscape seems to be dominated by gasoline cars (See Figure A.19), suggesting that an eventual gas-to-diesel switch caused by the carbon tax incentive would have produced all of its results between July 2008 and January 2011 before bottoming out; the evidence for this conclusion is not very strong as a result. Another potential mechanism behind an increase in air pollution could derive from an exceptionally high rate of replacement in BC's car fleet with respect to other Canadian provinces, caused by the willingness of BC's residents to increase their cars' fuel efficiency and realise savings at the pump. If the savings per each tank refuel were sufficient to offset the increase in gasoline prices due to the carbon tax, British Columbian residents could have potentially travelled more kilometres than prior to the tax, thereby increasing road congestion and hence pollution due to a rebound effect. As shown in Figure A.21 there has indeed been a rapid increase in truck and SUV sales in British Columbia after 2008; however, this increase is paralleled by similar jumps in truck sales in all large Canadian provinces[47], and it thus seems implausible to attribute it to the marginal effect of the carbon tax in raising fuel prices.

I instead exploit the information contained in the 2001, 2006, 2011 and 2016 waves of the Canadian census, which contains data on commute-to-work modes at the DA level for all Canadian CMAs. While the information on commute modes is not an exhaustive representation of all car trips made in each DA, the granularity of the data may shed light on whether residents of DAs located in British Columbia have adjusted their behaviour following the implementation of the carbon tax, substituting public transport or active commuting modes such as cycling and walking for car trips. In particular, I estimate the following equation:

$$Mode_{it} = \tau D_{it} + \theta_t + \eta_i + \varepsilon_{it} \tag{14}$$

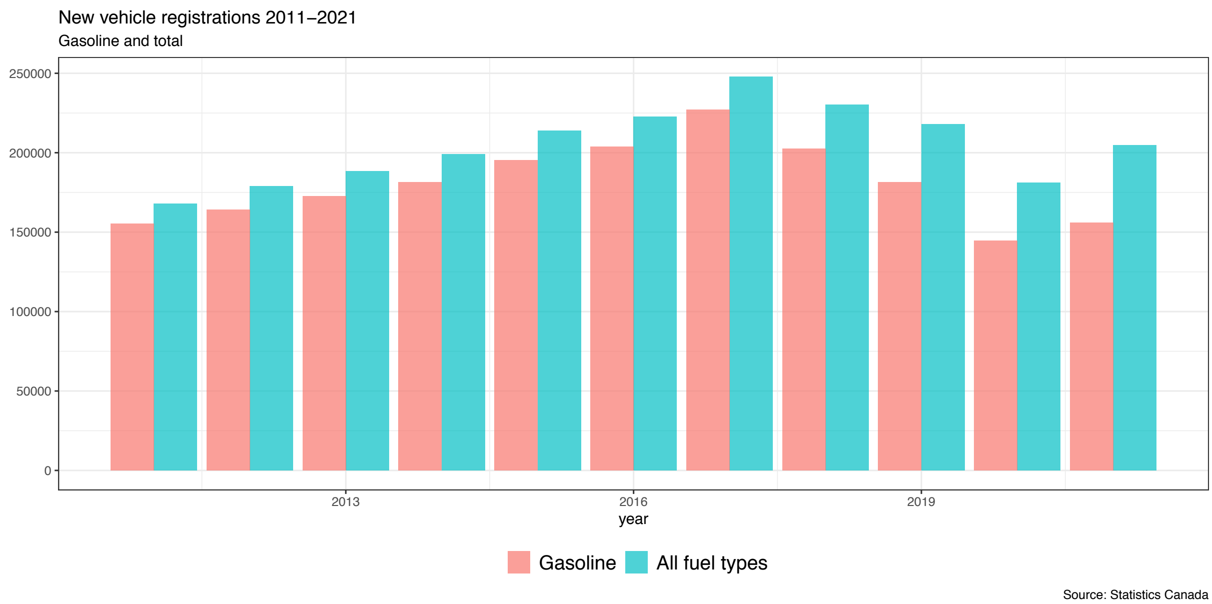
Where $Mode_{it}$ is the share of each commute mode (high emission, low emission, public transport and zero emission), $D_{it}$is the carbon tax DID binary variable, θ_t and η_i are time and unit-specific fixed effects, and ε_{it} is an idiosyncratic error term. In additional specifications, I also add a vector of controls X_{it} which account for population density, median income, and weather covariates (precipitation, maximum and minimum temperature, and wind speed), hence the estimating equation becomes:

$$Mode_{it} = \tau D_{it} + \beta X_{it} + \theta_t + \eta_i + \varepsilon_{it} \tag{15}$$

I initially run the TWFE-DID regressions for the whole sample, without trimming the control pool. In further specifications, I restrict the control sample to the units which receive positive ω_i weights in the SDID estimation of the main result, in order to ensure comparability across treatment and control cohorts and reduce the reliance on potentially violated parallel trends. Further, I retrieve the ω_i weights from the SDID estimation and weigh my restricted TWFE-DID regressions with the SDID weights, assigning equal weights $\frac{1}{N_{tr}}$ to the treatment cohort.

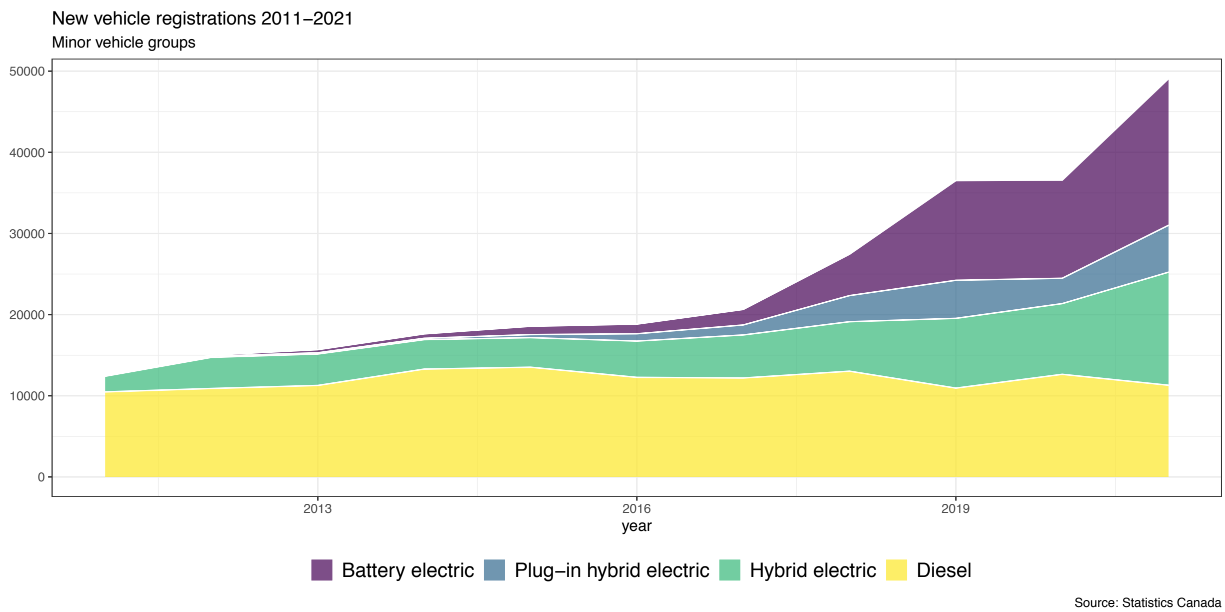
[47] Namely, Alberta, Ontario and Quebec.

FIGURE A.19 • NEW VEHICLE REGISTRATIONS IN BRITISH COLUMBIA BY MAJOR FUEL TYPES



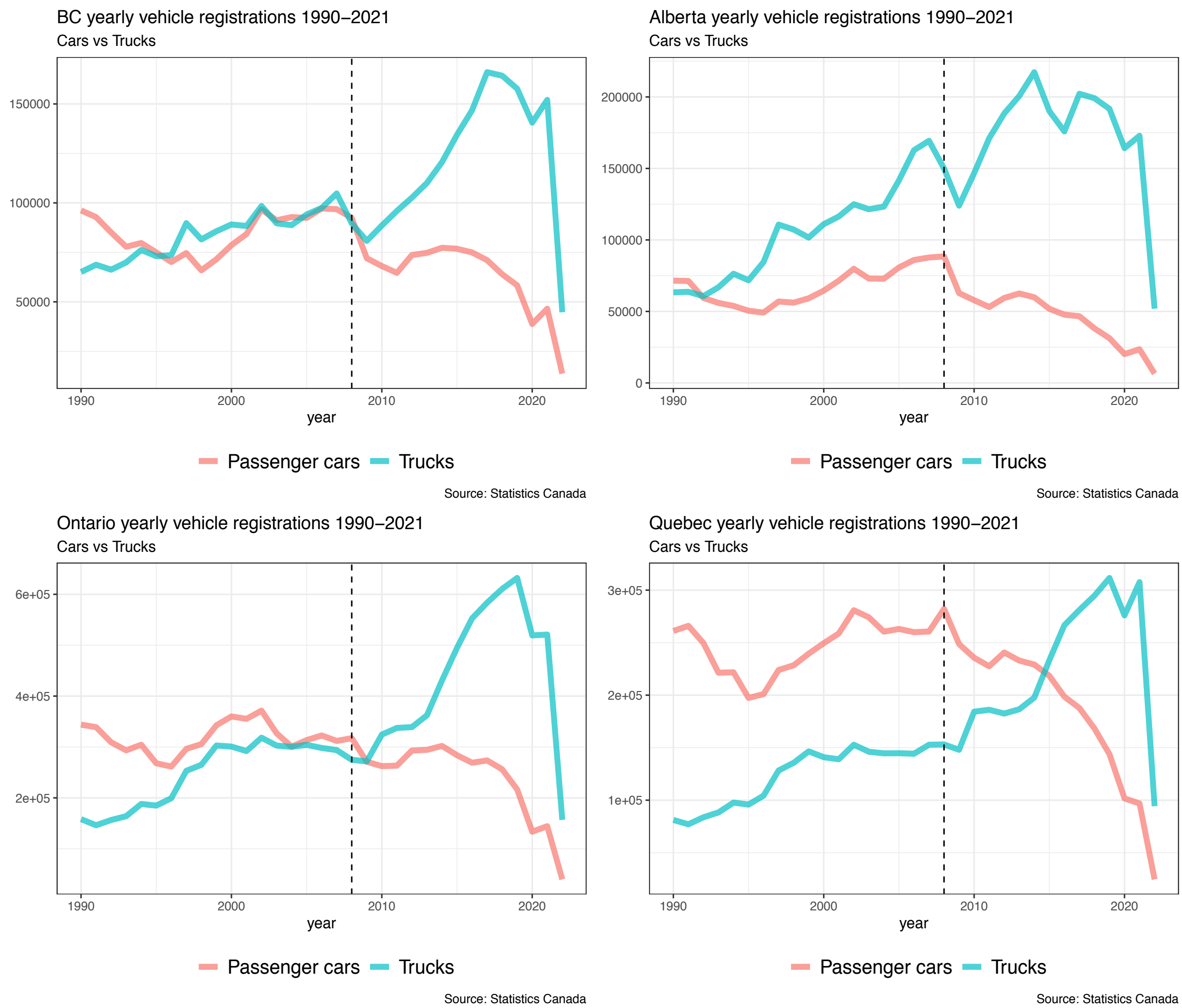
Notes: The plot illustrates new vehicle registrations for gasoline and all other fuel types in British Columbia between 2011 and 2021.

FIGURE A.20 • NEW MINOR VEHICLE GROUPS REGISTRATIONS IN BRITISH COLUMBIA



Notes: The plot illustrates new vehicle registrations for low emissions (battery electric, plug-in hybrid, hybrid) and diesel fuel types in British Columbia between 2011 and 2021.

FIGURE A.21 • PASSENGER CARS VS TRUCK AND SUV SALES IN CANADA MAJOR PROVINCES



Notes: The plot illustrates 1990-2021 trends in passenger cars and truck and SUV sales, for the four largest Canadian Provinces. Top row: British Columbia and Alberta. Bottom row: Ontario and Quebéc.

TABLE A.9 • DID RESULTS FOR LOW EMISSIONS COMMUTE MODE

	Low Emissions Commute Mode					
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.0408 (0.111)	0.0516 (0.0103)	0.0535 (0.0110)	0.0457 (0.0109)	0.0510 (0.0113)	0.0506 (0.0114)
DA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls				Yes	Yes	Yes
SDID control pool		Yes	Yes		Yes	Yes
SDID weights			Yes			Yes
R^2	0.87321	0.84174	0.84532	0.87715	0.84674	0.84996
Adj. R^2	0.83078	0.78876	0.79354	0.83560	0.79490	0.79920
N_{obs}	101358	38769	38769	100244	38348	38348

Notes: The dependent variable is the dissemination area level share of low emissions commutes. All regressions include dissemination area and year fixed effects. Columns (4)-(6) include controls for precipitation, maximum and minimum temperature, and wind speed, plus the natural logarithm of population and median income. Columns (2), (3), (5) and (6) restrict the control unit pool to DAs which receive positive weights in the main SDID regression.

TABLE A.10 • DID RESULTS FOR ZERO EMISSIONS COMMUTE MODE

	Zero Emissions Commute Mode					
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.0057 (0.0025)	0.0106 (0.0017)	0.0117 (0.0021)	0.0066 (0.0022)	0.0088 (0.0016)	0.0092 (0.0016)
DA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls				Yes	Yes	Yes
SDID control pool		Yes	Yes		Yes	Yes
SDID weights			Yes			Yes
R^2	0.80811	0.80808	0.81877	0.81200	0.81355	0.82463
Adj. R^2	0.74390	0.74383	0.75810	0.74841	0.75047	0.76531
N_{obs}	101358	38769	38769	100244	38348	38348

Notes: The dependent variable is the dissemination area level share of zero emissions commutes. All regressions include dissemination area and year fixed effects. Columns (4)-(6) include controls for precipitation, maximum and minimum temperature, and wind speed, plus the natural logarithm of population and median income. Columns (2), (3), (5) and (6) restrict the control unit pool to DAs which receive positive weights in the main SDID regression.

A5. ENVIRONMENTAL JUSTICE DYNAMICS

A5.1. Descriptive statistics

TABLE A.11 • TRENDS IN $PM_{2.5}$ BY QUINTILE OF EJ DIMENSIONS, BRITISH COLUMBIAN DAS

	EJ Dimension		
	Pop. Density	Diversity	Income
		Baseline (2000-2002 Average)	
Top Quintile	8.66	8.83	6.68
Bottom Quintile	6.48	6.83	8.53
EJ Gap	2.18	2.01	-1.85
		Post-treatment (2014-2016 Average)	
Top Quintile	6.63	6.67	5.47
Bottom Quintile	5.32	5.46	6.49
EJ Gap	1.31	1.21	-1.02

Notes: All values are expressed in µg/m³, for British Columbian DAs only. Baseline $PM_{2.5}$ levels are calculated as 2000-2002 averages for all quintiles, post treatment $PM_{2.5}$ levels are 2014-2016 averages. Quintiles are calculated on 2005-2007 levels for population density, and on 2006 Census levels for racial diversity and median income.

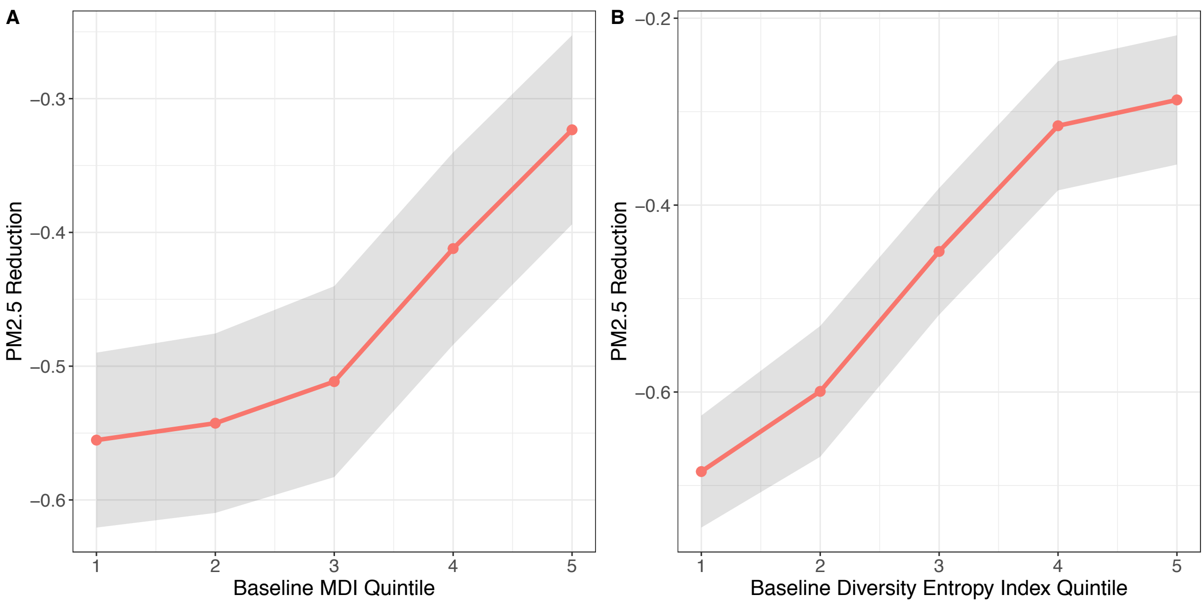
TABLE A.12 • TRENDS IN $PM_{2.5}$ BY QUINTILE OF EJ DIMENSIONS, CONTROL DAS

	EJ Dimension		
	Pop. Density	Diversity	Income
		Baseline (2000-2002 Average)	
Top Quintile	9.88	9.67	8.69
Bottom Quintile	7.71	8.28	9.60
EJ Gap	2.17	1.39	-0.91
		Post-treatment (2014-2016 Average)	
Top Quintile	7.05	7.10	6.41
Bottom Quintile	5.81	6.13	6.90
EJ Gap	1.24	0.97	-0.49

Notes: All values are expressed in µg/m³, for British Columbian DAs only. Baseline $PM_{2.5}$ levels are calculated as 2000-2002 averages for all quintiles, post treatment $PM_{2.5}$ levels are 2014-2016 averages. Quintiles are calculated on 2005-2007 levels for population density, and on 2006 Census levels for racial diversity and median income.

A5.2. Additional results

FIGURE A.22 • ADDITIONAL QUINTILE-SDID RESULTS FOR ENVIRONMENTAL JUSTICE GAPS

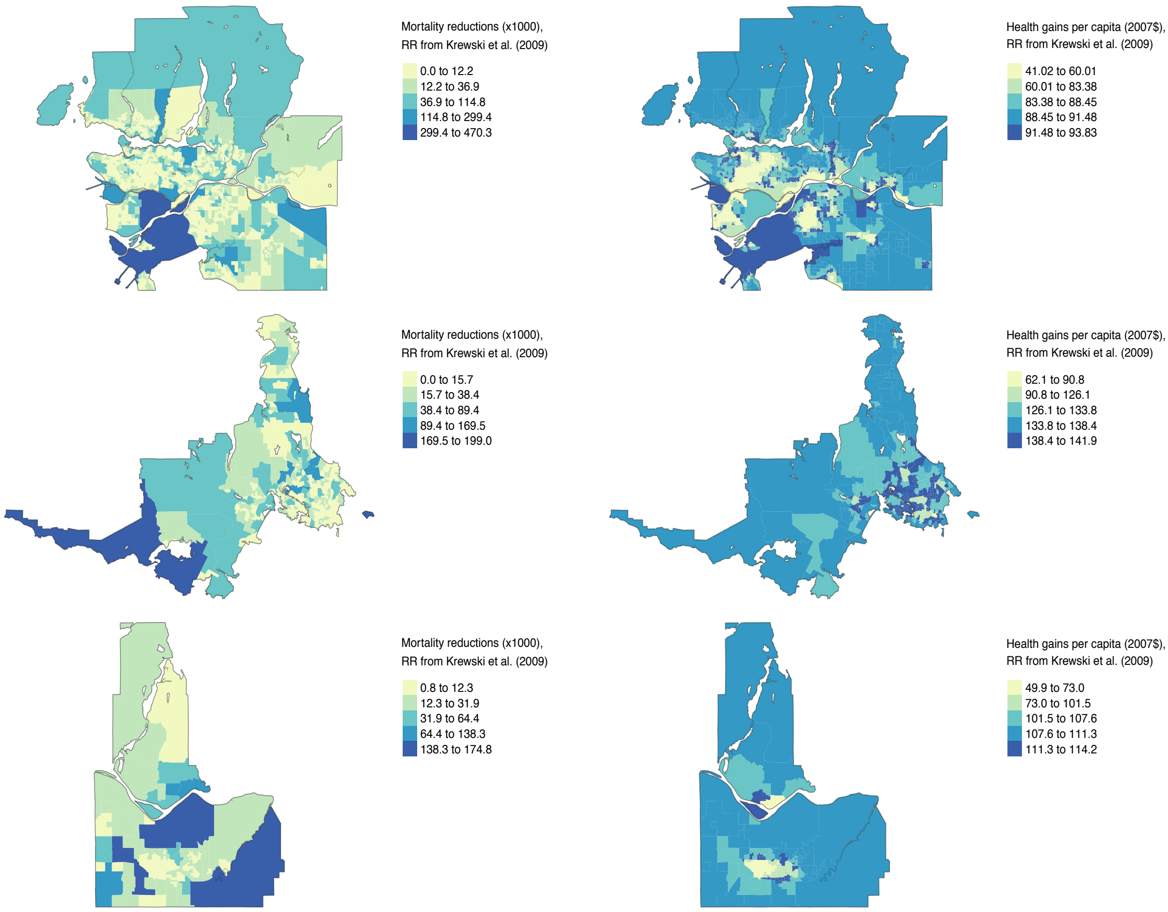


Notes: Results of SDID regressions by quintile of baseline characteristics. Panel A) Quintiles of Material Deprivation Index; B) Quintiles of Theil's Diversity Entropy Index. ATT point estimates reported in red, with 95% confidence intervals calculated with the Arkhangelsky *et al.* (2021) procedure with 200 bootstrap runs in grey shading.

A6. POLLUTION, HEALTH AND DISTRIBUTIONAL IMPLICATIONS

A6.1. Estimates using RR from Krewski et al. (2009)

FIGURE A.23 • MORTALITY REDUCTIONS AND MONETARY HEALTH GAINS



Notes: Spatial distribution of mortality reductions per 1000 residents (left panel) and health gains per capita (right panel) using the RR estimates from Krewski *et al.* (2009), for the Vancouver (top row), Victoria (middle row) and Abbotsford (bottom row) CMAs.

A6.2. Health-income relationships

FIGURE A.23 • SPATIAL RELATIONSHIP BETWEEN HEALTH GAINS AND MEDIAN INCOME

Notes: Bivariate distribution of health gains using the RR from Lepeule *et al.* (2012) (left panel) and Krewski *et al.* (2009) (right panel) and median income for the Vancouver (top row), Victoria (middle row) and Abbotsford (bottom row) CMAs.