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## Fuel Taxation and Environmental Externalities: Evidence from the World's Largest Environmental Tax Reform

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## Fuel Taxation and Environmental Externalities: Evidence from the World's Largest Environmental Tax Reform

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# Fuel taxation and environmental externalities: Evidence from the world's largest environmental tax reform

By Piero Basaglia, Sophie M. Behr, Moritz A. Drupp\*

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## Abstract

We investigate how fuel taxation reduces climate and pollution externalities by evaluating the world's largest environmental tax reform. Using spatially detailed emissions data from more than 1,000 European regions in a synthetic difference-in-differences framework, we evaluate the impact of Germany's 1999 ecological tax reform on transport-related carbon and air pollutant emissions. We document sizable aggregate reductions for all emissions, exceeding 10 percent on average per year relative to synthetic baselines. Using official damage valuations, we estimate avoided external costs of more than €100 billion, two-thirds of which stem from health benefits due to reduced air pollution. Emission reductions and associated monetized benefits are larger in lower-income regions, contrasting with a slightly regressive distribution of fuel costs. These findings underscore the importance of incorporating air quality co-benefits when evaluating the efficiency and distributional effects of fuel and carbon pricing.

**Keywords:** Environmental policy, externalities, fuel tax, carbon tax, synthetic difference-in-differences, tax elasticity, climate, pollution

**JEL codes:** Q58, H23, I18, R48

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# 1 Introduction

Fuel taxation is a key policy instrument to reduce negative externalities of fossil-fueled transportation (Parry et al., 2007; Sterner, 2007; Hintermann et al., 2025) and has seen renewed interest due to concerns about climate change, air pollution, and energy security (e.g., Grigolon et al., 2018; Parry et al., 2021). Understanding how fuel taxation affects fuel consumption and associated externalities is essential to effectively leverage this tool for economic policy. Many assessments primarily focus on carbon abatement and assume that demand responses to tax changes are equivalent to those of market-driven price variations and estimate limited impacts of carbon pricing through taxation (e.g., Green, 2021). In contrast, recent work highlights the considerable role of tax salience and persistence effects (e.g., Chetty et al., 2009; Li et al., 2014), which may suggest that more modest taxes may achieve politically targeted fuel reductions. Additionally, carbon abatement represents only part of the economic benefits that can justify fuel taxes. Transportation causes considerable externalities beyond carbon emissions, such as health damages linked to air pollution (e.g., Schlenker and Walker, 2016; Knittel et al., 2016), and reducing fossil fuel use can thus yield substantial health benefits (e.g., Shaw et al., 2014; Parry et al., 2015). Accounting for such health co-benefits may change the overall incidence of the policy and may contribute to gathering public support for fuel and carbon taxes.

We investigate the effectiveness of fuel taxation in reducing carbon and air pollutant emissions with a quasi-experimental assessment of the world’s largest environmental tax reform: the German eco-tax. The reform increased fuel taxes in Europe’s biggest transport sector in yearly steps from 1999 to 2003 up to 15.35 cents per liter. In 2003, implicit carbon costs of the eco-tax amounted to €58 (\$65) per tCO<sub>2</sub> for diesel and €66 (\$74) for gasoline. This was then the second highest effective carbon price globally—higher alone than federal fuel taxes in the US, where regulation has mainly focused on standards (Jacobsen et al., 2023), and only slightly lower than the Swedish carbon tax on transport fuels that was levied on a much smaller tax base (Andersson, 2019).

Our analysis starts by estimating effects of the eco-tax on emissions of CO<sub>2</sub>, PM<sub>2.5</sub>, and NO<sub>x</sub> in the German transport sector drawing on a synthetic difference-in-differences (SDID) estimation framework (Arkhangelsky et al., 2021). Leveraging high-resolution data on European transport emissions from more than 1,000 European regions, we build plausible counterfactuals for how carbon and air pollution emissions would have trended across German districts in the absence of environmental taxation. Our SDID results imply that, between 1999 and 2009, environmental taxation led to average emission reductions of around 15% for CO<sub>2</sub>, 25% for PM<sub>2.5</sub>, and 13% for NO<sub>x</sub>, which

corresponds to a reduction in external damages in the order of a hundred billion euros when evaluated using official governmental cost estimates.

Our findings are robust to a host of robustness tests and different quasi-experimental study designs, including alternative donor pools, adjusting for residual imbalances in time-varying observables, the exclusion of bordering regions to address concerns related to fuel tourism, whether pollution is measured in absolute terms or as concentrations, and leveraging alternative synthetic control and matrix-completion approaches (i.e., [Abadie 2021](#); [Athey et al. 2021](#); [Xu 2017](#)). We also show that emission reductions did not occur at the expense of reduced GDP, which might otherwise confound the estimation of the effects of environmental taxation due to potential spillovers induced by economic activity shifting to neighboring countries (also commonly referred to as *leakage* effects), and find that the eco-tax has induced low-carbon innovation, which may have contributed to the effectiveness of the policy. Finally, we further validate the robustness and external validity of our findings by harnessing the early gradual roll-out of other environmentally-motivated taxes in Finland and Sweden, within a staggered treatment adoption design to address the potential residual confounding impacts of idiosyncratic shocks in fuel demand.

While modeling studies consistently indicate considerable health benefits due to lower fossil fuel use (e.g., [Shaw et al., 2014](#); [Choma et al., 2021](#)), this paper is the first observational study to quantify the climate *and* pollution reduction benefits of fuel taxation in a quasi-experimental framework. Our assessment of the world’s largest environmental tax reform complements studies on the role of emission standards to reduce climate and pollution externalities in the transport sector (e.g., [Auffhammer and Kellogg, 2011](#); [Jacobsen et al., 2023](#); [Reynaert, 2021](#)) and substantially extends investigations on the effectiveness of environmental taxes that focused exclusively on carbon abatement in country-level comparative studies. We make several contributions.

First, our results show that a sole emphasis on CO<sub>2</sub> reductions when evaluating the pricing of fuel use through taxation (e.g., [Andersson, 2019](#); [Runst and Höhle, 2022](#); [Mideksa, 2024](#); [Leroutier, 2022](#)) or cap-and-trade schemes (e.g., [Bayer and Aklin, 2020](#); [Colmer et al., 2025](#)) considerably underestimates the potential of fuel or carbon price instruments to reduce environmental externalities. Specifically, we find that around two-thirds of the overall reduction in external damages costs of hundred billion Euros that we estimate due to the eco-tax relate to reductions in air pollution and their associated health benefits.

Second, we depart from previous quasi-experimental evaluations of carbon and fuel taxes by assembling a novel dataset combining spatially granular data on transport emissions with small-scale administrative records, which allows us to examine heterogeneity

in emission reductions and health co-benefits across 401 German districts.<sup>1</sup> While the consumer costs of fuel taxation tend to burden lower-income households disproportionately (e.g., Bento et al., 2009; Drupp et al., 2025; Sterner, 2012; Känzig, 2023), poorer households may also benefit disproportionately from reduced pollution (e.g., Hernandez-Cortes and Meng, 2023). We find that the eco-tax led to larger pollution reduction benefits per capita in low-income districts, and that benefits accrue to a greater extent in areas with higher baseline pollution. This provides new insights on environmental justice effects of environmental taxation for Europe, where evidence has been sparse (Banzhaf et al., 2019; Bos et al., 2025; Drupp et al., 2025).

We complement our quasi-experimental analyses with panel-data analyses to estimate price and tax elasticities and perform counterfactual simulations. We build on a large literature exploring effects of gasoline and energy prices on fuel demand and emissions (e.g., Dahl and Sterner, 1991; Levin et al., 2017; Linn, 2019; Parry et al., 2021), which often relies on fuel and energy prices as proxies for carbon prices and uses price changes over time to estimate impacts on fuel use. Yet, fuel prices are prone to endogeneity concerns, likely biasing price elasticity estimates downwards (e.g., Kilian, 2009; Davis and Kilian, 2011; Coglianese et al., 2017). We use annual cross-country panel variations in fuel-specific tax rate changes, coupled with an instrumental variable approach, and additional model specifications with leads to account for potential tax anticipation effects (cf. Kilian and Zhou, 2024). Our focus on fuel-specific demand adjustments departs from previous studies that rely on changes in gasoline use as a proxy for aggregate emission reductions (e.g., Davis and Kilian, 2011; Rivers and Schaufele, 2015) and helps to illuminate the role of fuel substitution. Accounting for gasoline-to-diesel substitution is crucial in the European context with its high diesel share (Zimmer and Koch, 2017), and allows quantifying trade-offs between climate and health benefits.

We first estimate price and tax elasticities of demand for gasoline and diesel to disentangle behavioral responses in Germany. We estimate a long-term tax-exclusive price elasticity of demand for gasoline (diesel) of -0.54 (-0.34) and an eco-tax elasticity of demand of -2.7 (-1.1). Fuel-specific eco-tax elasticities are thus around 3 to 5 times higher than the tax-exclusive price elasticity (a ratio referred to as *tax saliency ratio*), in line with prior findings that changes in taxes are more potent than equivalent market-driven price changes (e.g., Li et al., 2014; Rivers and Schaufele, 2015; Andersson, 2019).<sup>2</sup>

<sup>1</sup>A concurrent working paper by Sileci (2023) examines environmental equity impacts of the 2008 carbon tax in the Canadian province British Columbia across 26 metropolitan areas. By contrast, we examine effects not only in urban but also in rural areas across the whole country. Another concurrent paper by Runst and Höhle (2022) examined CO<sub>2</sub> effects of the eco-tax with a country-level synthetic control analysis, yielding similar effects to ours for CO<sub>2</sub> reductions.

<sup>2</sup>Kilian and Zhou (2024) reconsider the analysis by Li et al. (2014) using a distributed lag model and find that the tax elasticity is not significantly different from the tax-exclusive price elasticity in the US

This underscores potentially large biases in policy evaluations that rely on responses to market-driven fuel price changes as a proxy for the effect of environmental taxes.

We then use these fuel-specific tax elasticities to perform simulations and find that around three-quarters of the (simulated) reduction in CO<sub>2</sub> emissions is attributable to lower gasoline use, partly driven by gasoline-to-diesel substitution. Conversely, almost all decreases in PM<sub>2.5</sub>, and more than half of decreases in NO<sub>x</sub> emissions, are driven by lowered diesel use due to the eco-tax. This highlights important trade-offs that can arise between climate and air pollution targets, which is particularly relevant for price instruments set on the carbon content of fuels that can foster fuel substitution. Such fuel substitution is—with the exception of [Linn \(2019\)](#)—not accounted for in existing policy evaluations. We complement [Linn \(2019\)](#) by relaxing the assumption that consumers respond similarly to fuel taxes as to other changes in fuel prices. We find that accounting for tax salience effects reveals a much more sizable trade-off between climate and health benefits. This trade-off, and the associated inefficiency in targeting both climate and pollution targets with one price instrument, is a more general feature of second-best taxation (e.g., [Knittel and Sandler, 2018](#)), especially when it is not feasible to tax externalities directly ([Jacobsen et al., 2023](#)).

Finally, we explore additional underlying mechanisms for the sizable reductions in external climate and pollution damages due to the eco-tax. We find that the eco-tax has likely contributed to fostering fleet renewal of passenger cars and to fewer passenger-kilometers traveled without having reduced overall economic activity. Furthermore, we documented that the fuel price increase due to eco-tax has received substantial attention in newspapers (c.f., [Li et al., 2014](#)). This increased salience may have contributed to the large *tax saliency ratios* that form an important driver of the effectiveness of the eco-tax to reduce climate and pollution externalities.

The paper proceeds as follows. Section 2 provides the policy background of the eco-tax. Section 3 details the main methodologies employed in our research designs. Section 4 discusses the data. Section 5 presents results derived from the SDID estimator, while Section 6 reports results on fuel and tax elasticities, simulations. Section 7 discusses additional mediating mechanisms. Section 8 quantifies climate and health benefits, while Section 9 concludes. The Online Appendix (OA) contains additional results from alternative methods and supporting materials for our analyses.

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after accounting for anticipation effects. In our setting, even after accounting for anticipatory behavior, we still document sizable and significant *tax saliency ratios*.

## 2 Policy background

**The ecological fiscal reform in Germany.** While not officially labeled a carbon tax, the ecological fiscal reform (hereafter: eco-tax) effectively established a sizable implicit carbon price in Germany. It came into effect in April 1999 taxing fuels, gas, electricity, and heating oil ([Bundesgesetzblatt I, S.378, 1999](#); [Steiner and Cludius, 2010](#)). The eco-tax reform adopted a 'double dividend' approach. The reform targeted environmental objectives by internalizing the external costs of fossil fuel consumption. Yet, instead of directing the generated revenues towards environmental initiatives, the additional fiscal capacity was used to reduce pension fund contributions through non-wage labor costs.<sup>3</sup>

Owing to economic and social concerns, the eco-tax underwent extensive exemptions across several sectors. Consequently, it primarily affected the pricing of transport fuels and electricity use in less energy-intensive industries. To account for the mitigating impacts of these exemptions (e.g., [Gerster and Lamp, 2024](#)), we therefore focus solely on the transportation sector ([Knigge and Görlach, 2005](#); [Bach, 2009](#)). In each year between 1999 and 2003, the fuel tax on gasoline and diesel was increased by 3.07 cents (6 Pfennig) per liter ([Bach, 2009](#)). This resulted in a total tax increase of 15.35 cents per liter for gasoline and diesel. Effectively, this means that the eco-tax introduced an implicit carbon price of around 58€ (\$65) for diesel and 66€ (\$74) for gasoline between 1999 and 2003.<sup>4</sup> Thereby, within the timeframe of our study, the eco-tax represented the second highest tax on CO<sub>2</sub> globally, after Sweden (\$105) and before Finland (\$30) in Europe (cf. [Sumner et al. 2011](#)).

We provide descriptive statistics to illustrate the evolution of fuel taxation in Germany's transport sector before and after the eco-tax introduction in Figure 1, showing gasoline and diesel taxes from the late 1970s until 2009.<sup>5</sup> We provide real values and a comparisons with other existing tax rates in Figure A.3 in the OA.

**Concurrent unilateral environmental policies.** The eco-tax reform stood out as Germany's primary policy measure to mitigate transport-related emissions until the end of the 2000s. Nevertheless, a few noteworthy concurrent policy changes occurred during and close to the end of the post-treatment time frame (1999-2009), prompting

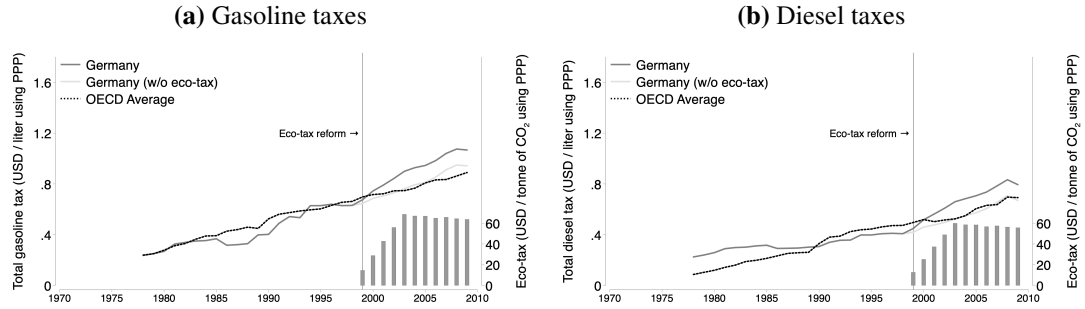
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<sup>3</sup>The eco-tax reform may thus have also induced positive effects on labor market outcomes. We do not investigate potential effects along these lines, as the German government introduced major labor legislation, the so-called "Hartz Reforms" in 2003 (see, e.g., [Dustmann et al., 2014](#)), which likely overshadow any potential effect that the eco-tax may have had on the labor market.

<sup>4</sup>Note that the combustion of one liter of gasoline emits 2.325 kg of CO<sub>2</sub>, of one liter of diesel 2.660 kg ([US EPA, 2005](#)). Leveraging emission factors, we can then express the eco-tax rate in euros per tonne of CO<sub>2</sub> as  $\frac{0.1535}{2.325} \times 1000 \approx 66\text{€}/\text{tCO}_2\text{e}$  and  $\frac{0.1535}{2.660} \times 1000 \approx 58\text{€}/\text{tCO}_2\text{e}$ .

<sup>5</sup>The VAT is levied on the eco-tax, which increases the eco-tax by its percentage. A slight increase of the eco-tax is visible in 2007 due to the increase of the VAT from 16% to 19% early in that year.

**Figure 1: Evolution of transport fuel taxes in Germany and OECD average**



Notes: Prices are in USD using Purchasing power parities (PPP). Source: Energy Prices and Taxes Statistics from the International Energy Agency (IEA). The eco-tax rates, expressed in terms of tonnes of CO<sub>2</sub> equivalent, adjusted for PPP, and includes the value-added tax (VAT), are taken from [Bach \(2009\)](#).

our decision to end our main estimation sample in 2009. First, Germany implemented a distance-based toll for all lorries of more than twelve tonnes gross weight on motorways in 2005. [Luechinger and Roth \(2016\)](#) study this policy and find insignificant effects on overall traffic volume but rather that traffic has been diverted to toll-free roads. Second, starting in 2008, some cities implemented low emission zones (LEZs) to restrict certain vehicles from entering city centers, with other municipalities later adopting and enhancing these standards. LEZs have led to emission reductions in regulated areas and neighboring cells (e.g., [Wolff and Perry, 2010](#); [Sarmiento et al., 2023](#); [Klauber et al., 2024](#)). Despite this, we consider it unlikely that LEZs sizably influenced our results in the last two years of our study as they were only established in a few cities by that time. Third, the German government responded to the 2008 financial crisis by paying a scrappage subsidy for the disposal of vehicles that were at least nine years old to increase new car sales. This program was in force from January 2009 until September 2009. [Helm et al. \(2023\)](#) detect local air pollution improvements following this subsidy. Finally, following the eco-tax, the next major taxation reform occurred in 2009 when vehicle circulation taxes were adjusted to consider CO<sub>2</sub> emissions for cars registered from July 2009, which [Klier and Linn \(2015\)](#) showed to have lead to fewer registrations. Our main time frame, therefore, ends with the start of the next nationwide policy actions in the transportation sector. Yet, as the additional policies towards the end of our time frame might have reduced emissions, we also explore an estimation sample that ends in 2007 to precede these potential confounders. Our results remain qualitatively unchanged to shortening the time frame.

### 3 Methodology

#### 3.1 Synthetic difference-in-differences estimation

To examine the effects of environmental fuel taxation, we use the SDID methodology (Arkhangelsky et al., 2021), which combines desirable features of synthetic control (SC) methods (e.g., Abadie, 2021; Athey et al., 2021; Xu, 2017) and a two-way fixed effects (TWFE) difference-in-differences (DID) approach. Drawing on Arkhangelsky et al. (2021), this section summarizes how we employ the SDID estimation procedure in our research designs and contrasts its relative strengths to the standard SC and TWFE-DID approaches in addressing potential bias in the identification of effects. Alternative counterfactual estimators used for robustness tests are described in the OA.

**The SDID estimator.** As an input requirement, the SDID estimation requires a balanced panel of  $N$  units or groups, observed over  $T$  time periods. We consider a setup where a subset of  $N$  ( $N_{tr} = N - N_{co}$ ) is regulated (e.g., German districts after the eco-tax) as indicated by a binary treatment indicator, which we denote by  $Eco_{it}$ . The indicator  $Eco_{it}$  equals 1 if unit  $i$  after time  $T_{pre}$  is subject to the eco-tax, and 0 otherwise. In this setting, the SDID estimation of the average treatment effect on the treated (or ATT denoted by  $\tau^{sdid}$ ) is written as:

$$\left( \hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta} \right) = \arg \min_{\tau, \mu, \alpha, \beta} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \alpha_i - \beta_t - Eco_{it} \tau)^2 \cdot \hat{\omega}_i^{sdid} \cdot \hat{\lambda}_t^{sdid} \right\}, \quad (1)$$

where the parameter  $\hat{\tau}^{sdid}$  is the ATT estimated in a TWFE regression with optimally chosen unit-specific ( $\hat{\omega}_i^{sdid}$ ) and time ( $\hat{\lambda}_t^{sdid}$ ) weights. The underlying intuition behind the inclusion of  $\hat{\omega}_i^{sdid}$  and  $\hat{\lambda}_t^{sdid}$  is that *unit-specific* weights allow to yield matching pre-intervention trends while *time-specific* weights are introduced in the regressions to reduce the influence of time periods that significantly differ from post-treatment periods and increase model precision. Crucially, matching pre-intervention trends is pivotal to assuming quasi-randomization (after re-weighting) in the identification.<sup>6</sup> In essence, the SDID estimator can be seen as a DID analysis with weighted observations. This approach allows the SDID estimator to sidestep some of the typical issues of standard DID and SC. These include the inability to estimate causal relationships when the parallel trends assumption is not satisfied for DID and the requirement in SC for the treated unit to be located within a *convex hull* of control units.

The inclusion of unit fixed effects ( $\alpha_i$ ) implies that the SDID estimator, by choosing unit weights ( $\hat{\omega}_i$ ), will match treated and control units based on pre-treatment trends, as the fixed effects ( $\alpha_i$ ) absorb any level differences. The presence of time effects ( $\beta_t$ )

<sup>6</sup>See Arkhangelsky et al. (2021) (Section 2.1, Algorithm 1) for weight estimation details.

allows for common temporal aggregate factors. In our setting, the latter refers to underlying trends or fluctuations in emissions that occur due to factors such as technological advancements, common macroeconomic shocks, or other external drivers that change emissions levels over time independently of changes in the eco-tax rate.

**Conditioning on covariates and inference.** To further condition Eq. 1 on time-varying covariates and adjust our estimations for potential imbalances in time-varying observables, we apply the SDID algorithm to the residuals:

$$Y_{it}^{\text{res}} = Y_{it} - X_{it}\hat{\beta}, \quad (2)$$

where  $\hat{\beta}$  is calculated by regressing  $Y_{it}$  on  $X_{it}$ . We can then conduct inference by constructing the following confidence intervals for the treatment effect,  $\tau^{\text{sdid}}$ :

$$\hat{\tau}^{\text{sdid}} \pm z_{\alpha/2} \sqrt{\hat{V}_{\tau}}, \quad (3)$$

where we implement the bootstrap procedure from (Arkhangelsky et al., 2021) (cf. Algorithm 2) to estimate the variance,  $\hat{V}_{\tau}$ . Specifically, this procedure generates a bootstrap dataset by sampling, with replacement, a portion of the original dataset. Then, it computes the SDID estimator ( $\hat{\tau}^b$ ) on this subset of the sample for each iteration,  $b$ , based on a selected number of replications (denoted by  $B$ ). The bootstrapped variance ( $\hat{V}_{\tau}^b$ ) is then defined as:

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

Following the iterative procedure described in Eq. 4, our confidence intervals are estimated based on 200 replications ( $B = 200$ ).

**The staggered adoption design.** The design outlined thus far operates under the assumption of block assignment, with a single adoption period for treated units (e.g., a single adopting country). We now lay out the details pertaining to a staggered adoption design, where treated units adopt treatment at varying points (e.g., multiple countries with environmental taxes). To isolate the impact of fuel taxation, we identify other European countries where environmental taxes were implemented without reinvesting their revenue into climate mitigation programs, namely Finland in 1990 and Sweden in 1991 (Sumner et al., 2011).

Drawing on Athey and Imbens (2022), here we focus on a staggered adoption configuration where units (e.g., regions) adopt the treatment of interest at a particular point in time, and then remain exposed to this treatment continuously thereafter. Consider a

row vector  $\mathbf{A} = (a^1, a^2, \dots, a^A)$  consisting of  $a$  elements which contains distinct adoption periods. The ATT can then be calculated in a two-step procedure. First, we apply the synthetic DID estimator to each of the adoption-specific samples:

$$\left( \hat{\tau}_a^{\text{sdid}}, \hat{\mu}_a, \hat{\alpha}_a, \hat{\beta}_a \right) = \arg \min_{\tau, \mu, \alpha, \beta} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \alpha_i - \beta_t - Eco_{it} \tau)^2 \cdot \hat{\omega}_{i,a}^{\text{sdid}} \cdot \hat{\lambda}_{t,a}^{\text{sdid}} \right\}. \quad (5)$$

Notably, adoption-specific unit ( $\hat{\omega}_{i,a}^{\text{sdid}}$ ) and time ( $\hat{\lambda}_{t,a}^{\text{sdid}}$ ) weights ease the quasi-randomization assumption, which is key to yield unbiased effects in our staggered setting (Athey and Imbens, 2022). Second, we compute a weighted average of the adoption-specific SDID estimates, where weights are assigned based on the relative number of treated units and time periods in each adoption group:

$$\widehat{ATT} = \sum_{a \in \mathbf{A}} \frac{T_{post}^a}{T_{post}} \cdot \hat{\tau}_a^{\text{sdid}}, \quad (6)$$

where  $T_{post}$  refers to total post-treatment periods observed in treated units.

**Comparison with alternative estimators.** The canonical TWFE-DID procedure essentially mirrors the SDID regression but assigns equal weights to all time periods and units (cf. Eq. 7), making diverging pre-treatment trends between treated and control units a potential threat to identifying causal effects. That is, TWFE-DID estimates will be biased when unobserved time-varying confounders exist, as we cannot plausibly assume that outcomes in control and treatment groups would have trended similarly in the absence of treatment, given pre-existing systematic differences. Formally, the TWFE-DID estimation of the ATT (denoted by  $\tau^{\text{did}}$ ) can be written as follows:

$$\left( \hat{\tau}^{\text{did}}, \hat{\mu}, \hat{\alpha}, \hat{\beta} \right) = \arg \min_{\tau, \mu, \alpha, \beta} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \alpha_i - \beta_t - Eco_{it} \tau)^2 \right\}. \quad (7)$$

The standard SC approach (e.g., Abadie and Gardeazabal, 2003), instead, maintains optimally chosen unit-specific weights, denoted as  $\hat{\omega}_i^{\text{sc}}$  (cf. Eq. 8). However, it does not optimize time periods through time weights and excludes unit fixed effects ( $\alpha_i$ ), implying that the SC and treated units should exhibit comparable pre-treatment levels and trends before re-weighting.

$$\left( \hat{\tau}^{\text{sc}}, \hat{\mu}, \hat{\beta} \right) = \arg \min_{\tau, \mu, \beta} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \beta_t - Eco_{it} \tau)^2 \cdot \hat{\omega}_i^{\text{sc}} \right\}. \quad (8)$$

While variants of the TWFE-DID (Eq. 7) and SC (Eq. 8) approaches have been commonly employed in earlier studies that have investigated the effectiveness of fuel taxes to reduce CO<sub>2</sub> per capita (e.g., Andersson, 2019; Leroutier, 2022), the SDID estimator improves model precision by disregarding pre-treatment periods that exhibit substantial

differences from the post-treatment periods (with time-specific weights), making the SDID estimator doubly robust to both diverging pre-trends and model mis-specification (Arkhangelsky et al., 2021). Finally, in contrast to other approaches to address divergent pre-trends in a TWFE-DID estimation, such as one-to-one matching with propensity scores (see Cui et al., 2021, Dechezleprêtre et al., 2023, and Colmer et al., 2025 for examples), our approach avoids discarding non-matching observations. Instead, our estimation strategy assigns them lower unit weights, retaining a larger estimation sample which allows us to preserve greater power for inference and comprehensively explore results heterogeneity.

To facilitate direct comparisons, each of the three estimators can be reformulated as a weighted average difference in adjusted outcomes ( $\hat{\delta}_i$ ) using the appropriate unit-specific weights ( $\hat{\omega}_i$ ):

$$\hat{\tau} = \hat{\delta}_{tr} - \sum_{i=1}^{N_{co}} \hat{\omega}_i \hat{\delta}_i \quad \text{where} \quad \hat{\delta}_{tr} = \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^N \hat{\delta}_i. \quad (9)$$

A first key difference is that while the TWFE-DID estimation leverages constant weights ( $\hat{\omega}_i = N_{co}^{-1}$ ) across untreated units ( $\hat{\delta}_i$ ), the SC and SDID approaches generate a set of weights to approximately match pre-treatment trends of unexposed units with those for the exposed ones. Secondly, for the adjusted outcomes ( $\hat{\delta}_i$ ), the SDID estimator further selects time weights to balance pre- and post-exposure periods for unexposed units:

$$\hat{\delta}_i^{sdid} = \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^T Y_{it} - \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} Y_{it}. \quad (10)$$

### 3.2 Semi-elasticity models

We subsequently complement our causal inference analyses by estimating price and tax elasticities of gasoline and diesel demand and use these to perform simulations to investigate tax effectiveness using log-linear semi-elasticity models. We estimate fuel-specific elasticities, using two different specifications. First, we calculate real price elasticities and compare them to typical fuel demand elasticities (cf. Eq. 11: *Real price elasticities*). Second, in line with Li et al. (2014) and Andersson (2019), we split the real price into its three main elements: (i) the eco-tax, (ii) other existing fuel taxes (henceforth the energy tax), and (iii) the remaining tax-exclusive component, here called the raw price (cf. Eq. 12: *Eco-tax elasticities*).

**Real price and tax elasticity in Germany.** We first estimate a set of models based on variation in fuel demand within Germany and use the estimated elasticities from Eq.

12 to simulate predicted pathways of CO<sub>2</sub> and air pollution emissions under different taxation regimes.<sup>7</sup> The static log-linear models for Germany are expressed as:

$$\log(y_t) = \beta_0 + \varphi_1 p_t^{real} + \beta_2 D_t^{eco} + \lambda' \mathbf{X}_t + \varepsilon_t \quad (11)$$

$$\log(y_t) = \beta_0 + \varphi_2 p_t^{excl} + \varphi_3 p_t^{eco} + \varphi_4 p_t^{energy} + \beta_2 D_t^{eco} + \lambda' \mathbf{X}_t + \varepsilon_t \quad (12)$$

Elasticity estimates obtained leveraging annual data within a static model typically approach long-term elasticities (Sterner, 2007), or are alternatively regarded as “intermediate” (Dahl and Sterner, 1991). Outcome  $y_t$  refers to log fuel consumption per capita for gasoline or diesel in liters.<sup>8</sup>  $p_t^{real}$  is the real retail price, including VAT.  $p_t^{excl}$  is the retail price excluding the energy and eco-tax but with VAT, in real terms.  $p_t^{eco}$  and  $p_t^{energy}$  refer to the eco and energy tax, respectively, including VAT and are included in the models as separate terms (cf. Eq. 12).  $D_t^{eco}$  is a dummy equal to one after the implementation of the eco-tax and zero otherwise.  $\mathbf{X}_t$  is a vector of control variables that includes GDP per capita, the unemployment rate, and a time trend. The error terms are denoted by  $\varepsilon_t$ . We estimate the model using an OLS regression. We use the Newey-West-estimator, robust to autocorrelation and heteroskedasticity.<sup>9</sup>

A standard concern with estimating fuel elasticities is an endogeneity problem, where fuel demand can also affect supply and thus prices (e.g., Kilian, 2009; Coglianese et al., 2017; Kilian and Zhou, 2024). Endogeneity due to reverse causality is arguably a lesser source of concern in a single EU country setting, as crude oil prices are set in a global market and changes in demand in a single country are thus expected to have a relatively marginal impact on overall demand. One possibility to address this issue is to adopt an instrumental variable (IV) approach. In line with Li et al. (2014) and Andersson (2019), we complement our OLS regressions with an IV approach and use the (Brent) crude oil price as an IV to validate the demand elasticities of the real fuel price.

**Fixed effects models with cross-country panel data.** We further estimate a set of fuel-specific fixed effects models harnessing cross-country panel variation in fuel prices and tax rates to refine and validate our set of *Real* and *Eco-tax elasticities* for Germany. Crucially, the additional variation across jurisdictions in the estimation sample allows us to include a host of fixed effects to control more precisely for unobserved time-varying

<sup>7</sup>We refer to this specification as our *Baseline* model when discussing results in Section 6.

<sup>8</sup>Prior to taking logs, we convert fuel consumption to liters.

<sup>9</sup>Standard errors are calculated using lags chosen following Newey and West (1994).

confounding factors. The resulting static log-linear fixed effects models are written as:

$$\log(y_{it}) = \beta_0 + \phi_1 p_{it}^{real} + \lambda' \mathbf{X}_{it} + \gamma_i + \psi_t + D_t^{eco} \times \phi_i + \varepsilon_{it} \quad (13)$$

$$\log(y_{it}) = \beta_0 + \phi_2 p_{it}^{excl} + \phi_3 p_{it}^{eco} + \phi_4 p_{it}^{energy} + \lambda' \mathbf{X}_{it} + \gamma_i + \psi_t + D_t^{eco} \times \phi_i + \varepsilon_{it} \quad (14)$$

One key difference vis-a-vis Eq. 11 and 12 is the inclusion of country ( $\gamma_i$ ) and time fixed effects ( $\psi_t$ ). The former absorb any time-invariant characteristics that might affect fuel demand in each country, allowing us to focus on changes within countries over time. The latter captures common time trends that affect fuel demand across all countries in the same way (e.g., macroeconomic factors, technological advancements, or global demand changes). The models allow for spatial autocorrelation by clustering standard errors at the country-year level. We also now include our dummy indicator,  $D_t^{eco}$ , interacted with country-specific dummies,  $\phi_i$ , to absorb any unobserved country-specific shocks affecting fuel demand after the implementation of the eco-tax (e.g., other nationwide policies affecting fuel demand). Finally, we add an EU-specific time trend among a vector of cross-country control variables,  $\mathbf{X}_t$ , to account for common trends in fuel demand (e.g., EU-wide market and/or policy reforms).

## 4 Data

Our analysis is structured in two parts, which combine several data. First, we use the SDID estimator to evaluate plausibly causal effects of the eco taxes on  $\text{CO}_2$ ,  $\text{PM}_{2.5}$  and  $\text{NO}_x$  emissions. Second, we perform complementary (non-causal) analyses on underlying mechanisms. To this end, we estimate price and tax elasticities relying on a cross-country panel dataset. Table A.1 in the OA provides all data sources.

**Emissions in the transport sector.** To analyze the effect of the eco-tax reform on  $\text{CO}_2$ ,  $\text{PM}_{2.5}$ , and  $\text{NO}_x$  emissions from the transport sector, we draw on several panel datasets from the Emission Database for Global Atmospheric Research (EDGAR) compiled by the European Union (EU) Joint Research Centre (JRC). Data from EDGAR offers the key advantage of providing worldwide emissions data, disaggregated by sectoral definitions, in line with guidelines from the Intergovernmental Panel on Climate Change (IPCC), which allows us to isolate carbon and pollution emissions originating specifically from the transport sector (i.e., IPCC sector code 1A3b). EDGAR is widely used to support policy design, treaty compliance, the IPCC, and emission verification to back countries' emission reporting to the UN Climate Change Convention Secretariat (Crippa et al., 2020).

Global annual gridded maps (with a resolution of around 11km x 11km), plotting sector-specific emissions, are available from 1970 onward. We extract information on transport-related CO<sub>2</sub> emissions (EDGAR v8.0) as well as exhaust and non-exhaust emissions of PM<sub>2.5</sub> and NO<sub>x</sub> (EDGAR v6.1) from 1970 to 2009, which corresponds to the end of our estimation sample.<sup>10</sup> Within the transport sector, emissions are calculated using national-level activity data, such as fuel consumption and vehicle kilometers traveled, combined with technology-specific emission factors. These emissions are then spatially disaggregated using proxies, including road network density, traffic statistics, fleet composition, and urban population distribution. Variation in pollution estimates stems from annual changes in transport activity (e.g., total distance traveled), fleet turnover (the replacement of older vehicles with newer, lower-emission technologies), and shifts in fuel use (e.g., modal shifts to rail or public transport). These changes are incorporated in EDGAR through updated statistical inputs and the application of time-dependent emission factors. Emissions data is thus not observed, but represents estimates, akin to weather re-analysis data. EDGAR’s spatial distribution approach is detailed in [Crippa et al. \(2024\)](#).

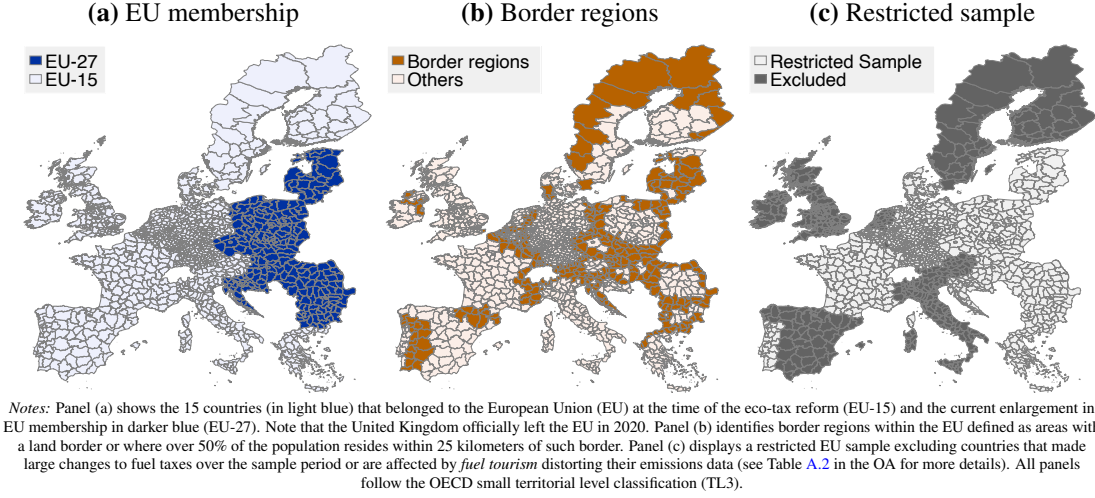
We aggregate transport emissions from the EDGAR grid to the EU territorial grids to obtain cumulative emission levels (in tonnes of CO<sub>2</sub> and kilograms of PM<sub>2.5</sub> and NO<sub>x</sub>) for each NUTS-3 administrative region, which represents our unit of analysis.<sup>11</sup> In Germany, this level corresponds to the 401 districts (*Kreise* or *kreisfreie Städte*) across its 16 states. Drawing from the literature, we focus on per capita emissions levels (in tonnes or kilograms), which we obtain by combining aggregated data from EDGAR with regional population records from the OECD (e.g., [Andersson 2019](#); [Leroutier 2022](#)). We limit our main analyses to current EU members (hereafter EU27) to address concerns that effects may be partly confounded by post-treatment EU-wide regulation changes, such as emission standards (e.g., [Reynaert, 2021](#)). We also consider two alternative samples: (a) EU15, comprising EU members at the time of the eco-tax reform, and (b) a restricted sample excluding countries that made large fuel taxation reforms in the sample period or whose emissions data may be distorted by *fuel tourism* (cf. Figure 2). See Table A.2 in the OA for more details.

As a robustness check, we employ an alternative dataset of PM<sub>2.5</sub> concentrations produced by [Shen et al. \(2024\)](#). This dataset provides a measure of PM pollution con-

<sup>10</sup>Transport emissions include road, rail, domestic aviation, inland waterways, and shipping ([Crippa et al., 2022](#)), but road transport dominated in 1999, accounting for 97% of CO<sub>2</sub> emissions; rail (1.0%) and aviation (1.4%) contributed marginally ([Umweltbundesamt, 2022](#)).

<sup>11</sup>The Nomenclature of Territorial Units for Statistics (NUTS) is a geographical nomenclature that subdivides the economic territory of the EU into distinct regions (i.e., NUTS-1, 2, and 3, progressing from broader to smaller territorial divisions).

**Figure 2: European territorial grids in the estimation samples**



centrations derived through a deep learning algorithm supplied with satellite, station and simulation data. We use this dataset to further validate our main results using a different pollution measurement (see Section E of the OA). However, it comes with notable limitations: it begins in 1998, which leaves us with only one pre-treatment year, covers  $PM_{2.5}$  concentrations exclusively, and does not distinguish between different emission sources, which may introduce additional noise in the identification. These constraints justify the use of the EDGAR dataset as our primary source for the main analysis.

**Consumption and price of transport fuels across countries.** To estimate price and tax elasticities and disentangle the different taxation changes, we first construct an annual time-series dataset for Germany, spanning from 1971 to 2009.<sup>12</sup> The data for the gasoline and diesel prices reflect yearly consumer prices for both fuels including VAT. We convert all nominal prices to real prices, including the energy and eco-tax rates and the strategic reserve component (the OA details data sources). As VAT is not only imposed on the tax-free price  $p$  but also on the eco and energy taxes,  $\tau^{eco}$  and  $\tau^{energy}$ , and the strategic reserve,  $\tau^{sr}$ , in the same way as on the price, the retail price  $p^r$  can be defined as:

$$p^r = (p + \tau^{eco} + \tau^{energy} + \tau^{sr}) * (1 + VAT) \quad (15)$$

<sup>12</sup>A peculiarity of Germany is its division until the year 1990. As there was no market economy in East Germany, there were no market prices and no taxes in the same sense as in West Germany. All prices we use thus relate only to West Germany prior to 1991, while price data from 1991 onwards, and all fuel consumption data, reflects the entirety of modern Germany.

To account for this, VAT is already included in each retail price element.<sup>13</sup> All prices given in Deutsche Mark (DM) are converted to Euro, and all nominal prices and absolute tax rates into real 1995 values. We chose 1995 as a convenient base year close to the implementation of the eco-tax. Whenever a tax rate changed within a year, we weighted rates according to the date at which the change took place and used these average tax rates. The (Brent) crude oil price used for the IV regressions is from the International Energy Agency (IEA), converted from USD per barrel to €/l using the [Eurostat \(2020\)](#) €/USD rate.

Second, we construct an annual panel dataset with country-level diesel and gasoline consumption and prices to expand our country-level time series. Data on per capita gasoline and diesel fuel consumption in the road transport sector (in kg of oil equivalent) are sourced from the International Road Federation’s World Road Statistics and the International Energy Agency (IEA), as compiled and adjusted by the World Bank using annual population estimates (see [A.1](#) of the OA). Data on gasoline (diesel) prices and taxes are consistently available from the IEA for 24 (19) major countries starting from 1978 onwards.<sup>14</sup> We harness the additional cross-country variation to estimate a set of fuel-specific price and tax semi-elasticity models which employ a host of fixed effects to control more precisely for unobserved time-varying confounding factors.

**Additional data.** To study the heterogeneity of emission reductions across geographical and socio-economic characteristics and shed light on potential mechanisms and complementary outcomes, we collect a series of additional data.

First, to conduct sensitivity analyses, we gather country-level economic activity data to further condition our analyses on time-varying observables and adjust our estimations for potential residual imbalances in GDP growth patterns across treated and control groups. GDP data refers to expenditure-side real GDP in purchasing power parities (in 2011 USD) from the Penn World Table.

Second, to measure how the eco-tax may have affected innovation, we use patent data from the OECD Patent Database. We extract a panel dataset of climate change mitigation patents related to transportation (Y02T category) filed by inventors in OECD countries spanning from 1985 (earliest availability) to 2009. We focus on triadic patent families to improve the quality and the international comparability of patent counts.<sup>15</sup>

<sup>13</sup>If the eco-tax was raised by 10 cents, the fuel price would increase by 11.90 cents with a VAT rate of 19%. Thus, the eco and energy tax rates include VAT. In our calculations, the price increase is attributed to a change in the eco-tax rate.

<sup>14</sup>The difference in the number of jurisdictions covered by the IEA data for gasoline and diesel prices stems from the lack of a sizable market for diesel in a number of jurisdictions.

<sup>15</sup>Triadic patents are a sub-set of patents taken at the European Patent Office, the Japan Patent Office and the US Patent and Trademark Office that protect the same invention. We treat multiple application

Triadic patents are generally of higher value: patentees only take on the additional costs and delays of extending protection to other countries if they deem it worthwhile (Aghion et al., 2016).<sup>16</sup> Patents in our data are counted according to the earliest priority date, corresponding to the first patent application worldwide.

Third, to investigate the role of fleet renewal, we obtain data on the share of new passenger cars in the German fleet (aged 2 years or less) from the UNECE Statistical Database. Fourth, to examine how the eco-tax may have affected emissions via reduced travel volumes, we obtain data on road passenger-kilometers driven from OECD Statistics.

Fifth, to assess how the salience of the eco-tax in the media may have played a role, we develop a newspaper-based index to capture the evolution of salience related to environmental taxation based on textual analysis of newspaper articles (Gentzkow et al., 2019). To this end, we rely on the four largest newspapers in the Factiva database, which stores all articles published by major newspaper in print or online format. To obtain article counts, we rely on text-based search strategies that identify around 5,700 unique articles. After scaling the raw counts to ensure that index spikes are not driven by newspaper-specific publishing trends, we standardize each newspaper's series, average across all papers, and normalize the resulting index to 100 over the period, following the same standardization and normalization procedure of Baker et al. (2016). A description of our search strategies and the steps to construct newspaper-based indices is detailed in Section F.2 of the OA.

Sixth, we obtain socio-economic information for Germany aggregated at the district-level from the Leibniz Institute for Economic Research (Breidenbach and Eilers, 2018a). In particular, we extract gridded data on the distribution of household-level purchasing power, which comprises records on labor, capital, rental and leasing income minus taxes and social security contributions (i.e., social transfers such as unemployment benefits, child-allowances and pensions). Finally, we retrieve NUTS-3-level statistics from Eurostat to consistently identify the border and urban-rural classification of each European region.<sup>17</sup>

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filings of an invention (i.e., a patent family) as one innovation. We focus on patent families to capture the number of low-carbon technologies that are developed in Germany rather than the count of underlying patent applications.

<sup>16</sup>Considering the number of jurisdictions in which a patent application is filed is a common approach to capture patent quality (e.g., Calel and Dechezleprêtre, 2016).

<sup>17</sup>The European urban-rural typology categorizes areas into three groups: (i) *Predominantly urban* regions, where at least 80% of the population resides in urban clusters, *intermediate* regions, where more than 50% but less than 80% of the population lives in urban clusters, and *predominantly rural* regions, where at least 50% of the population resides in rural grid cells.

## 5 Average treatment effects of the eco-tax reform on environmental externalities

In this section, we present the average treatment effects of the eco-tax reform on CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions, leveraging the SDID estimator described in Section 3.1. We additionally discuss findings from several robustness tests in subsection 5.1, including a complementary research design with a staggered configuration, which leverages the gradual rollout of similar environmental taxation reforms in other EU countries in the 1990s, namely Finland (Mideksa, 2024) and Sweden (Andersson, 2019).

Table 1 summarizes our baseline ATTs for the SDID estimation. Figure 3 offers a graphical representation of each estimation. The SDID estimator re-weights the unexposed EU-27 control regions to make their time trend parallel to Germany pre-intervention, and then carries out a DID analysis to the re-weighted panel. Crucially, due to the presence of time weights ( $\hat{\lambda}_t^{\text{sdid}}$ ), we only focus on a subset of the pre-treatment periods during this final step. Pre-treatment time-weights are represented in light blue at the bottom of Panels (a) - (c) in Figure 3. Overall, the estimator performs well in approximating parallel pre-trends and assigns positive weights to years where treated and control units show similar trends. Panel (d) displays the composition of the SDID donor pools by aggregating unit-specific weights ( $\hat{\omega}_i^{\text{sdid}}$ ) at the country level. In line with Arkhangelsky et al. (2021), our SDID estimation yields more balanced weighting than previous SC applications (e.g., Andersson, 2019; Leroutier, 2022), with no single country receiving, on average, more than 17% of the weight.

The estimated ATTs point to sizable decreases in CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions in the transport sector following the eco-tax reform. First, between 1999 and 2009, mean annual emission reduction amounted to 0.37 metric tonnes of CO<sub>2</sub> per capita, which cumulatively sums up to 334,970,340 tonnes of CO<sub>2</sub>. Notably, our 95% confidence intervals encompass mean reductions estimated in Andersson (2019) from 2001 to 2005, amounting to around 0.35 metric tonnes, coinciding with the period when the Swedish carbon tax reached and later surpassed the eco-tax rate.<sup>18</sup> Second, we find that, on average, 0.17 kg of per capita PM<sub>2.5</sub> less were emitted each year in comparison to a scenario with no eco-tax, which amounts to total PM<sub>2.5</sub> savings of around 158,432 tons. Finally, our SDID estimation suggests that, after the eco-tax, per capita NO<sub>x</sub> emissions were lower by 2.2 kg, on average, with a cumulative reduction in NO<sub>x</sub> of 2,030,644 tonnes.

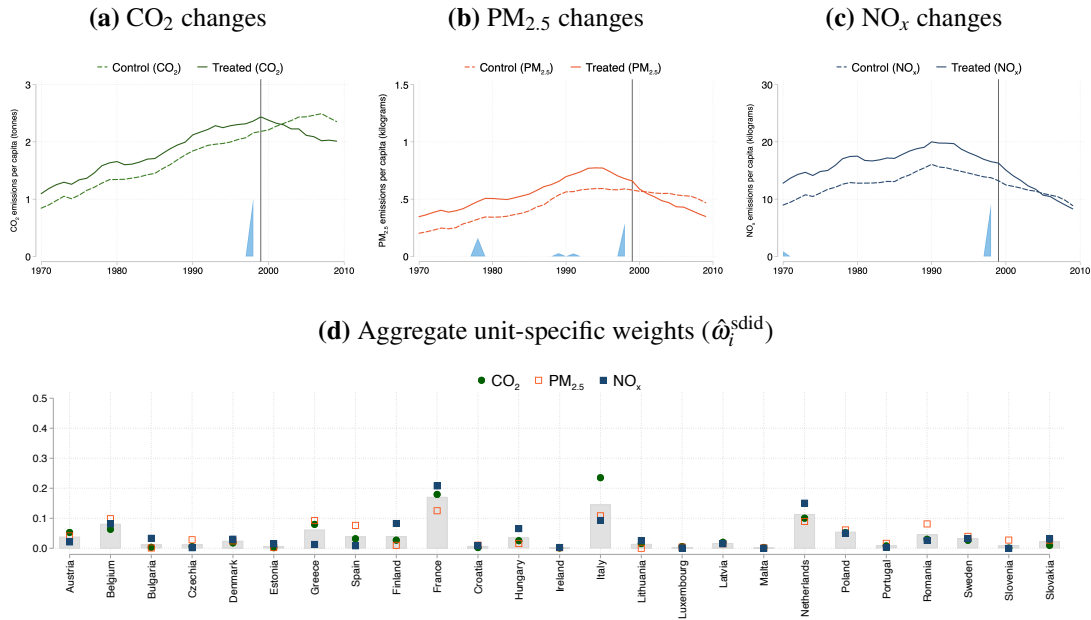
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<sup>18</sup>Using historical exchange rates, the Swedish carbon tax rate per liter increased from approximately 11.4 to 19.5 euro cents from 2001 to 2005 (The Swedish Tax Agency, 2023).

**Table 1:** Average SDID effects of environmental taxation

	CO <sub>2</sub> emissions (t)	PM <sub>2.5</sub> emissions (kg)	NO <sub>x</sub> emissions (kg)
Mean estimate ( $\hat{\tau}^{\text{sdid}}$ from Eq. 1)	-0.370	-0.175	-2.243
Standard error ( $\sqrt{\hat{V}_{\tau}}$ from Eq. 4)	(0.015)	(0.009)	(0.075)
Percentage change relative to baseline (%)	-15%	-25%	-13%
Observations	45440	45440	45440
Countries	EU-27	EU-27	EU-27

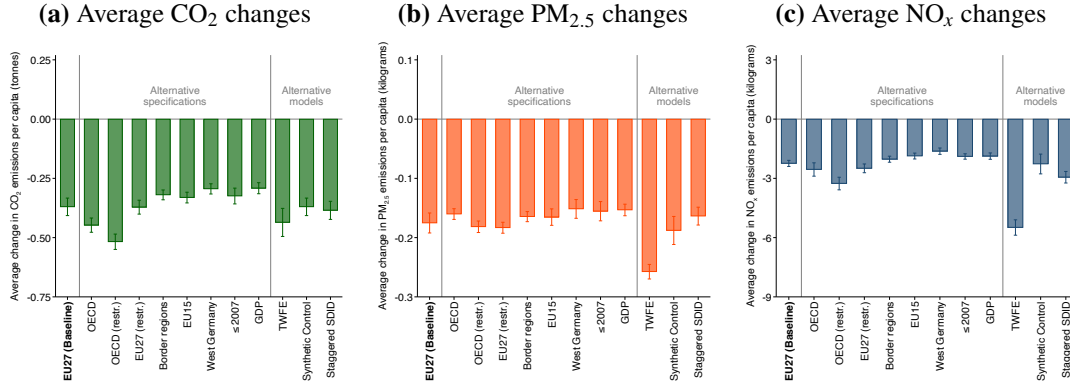
Notes: All outcome variables are expressed in per capita terms and the unit of measurement is indicated in the column heading. The table displays the estimated average effects of the eco-tax on CO<sub>2</sub>, PM<sub>2.5</sub>, and NO<sub>x</sub> emissions leveraging the SDID estimation procedure introduced in Section 3.1. Standard errors were computed using the bootstrap variance estimation procedure described in Eq. 4 with 200 replications. Percentage changes were calculated as the ratio of mean estimates ( $\hat{\tau}^{\text{sdid}}$ ) to baseline emissions in Germany in 1998 (i.e., the year prior to the eco-tax reform) amounting to around 2.36 tonnes per capita for CO<sub>2</sub>, 0.68 kilograms per capita for PM<sub>2.5</sub>, and 16.55 kilograms per capita for NO<sub>x</sub>.

**Figure 3:** Graphical SDID effects of environmental taxation

Notes: Panels (a) - (c) plot average trends in air emissions over time for German districts and the relevant weighted average of control European NUTS-3 regions, with the weights used to average pre-treatment time periods at the bottom of the graphs. Panel (d) displays the composition of the SDID donor pools by aggregating unit-specific weights ( $\hat{\omega}_i^{\text{sdid}}$ ) at the country level. The grey bars indicate the average aggregate weights by country.

We additionally compute mean annual changes in emissions in percentage terms to provide perspective on the magnitude of the effects. Percentage changes are calculated as the ratio of mean estimates ( $\hat{\tau}^{\text{sdid}}$ ) to baseline emissions in Germany in the year prior to the eco-tax reform. CO<sub>2</sub> per capita emissions decrease, on average, by 15% between 1999 and 2009, while PM<sub>2.5</sub> and NO<sub>x</sub> emission reductions amount to 25% and 13%, respectively.

**Figure 4:** Average treatment effects across specifications and models



Notes: The panels above compare our baseline ATTs to (i) alternative specifications and (ii) alternative models with a different estimator or study design. For more details on the restricted sample (denoted by *restr.*), see Section 4 and Table A.2 in Section A of the OA.

## 5.1 Robustness tests

We now discuss further results from (i) additional SDID specifications and (ii) alternative models based on different estimators and a staggered design. These robustness analyses are summarized in Figure 4. Additional country-level analyses and diagnostics are presented in Section B in the OA.

**Alternative SDID specifications.** Our baseline estimates from Table 1 are robust to various data and specification changes. First, we consider alternative compositions of donor pools: (a) extending our sample to other OECD countries, (b) leveraging the restricted sample described in Section 4, (c) restricting the sample to EU-15 countries, (d) dropping border regions due to concerns related to fuel tourism, and (e) dropping districts in Eastern Germany to mitigate concerns regarding the local impacts of their EU economic integration after German reunification. While relying on all OECD countries allows us to amplify statistical power, we note that this could potentially overstate the impact of the eco-tax, due to concurrent EU-wide shocks (such as standards). In contrast, by focusing on EU-15 countries we trade-off statistical power to rule out that the observed effects are sizably influenced by some control countries joining the EU during the post-treatment period. Second, we consider a shorter time frame ending in 2007 to ease concerns related to unilateral environmental policies implemented towards the end of our considered time frame (cf. Section 2). Finally, we condition our baseline model to national GDP per capita to control for how economic activity variations over time have affected emissions.<sup>19</sup>

<sup>19</sup>To rule out potential endogeneity concerns, we later test in Section 7 whether the introduction of the eco-tax led to significant impacts on economic activities in Germany.

**Alternative estimators.** We also compare our SDID estimations to the TWFE-DID and SC approaches described in Section 3.1. We observe that without any re-weighting a simple DID estimation tends to overestimate the impacts of the eco-tax. The inclusion of unit weights ( $\hat{\omega}_i^{\text{sc}}$ ) in the SC method already mitigates most of the upward bias, yielding comparable estimates for CO<sub>2</sub> reductions and slightly higher decreases in PM<sub>2.5</sub> and NO<sub>x</sub>. Overall, the further use of time weights ( $\hat{\lambda}_t^{\text{sdid}}$ ) leads to more conservative baseline estimates.

**Alternative design.** We finally report complementary results from a staggered adoption design leveraging the early introduction of similar environmental fuel taxes within other European transport sectors in our sample to mitigate the concern that post-treatment idiosyncratic shocks could confound our SDID estimations for Germany and investigate their external validity. The bar denoted by *Staggered SDID* in Figure 4 displays the average treatment effects of environmental fuel taxes on air emissions (i.e.,  $\hat{\tau}^{\text{sdid}}$  from Eq. 6) harnessing their gradual rollout in Finland (in 1990), Sweden (in 1991), and Germany (in 1999). Overall, these findings further support our baseline estimates for Germany. Additional insights on country-level heterogeneity are presented in the OA.

## 6 Results on fuel and tax elasticities

This section leverages the semi-elasticity models described in Section 3.2 to disentangle the effects of the eco-tax, the energy tax, and VAT to compare behavioral responses. We report price elasticities for gasoline and diesel leveraging both national time series and cross-country panel variation.

### 6.1 Real price semi-elasticities for gasoline and diesel

Tables 2a and 2b report estimates from *Real price elasticities* specifications (cf. Section 3.2) for gasoline and diesel consumption.<sup>20</sup> Using our estimate from column (1) in Table 2a, we derive a real price elasticity of gasoline of -0.54.<sup>21</sup> The IV regression yields a very similar price elasticity of -0.50 (column (2) of Table 2a), indicating that the endogeneity of gasoline prices is likely not a major concern in our setting. To test the instrument’s relevance condition, we use an F-test for that single instrument. For the

<sup>20</sup>See Tables C.2a and C.2b in the OA for results using a shorter time frame (1991–2009).

<sup>21</sup>To calculate elasticities from our log-level model estimates ( $\log(Y) = a + bX$ ), the coefficient for each tax is multiplied by the average sample mean of the real fuel price (90 cents for gasoline and 76 cents for diesel), as the elasticity of demand is given by  $\varepsilon = \frac{dY}{dX} * \frac{X}{Y}$ . This implies that  $\frac{dY}{dX} = be^a e^{bX}$ . Plugging in, we obtain  $\varepsilon = \frac{be^a e^{bX}}{e^a e^{bX}} * X = bX$ .

**Table 2: Real price semi-elasticities for transport fuels**

(a) Gasoline consumption				(b) Diesel consumption			
	(1)	(2)	(3)		(1)	(2)	(3)
	OLS: Baseline	IV: Brent crude	OLS: Fixed effects		OLS: Baseline	IV: Brent crude	OLS: Fixed effects
Gasoline Price	-0.00603** (0.00278)	-0.00553* (0.00305)	-0.00553*** (0.00103)	Diesel Price	-0.00440*** (0.00103)	-0.00361*** (0.000856)	-0.00454*** (0.00147)
Instrument F-statistic		69.47		Instrument F-statistic		168.86	
Price elasticity	-0.54	-0.50	-0.50	Price elasticity	-0.34	-0.28	-0.34
Sample	Germany	Germany	OECD	Sample	Germany	Germany	OECD
Controls	✓	✓	✓	Controls	✓	✓	✓
Observations	38	38	765	Observations	39	39	574

Notes: The dependent variable is the log of fuel consumption in liters per capita, which refers to total fuel consumption or either gasoline or diesel consumption (as indicated by the column heading). Columns (2) use the Brent crude oil price as an instrumental variable for the real fuel price. Results for gasoline consumption refer to 1972-2009 in column (1) due to missing price data prior to 1972. Newey-West standard errors in parentheses are heteroskedasticity and autocorrelation robust. Standard errors in columns (1) - (2) are calculated relying on the automatic bandwidth selection procedure following Newey and West (1994). Standard errors in column (3) are clustered at the country-year level \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

price of gasoline, the F-statistic is 69.47 suggesting that the relevance condition is fulfilled and that Brent crude oil price can be considered a suitable instrument for gasoline prices. The cross-country elasticity based on OECD data presented in column (3) also yields a very similar elasticity of 0.50. Table 2b displays results for diesel consumption from the real price elasticity specification (cf. Section 3.2). The real price elasticity of demand for diesel shown in column (1) of Table 2b is somewhat lower than for gasoline at -0.34. The IV regression in column (2) yields an estimate of -0.28, which deviates slightly more than the IV and OLS regressions for gasoline, but is still sufficiently close to corroborate the magnitude of the real price elasticity for diesel. Once again, our real price elasticity for Germany is almost identical to what we yield in column (3) harnessing cross-country variation across OECD jurisdictions, indicating that Germany does not display distinctive fuel price elasticity patterns compared to other OECD countries, reinforcing the broader applicability of our results. Overall, our estimates fall into the range of price elasticities of demand in the literature (e.g., Frondel and Vance, 2014).

## 6.2 Tax semi-elasticities for gasoline and diesel

Table 3a displays results for gasoline consumption from the *Eco-tax elasticities* specifications (cf. Section 3.2).<sup>22</sup> The OLS results in column (1) in Table 3a indicate that the price elasticity of demand for the price excluding the energy and the eco-tax (but including the VAT) is -0.32. The energy tax elasticity of demand, instead, amounts to -0.22. Both elasticities are computed relying on coefficients that exhibit a considerably lower significance. This contrasts the eco-tax elasticity of demand, which is estimated at -2.7 and is thus around 8.5 times larger than the tax-exclusive price elasticity. The eco-tax elasticity of diesel demand is also significantly higher than that for the real

<sup>22</sup>We cannot reject the hypothesis of full pass-through, see Section C in the OA.

**Table 3: Eco-tax semi-elasticities for transport fuels**

(a) Gasoline consumption				(b) Diesel consumption			
	(1)	(2)	(3)		(1)	(2)	(3)
	OLS: Baseline	OLS: Fixed effects	OLS: Fixed effects		OLS: Baseline	OLS: Fixed effects	OLS: Fixed effects
Raw price of Gasoline	-0.00357* (0.00179)	-0.00256 (0.00165)	-0.00427** (0.00163)	Raw price of Diesel	-0.00346*** (0.00104)	-0.00525*** (0.00164)	-0.00506** (0.00187)
Energy Tax on Gasoline	-0.00242 (0.00476)	-0.00485*** (0.00128)	-0.00413*** (0.000569)	Energy Tax on Diesel	-0.00729** (0.00292)	0.000388 (0.00152)	0.000937 (0.00155)
Eco-tax on Gasoline	-0.0306*** (0.00700)	-0.0296*** (0.00479)	-0.0247*** (0.00350)	Eco-tax on Diesel	-0.0143*** (0.00359)	-0.0232*** (0.00351)	-0.0197*** (0.00328)
Raw price = Eco-tax (p-value)	<0.001	<0.001	<0.001	Raw price = Eco-tax (p-value)	<0.001	<0.001	<0.001
Eco-tax elasticity	-2.7	-2.7	-2.2	Eco-tax elasticity	-1.1	-1.7	-1.5
Sample	Germany	OECD	EU	Sample	Germany	OECD	EU
Controls	✓	✓	✓	Controls	✓	✓	✓
Observations	38	765	509	Observations	39	574	415

Notes: The dependent variable is the log of fuel consumption in liters per capita, which refers to total fuel consumption or either gasoline or diesel consumption (as indicated by the column heading). Results for gasoline consumption in column (1) refer to 1972-2009 due to missing price data prior to 1972. Newey-West standard errors in parentheses are heteroskedasticity and autocorrelation robust. Standard errors in column (1) are calculated relying on the automatic bandwidth selection procedure following Newey and West (1994). Standard errors in columns (2) - (3) are clustered at the country-year level \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

price. Table 3b displays the results for the different tax rates for diesel. Using column (1) in Table 3b, the elasticity for the real price, excluding the energy and eco-tax, is -0.26. The energy tax elasticity of demand is -0.56, slightly higher than the price elasticity. The eco-tax elasticity is again the highest level at -1.1, about 4 times larger than the tax-exclusive price elasticity. These magnitudes and the corresponding *tax saliency ratios* are corroborated by our set of fixed effects models both when leveraging panel variation across OECD jurisdictions in column (2) and restricting the sample to EU members only in column (3). It follows that an increase in the eco-tax predicts a stronger response in demand than that of a market-driven price change for both gasoline and diesel.<sup>23</sup>

Li et al. (2014) discuss two underlying reasons that may reconcile our findings and explain the estimated stronger response to the eco-tax. The first one is *persistence*, meaning that consumers rely on tax changes to build expectations for the future price of gasoline. A tax increase may thus be perceived as more enduring than market-driven price fluctuations, which, in turn, would stimulate a stronger consumer response. The second is *saliency*, meaning that consumers are more aware of the price increase due to media coverage. In Section 7, we examine whether the introduction of the eco-tax was accompanied by an increase in its saliency in newspaper coverage.

<sup>23</sup>We additionally amend our semi-elasticity models with a lead to test if consumers increased their purchases of fuel in anticipation of tax increases, which may bias estimated price and eco-tax coefficients (Coglianese et al., 2017). We do not find evidence of anticipatory effects, and the estimated real price and eco-tax elasticities are very similar to the main result reported in Tables 2a - 3b (see Figure C.1 in the OA). One explanation is that anticipatory behavior is a lesser source of concern when dealing with yearly data than relying on monthly variation.

### 6.3 Emission scenarios

We next rely on fuel-specific price and tax elasticities estimates from columns (1) in Tables 3a and 3b in a *Simulation Approach* to predict CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions across three taxation scenarios: (1) A scenario where no VAT and no taxes are introduced, (2) a scenario where either VAT or VAT and the energy tax is added, and (3) a scenario where all are implemented.<sup>24</sup>

**Predicted emissions in the Simulation Approach.** Panels (a) and (b) in Figure 5 summarize the estimated evolution of CO<sub>2</sub> (left-hand side primary y-axis) and PM<sub>2.5</sub> (right-hand side secondary y-axis) emissions by fuel in the German transport sector under different tax regimes. The black line represents predicted emissions accounting for all existing tax measures, including the eco-tax, energy tax, and VAT. The purple line plots the estimated evolution of emissions in the absence of the eco-tax, while the yellow line depicts expected emissions with neither the eco-tax nor the energy tax, solely incorporating VAT. The green line shows predicted emissions without any tax policies. The gap between the black and purple line highlights the estimated emission gap attributable to the eco-tax, while the other lines represent alternative counterfactuals.

Panel (a) in Figure 5 shows that, between the years 1999 and 2009, the decrease in emissions of CO<sub>2</sub> (PM<sub>2.5</sub>) from gasoline induced by the eco-tax was around 0.27 tons (0.002 kg) per capita on average per year. Similarly, Panel (b) provides the estimated emission reductions for diesel. The corresponding mean decline in annual emissions of CO<sub>2</sub> (PM<sub>2.5</sub>) from diesel induced by the eco-tax was around 0.11 tons (0.04 kg) per capita, i.e. less marked than for gasoline due to the lower eco-tax elasticity for diesel.<sup>25</sup>

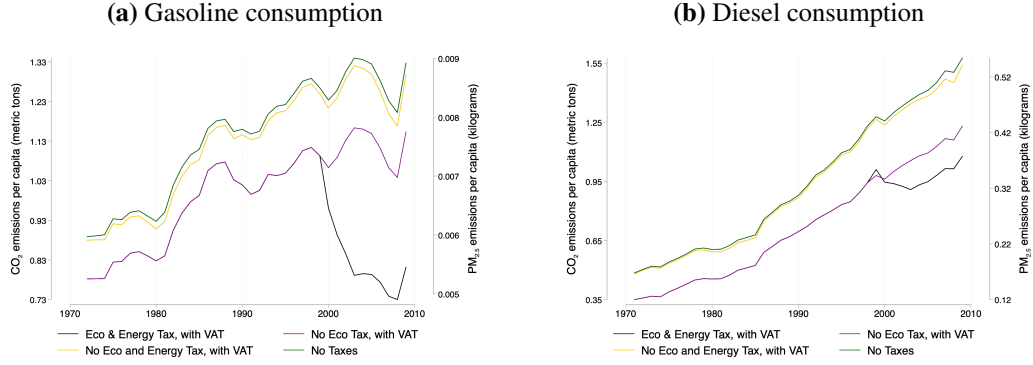
Panels (a) and (b) in Figure 6 contrast the estimated share of aggregate reductions in emissions attributable to contractions in gasoline or diesel use for CO<sub>2</sub> and PM<sub>2.5</sub>, also including reductions in NO<sub>x</sub> emissions. On average, contractions in gasoline (diesel) use were responsible for 72% (28%) of overall reductions in CO<sub>2</sub> emissions. Conversely, reduced diesel use is responsible for almost all (95%) of the reduction of PM<sub>2.5</sub> emissions. In other words, reductions in diesel consumption have contributed around 21 (0.4) times more to the decline in PM<sub>2.5</sub> (CO<sub>2</sub>) emissions relative to gasoline.

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<sup>24</sup>The combustion of one liter gasoline (diesel) emits 2.235kg (2.66kg) of CO<sub>2</sub> (US EPA, 2005). Using this factor, the predicted log gasoline (diesel) consumption values can first be turned into liters and then CO<sub>2</sub> emissions. To estimate PM<sub>2.5</sub> exhaust emissions from fuel consumption, we rely on average emission factors by the European Environment Agency (EEA) for gasoline (diesel) vehicles in Germany (Ntziachristos and Samaras, 2019) of 0.02 grams (1.12 grams) of PM<sub>2.5</sub> per kg of gasoline (diesel). Although EEA only reports emission factors for PM without specifying the size range, it clarifies that PM mass emissions in vehicle exhaust mainly fall in the PM<sub>2.5</sub> category.

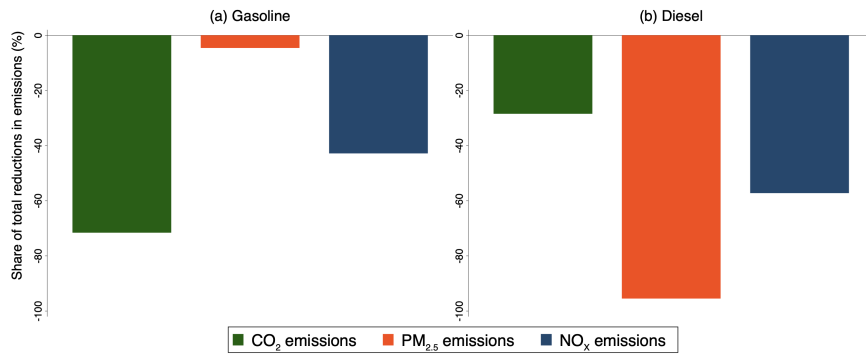
<sup>25</sup>Note that simulations are not directly comparable to the SDID results for PM<sub>2.5</sub>, as the former only accounts for exhaust emissions, thus missing a share of PM<sub>2.5</sub> emission reductions.

**Figure 5: Predicted emissions by fuel under different taxation scenarios**



*Notes:* The figures plot predicted emissions from the eco-tax specification of our log-level semi-elasticity models (cf. Section 3.2) under different taxation scenarios. We rely on the estimated fuel-specific price and tax elasticities computed from our estimates from column (1) in Tables 3a and 3b. Panel (a) refers to predicted emissions from gasoline consumption, while Panel (b) covers diesel. In each panel, the left-hand side primary y-axis refers to per capita CO<sub>2</sub> in metric tons, while the right-hand side secondary y-axis refers to per capita PM<sub>2.5</sub> in kg. The top green line displays predicted emissions when the eco and energy tax elasticities are set to zero, and VAT is deducted from the fuel price. For the yellow line, the eco and energy tax elasticities are set to zero but VAT is included. The purple line shows how predicted emissions change when the eco-tax is set to zero, but we include the energy tax and VAT. The black line provides predicted emissions using the full model with differentiated tax and price elasticities. The corresponding simulations for NO<sub>x</sub> emissions can be found in Figure C.2 in the OA.

**Figure 6: Share of total emission reductions by fuel due to the eco-tax**



*Notes:* The figures above plot the share of total predicted emissions reductions by fuel type from our log-level semi-elasticity models (cf. Section 3.2). The share of total emission reductions for each fuel type is computed from the estimated post-treatment gap in emissions from gasoline (diesel) consumption due to the eco-tax, which refers to the distance between the bottom black line and the purple line in Figure 5.

## 7 Exploration of mechanisms

**Fleet renewal and passenger-kilometers.** An important argument for regulating emissions in the transport sector is that it can prompt a more rapid adoption of more efficient vehicles (e.g., Jacobsen et al., 2023). Panel (a) of Figure 7 provides descriptive evidence of the change in fleet renewal rate by plotting the share of new passenger car registrations in the German fleet over time. We observe a discontinuity following 1999: after the eco-tax reform, the share of new passenger cars increased on average by 2%. It seems plausible that the eco-tax has played a role in accelerating cleaner vehicles adop-

tion, which could, at least partly, explain the contraction in emissions. We then resort to our semi-elasticity models to investigate how changes in the eco-tax rate affected the volume of road passenger transport, proxied by passenger-kilometers (pkm). Panel (b) of Figure 7 shows that, on average, the eco-tax is associated with a decrease in pkm by around 6.5% (5.7%) for gasoline (diesel).<sup>26</sup> These results offer suggestive evidence that a share of the estimated emission reductions may be due to both an accelerated fleet renewal and a reduction in the volume of road transport.

**Salience.** Our analysis continues by providing suggestive evidence of the role of salience of the eco-tax in the media, drawing on a growing number of economic studies leveraging newspaper data as a source of variation in the salience of events (e.g., Li et al., 2014; Baker et al., 2016). Panel (c) of Figure 7 displays our *environmental taxation salience* introduced in Section 4, which traces variations in the salience of the public debate on environmental taxes. Salience rises sharply before and shortly after the eco-tax’s introduction. This increased salience in the media may have affected behavioral responses, alongside other features of the tax—such as its perceived persistence—contributing to the substantially higher tax elasticity compared to the market price elasticity.

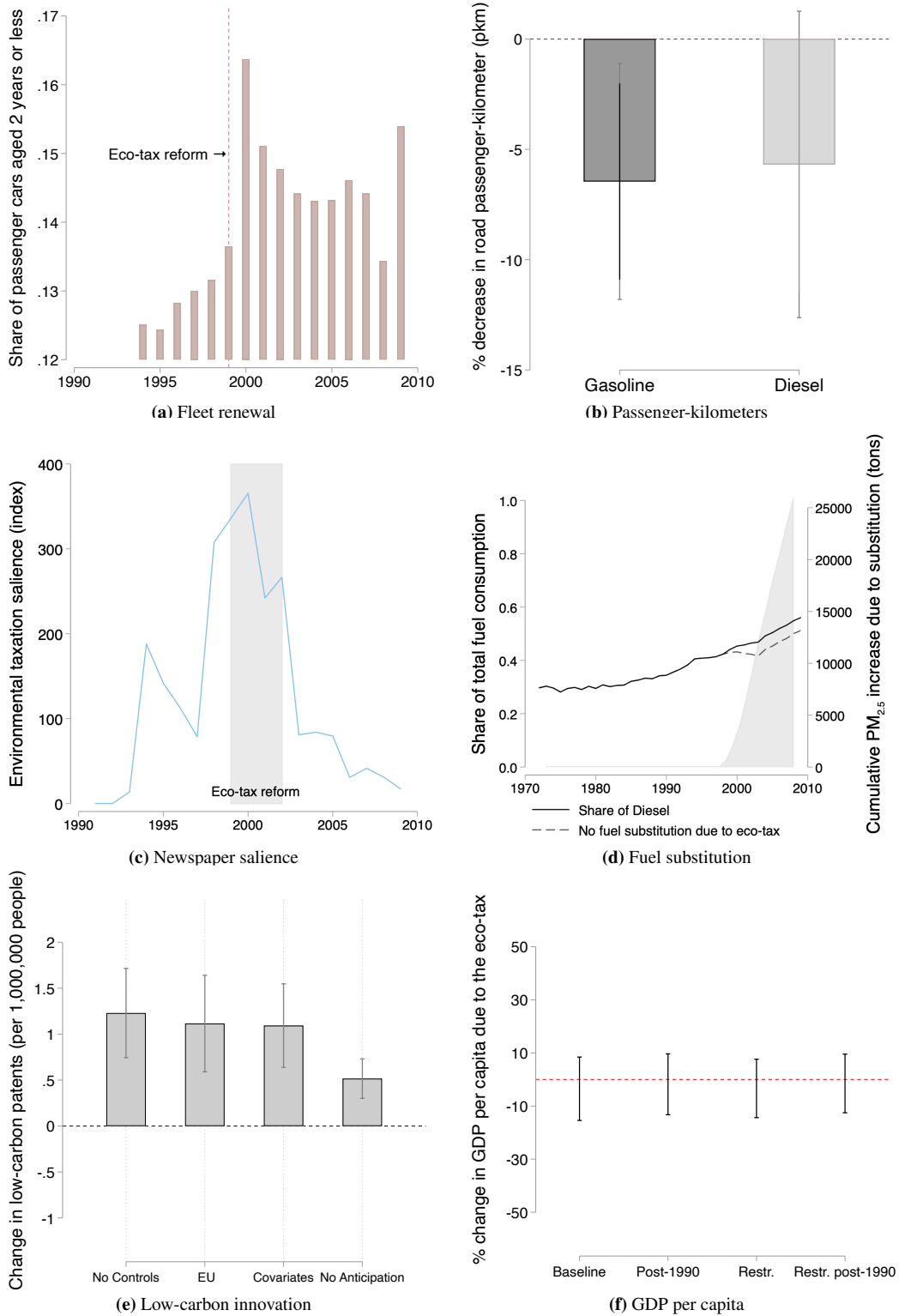
**Fuel substitution and abatement trade-offs.** Diesel fuel vehicles contribute considerably more to emissions of fine particulates, such as PM<sub>2.5</sub>, than gasoline vehicles.<sup>27</sup> However, diesel vehicles have lower CO<sub>2</sub> emissions rates per kilometer traveled compared to gasoline vehicles, by around 20% for otherwise virtually identical vehicles (Linn, 2019), as diesel engines are typically much more fuel-efficient. It follows that policy measures that foster a switch from gasoline vehicles to diesel vehicles (e.g., taxes based on the carbon content of fuels), could, in turn, lead to a decrease in CO<sub>2</sub> emissions but also an increase in PM<sub>2.5</sub> emissions. Previous research on fuel and carbon taxation has not explicitly considered this trade-off in policy evaluations, except for Linn (2019).<sup>28</sup>

<sup>26</sup>We provide suggestive evidence that the eco-tax, via reduced pkm, contributed to fewer road casualties—a major externality of road transport (e.g., Anderson and Auffhammer, 2014). Using our semi-elasticity models, we estimate an average 11% drop in casualties following the tax (cf. Figure C.4 in the OA). This suggests that our focus on climate and air pollution co-benefits likely understates the full benefits of the eco-tax.

<sup>27</sup>Relying on EEA emission factors for Germany, the average PM<sub>2.5</sub> emission factor for diesel vehicles is around 56 times larger than for gasoline (Ntziachristos and Samaras, 2019).

<sup>28</sup>A related channel is a modal shift from road to rail. Expanded rail infrastructure may have also contributed to reduced pollution (e.g., Lalive et al., 2018). While passenger transport on rail has continuously increased in Germany between 1994 and 2009, this development has been less pronounced than in France, the largest synthetic donor country (OECD, 2025).

**Figure 7: Mechanisms of reductions in emissions**



*Notes:* Panel (a) plots the share of new passenger cars in the German fleet (aged 2 years or less). Panel (b) plots the estimated percentage reductions in passenger-kilometers (pkm) by fuel for the average eco-tax rate of 13 cents leveraging our semi-elasticity models (cf. Section 3.2). Panel (c) plots the estimated percentage changes in GDP per capita due to the eco-tax with an SDID estimator. Standard errors used to construct confidence intervals have been computed using the placebo variance estimation (Algorithm 4) described in Arkhangelsky et al. (2021). Panel (d) plots the annual predicted substitution towards diesel inferred from our semi-elasticity models (cf. Table C.3b in the OA for more details). Panel (e) plots the estimated change in low-carbon triadic patents per 1 million people following the introduction of the eco-tax. Panel (f) displays our *salience index* of environmental taxation as captured in major newspapers, introduced in Section 4.

Panel (d) of Figure 7 plots the estimated gasoline-to-diesel substitution induced by the eco-tax (cf., Table C.3b in the OA), implying that part of the contraction in CO<sub>2</sub> linked to reduced gasoline use came at the expense of greater PM<sub>2.5</sub> emissions due to fuel substitution. We estimate that the share of diesel consumption is predicted to have increased by around 4% more than it would have had in the absence of the eco-tax throughout the post-treatment period. Our calculations suggest that gasoline-to-diesel substitution due to the eco-tax led to a cumulative increase in PM<sub>2.5</sub> exhaust emissions of around 25,000 tons.

**Innovation.** The introduction of higher environmental taxes can affect firms' innovation behavior, which can, in turn, affect the potential to reduce emissions. Here, we analyze how the eco-tax has affected low-carbon triadic patents in the transport sector using the SDID approach at a country level.<sup>29</sup> We backdate the start of the post-treatment period to 1995, when the eco-tax bill began to be discussed in parliament (Beuermann and Santarius, 2006), to account for potential anticipatory effects, which are not uncommon in innovation dynamics (Lemoine, 2017). We consider four different model specifications. The first is a simple baseline specification with no controls, focusing on OECD countries (*No Controls*). The second restricts the sample to European Union countries to allow for a more homogeneous comparison group (*EU*). The third specification includes a set of covariates, adding a dummy for EU membership and controlling for the total number of patents per capita in each country (*Covariates*). Finally, the fourth specification discards potential anticipation effects and restricts the post-treatment period to 1999 onwards (*No Anticipation*).

Panel (e) of Figure 7 shows a sizeable increase in low-carbon triadic patents following the introduction of the eco-tax. Our most conservative estimate links the eco-tax reform with an additional 0.51 patents per million population each year. This implies that between 1999 and 2009, around 3.5% of transportation-related carbon mitigation patents may be associated with the effects of the eco-tax. This finding complements previous studies on the innovation response of regulated companies to carbon pricing schemes (e.g., Calel and Dechezleprêtre 2016), which generally find limited aggregate effects.<sup>30</sup>

<sup>29</sup>We opted for a countrywide analysis because innovation tends to be concentrated in a few districts, and leveraging a more disaggregated level of analysis would result in a zero-inflated outcome distribution, which makes synthetic control approaches less reliable (Abadie, 2021).

<sup>30</sup>Two key differences may explain our larger magnitudes. First, employing an economy-wide approach can additionally capture innovation occurring along the supply chain and across unregulated agents, due to the pass-through of regulatory costs or knowledge spillovers (Popp, 2019). Second, innovation in the automotive industry is arguably of greater importance in Germany than in other countries that do not feature comparatively large automobile industries.

**Decoupling.** A common contention against the implementation of carbon taxation revolves around potential detrimental effects on economic growth. We thus investigate whether the observed reduction in emissions may have occurred alongside a reduction in economic activity. Panel (f) of Figure 7 plots the ATTs of a set of SDID estimations where we examine the impact of the eco-tax on the evolution of GDP per capita in Germany relative to synthetic counterfactuals based on other OECD peers. Specifically, we rely on both the entire balanced sample of OECD countries and its restricted version (cf. Section 4). We additionally consider a shorter time frame starting after the German reunification in 1990. Across the different specifications, we do not document any significant negative effects on German GDP from the eco-tax reform.

## 8 Reductions in external damages

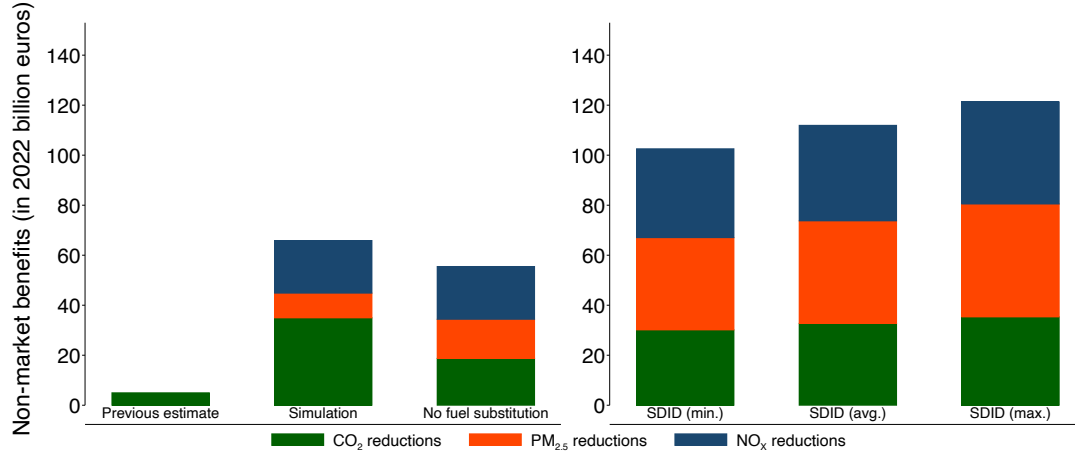
Previous sections have demonstrated that reductions in emissions are significant and sizable. In this section, we quantify how economically substantial the associated reductions in external damages are and assess how they are distributed across German districts, with a special emphasis on how they are distributed along income levels.

**Aggregate reductions in external damages.** To quantify societal benefits from reduced climate and pollution costs, we apply official cost estimates from the first comprehensive guidelines by the [Umweltbundesamt \(2012\)](#). They recommend using a social cost per ton of CO<sub>2</sub> emitted in 2010 by 80 Euros (in 2010 Euros), and provides disaggregated cost estimates for PM<sub>2.5</sub> in the transport sector, distinguishing costs of PM<sub>2.5</sub> exhaust emissions released within cities, denoted ‘urban’ (364,100 €/t) and outside of cities, which we denote as ‘non-urban’ (122,800 €/t), recognizing that within city emissions contribute more to human health costs. Using their reported breakdown of the share of PM<sub>2.5</sub> within and outside of cities for different transport modes, we compute a weighted average of PM<sub>2.5</sub> damages. External costs of NO<sub>x</sub> are not distinguished across locations, with an average cost estimate of 15,400 €/t.<sup>31</sup> We convert all cost estimates from the base year 2010 to 2022 values using official inflation statistics.

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<sup>31</sup>The cost estimates provided by [Umweltbundesamt \(2012\)](#) were derived from the EU NEEDS project which—in the time frame relevant for our historical analysis—provided the most comprehensive cost estimates available. In terms of damage sources, the full PM<sub>2.5</sub> damages were related to (human) health damages, which compares to a health damages share of 82% for NO<sub>x</sub>, where the remaining share of damages derives from biodiversity loss (14%), crop yield damages (3%) and material damages (1%). See [Umweltbundesamt \(2012\)](#) for details. These cost estimates have recently been revised upwards, with the latest guidance from 2024. We retain the 2012 cost estimates, as this was closest to the time frame of our analysis, but note that cost estimates are conservative compared to more recent estimates.

**Figure 8:** Reductions in climate and pollution damages due to the eco-tax



*Notes:* The figure plots the estimated reductions in external climate and pollution damages based on estimates from (a) the Simulation Approach and (b) the Synthetic Difference-in-Differences Estimation on CO<sub>2</sub> (green), PM<sub>2.5</sub> (orange), and NO<sub>x</sub> (blue) reductions and compares their magnitudes with the implied estimates from a prior analysis by [Steiner and Cludius \(2010\)](#). Simulation results for PM<sub>2.5</sub> emissions do not account for non-exhaust emissions. Aggregate cost reductions are computed relying on pollutant-specific official cost estimates provided by the [Umweltbundesamt \(2012\)](#) and expressed in 2022 Euros.

We start with an aggregate assessment of how the eco-tax has reduced climate and pollution damages and contrast our SDID results to estimates based on simulations. First, we consider results from a previous report, which focuses on carbon reductions only and suggests that environmental improvements due to the German eco-tax have been limited ([Steiner and Cludius, 2010](#)).<sup>32</sup> Evaluating estimated emission reductions using their elasticities with the cost of carbon by the [Umweltbundesamt \(2012\)](#) in 2022 Euros yields a climate benefit of 4.9 billion Euros (first bar of Panel (a) in Figure 8).

We contrast this prior assessment with results from our Simulation approach (Panel (a) in Figure 8). Simulating emission reductions of CO<sub>2</sub> relative to the counterfactual without the eco-tax yields 344 million fewer tons, and an aggregate climate benefit of around 35 billion Euros. We further simulate reductions of PM<sub>2.5</sub> and NO<sub>x</sub> emissions of 36,368 tons and 1.08 million tons,<sup>33</sup> translating into pollution reduction benefits of 31 billion Euros. In sum, our Simulation Approach suggests that the eco-tax has reduced external damages by 66 billion Euros, which is 13 times the previous estimate.

We further consider an alternative scenario with *no fuel substitution* from gasoline to diesel induced by the eco-tax. We compute the *no fuel substitution* scenario by hold-

<sup>32</sup>[Steiner and Cludius \(2010\)](#) estimate a price elasticity of fuel demand of -0.18 based on household survey data and attribute -0.1 to the tax elasticity component, with which they quantify reductions of CO<sub>2</sub> emissions due to the eco-tax amounting to 120 kg CO<sub>2</sub> per household per year. Multiplying with household numbers in Germany from 1999 to 2009, this sums up to 50.73 million tons of CO<sub>2</sub> emissions.

<sup>33</sup>To estimate NO<sub>x</sub> emissions from fuel consumption, we rely on estimates from the EEA on average emission factors for gasoline (diesel) vehicles in Germany ([Ntziachristos and Samaras, 2019](#)) of 5.61 (20.1) grams of NO<sub>x</sub> per kg of gasoline (diesel).

ing annual traveled km per capita fixed. As gasoline vehicles are less fuel efficient than comparable diesel vehicles, we assume that the foregone increase in diesel use due to fuel substitution translates into a 1.2 times increase in gasoline use to account for lower fuel efficiency drawing on [Linn \(2019\)](#). Foregone gasoline-to-diesel substitution is computed using column (3) in Table C.3b in the OA. We then add (subtract) the estimated foregone substitution towards diesel to predicted gasoline (diesel) use from column (1) in Tables 3a and 3b. Without fuel substitution, external damage reductions would have amounted to 55.5 billion Euros with *no fuel substitution*, with a very different composition: While not switching to diesel would have led to much lower climate benefits (34.9 vs. 18.7 billion Euros), benefits due to reducing PM<sub>2.5</sub> would have been higher (30.9 vs. 36.7 billion Euros).

We now move to quantifying externality reductions using our SDID estimates.<sup>34</sup> The first three bars in Panel (b) of Figure 8 show results of our preferred SDID specifications presented in Table 1 yielding minimal, average, and maximal emission reductions based on point estimates and their 95% confidence intervals. The average estimates from our preferred specification suggest benefits from reduced carbon and pollution costs due to the eco-tax of 112 billion euros, more than 22 times as much as the estimate by [Steiner and Cludius \(2010\)](#).<sup>35</sup> Our baseline SDID results thus suggest that the eco-tax has reduced external damages by 120 Euros per capita on average per year, amounting to around 0.7 percent of the average purchasing power per-capita in the year 2005.

Overall, our results indicate that the eco-tax was orders of magnitude more effective in reducing external damages than previously suggested. Crucially, evaluations of fuel or carbon taxes that focus solely on climate benefits (e.g., [Andersson, 2019](#); [Mideksa, 2024](#)) miss a substantial share of benefits. For the case of the German eco-tax, we estimate that neglecting health co-benefits due to reduced pollution would miss the majority share—amounting to around 70 percent of reductions in external damages.

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<sup>34</sup>Note that the SDID and simulations for PM<sub>2.5</sub> are not directly comparable, as the simulation relies on conversion factors that do not include non-exhaust emissions ([Ntziachristos and Samaras, 2019](#)) and thereby leads to a non-negligible underestimate of pollution reductions.

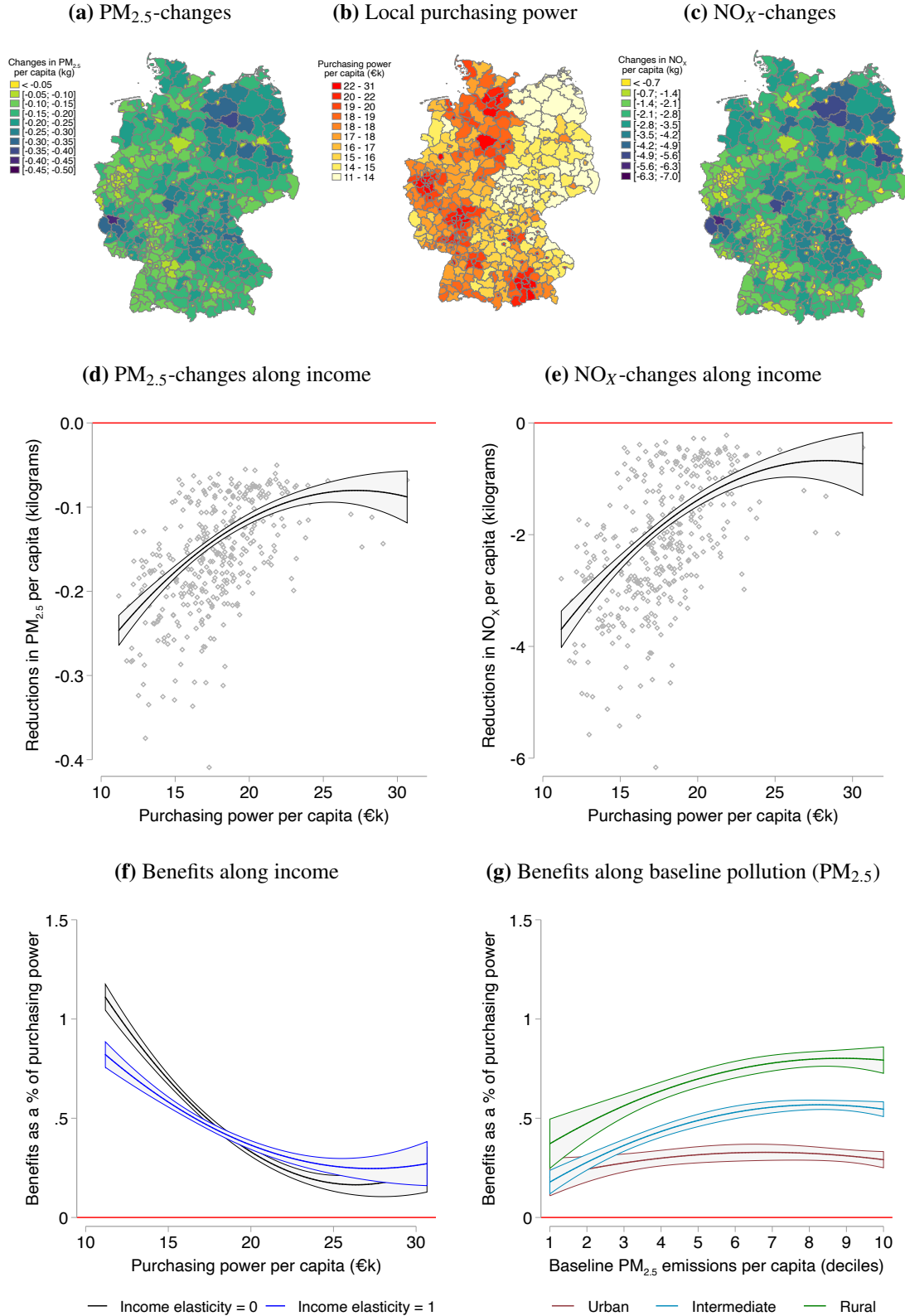
<sup>35</sup>Note that both EDGAR data and the emission factors used in the Simulation approach are based on laboratory emission rates, which tend to underestimate actual on-road NO<sub>x</sub> and PM<sub>2.5</sub> emissions ([Crippa et al., 2018](#)), also partly due to the recent *Dieselpgate* scandal ([Grange et al., 2020](#)). Our estimated impacts for on-road emissions may thus represent lower-bound estimates.

**Distribution of pollution-reduction benefits.** We next examine how pollution reduction benefits are distributed. In Panels (a) and (c) of Figure 9, we show the heterogeneous pollution reductions per capita across the 401 German districts. We combine this data with high-resolution spatial data of purchasing power (total available income after taxes and transfers) from the RWI-GEO-GRID (Breidenbach and Eilers, 2018b; RWI microm, 2020) for the year 2005, which we also aggregate to average purchasing power at a district level. We denote this as "income" and illustrate its distribution in Panel (b) of Figure 9. In a second step, we combine incomes and pollution reductions, separately for  $PM_{2.5}$  and  $NO_X$ , per district and depict the relationship between income as well as per capita changes in pollution reductions on average from 1999 to 2009, showing effects for  $PM_{2.5}$  in Panel (d) and for  $NO_X$  in Panel (e). Each individual dot in the respective scatterplots signifies a single district. We further provide a non-linear (quadratic) fit and find that—for both pollutants—pollution reductions are larger when incomes are lower, i.e. that poorer districts experience larger pollution reductions. Pollution reductions are thus distributed regressively (i.e., pro-poor). The result that pollution reductions accrue disproportionately in poorer districts also holds when employing an alternative specification based on the satellite-derived concentration data for overall  $PM_{2.5}$  pollution levels from Shen et al. (2024); the corresponding estimates are reported in Section E of the OA.

In Panel (f) of Figure 9 we report the distribution of average monetized pollution reductions benefits per capita for  $PM_{2.5}$  and  $NO_X$  combined and relate these benefits to incomes. We hereby contrast two non-linear (quadratic) fits: One using the implicit assumption of an income elasticity of pollution reduction benefits of zero in the official guidance by the Umweltbundesamt (2012), and one with the assumption of an income elasticity of unity.<sup>36</sup> We show that the benefits from pollution reductions due to the eco-tax are also distributed regressively, i.e. they are disproportionately higher in poorer districts. Specifically, benefits amount to around 1 percent for the lowest income segment and less than 0.5 percent for the richer half of the districts. Unsurprisingly, the distribution of benefits is less regressive when assuming an income elasticity of unity. In both cases, we find that the health benefits from pollution reductions due to the eco-tax are distributed pro-poor across districts, with a Suits index of -0.195 (-0.126) with an income elasticity of zero (unity).

<sup>36</sup>While guidelines on benefit-cost analysis commonly do not distinguish benefits across income levels, making the normative assumption that the value of a statistical life (VSL) within a country is independent of individual incomes, an income elasticity of zero is not a good descriptive assumption. We contrast this with an alternative assumption of an income elasticity of unity, implying that benefits increase proportionally with incomes. This value has been recommended as a generic default for policy evaluation (Drupp et al., 2024a) and has been found to rationalize prior VSL estimates (Ito and Zhang, 2020). Empirical evidence typically lies in-between an income elasticity of zero and unity (Drupp et al., 2025).

**Figure 9: Distribution of pollution changes and health co-benefits**



*Notes:* Panel (a) maps the distribution of the changes in PM<sub>2.5</sub> per capita, while Panel (c) provides an analogue for NO<sub>x</sub>. Panel (b) maps purchasing power per-capita in 2005 (in thousand EUR). Panels (d) and (e) combine information from Panels (a-c) and plot the reductions PM<sub>2.5</sub> and NO<sub>x</sub> along purchasing power with scatterplots and quadratic fits. Panel (f) plots predicted pollution reduction benefits along the purchasing power distribution, based on a quadratic regression of benefits on purchasing power and its square, under two benchmark assumptions for the income elasticity of benefits: zero and one. Panel (g) plots fitted pollution reduction benefits along baseline PM<sub>2.5</sub> pollution deciles for an income elasticity of zero as in the German Environment Agency guidance [Umweltbundesamt \(2012\)](#), split by whether districts are classified as urban, intermediate or rural.

While determining the costs induced by the eco-tax and its distribution is challenging,<sup>37</sup> rendering a comprehensive welfare assessment out of reach, we can compare our results on the incidence of benefits to the distributional effects of fuel taxes on the cost-side concerning the primary effect of higher fuel prices. Here, the literature has found that the distributional effect depends on the measure of income, while costs tend to accrue disproportionately to the poor (rich) when using a temporary (lifetime) measure of income, with a Suits index of -0.067 (0.008), respectively (see, e.g., [Stern, 2012](#)). A recent study for Germany, using a temporary measure of income but focusing on private passenger cars only, [Jacobs et al. \(2022\)](#) has found a Suits index of the overall fuel tax of -0.0307. Thus, the regressive effect on the cost side is far less pronounced as the regressive distribution of health co-benefits that we have documented here, suggesting that the eco-tax may have had a pro-poor effect overall.

Panel (g) of Figure 9 shows the distribution of pollution reduction benefits, for both PM<sub>2.5</sub> and NO<sub>x</sub>, as a percent of purchasing power not along income but along baseline PM<sub>2.5</sub> pollution prior to the introduction of the eco-tax. We hereby consider the case with an income elasticity of zero and further investigate the heterogeneity of effects along a common territorial typology: Urban, intermediate and rural. We find that while pollution reduction benefits due to the eco-tax tend to be higher the higher the level of baseline pollution, this relationship is pretty flat in urban areas and strongly pronounced in rural areas. Overall, we thus find that districts with a lower per capita purchasing power, higher initial pollution levels, and located in rural areas disproportionately benefit from the pollution reductions. The eco-tax has therefore contributed to environmental justice along a number of dimensions.

## 9 Conclusion

This paper provides the most comprehensive assessment of how fuel taxation has reduced climate and pollution externalities with a quasi-experimental evaluation of the world's largest environmental tax reform. Our synthetic difference-in-differences (SDID) approach, accompanied by a battery of alternative specifications as well as related inference designs, shows that the German eco-tax introduced in 1999 has led to sizable reductions in CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions from 1999 to 2009, with emission reduc-

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<sup>37</sup>Besides the primary incidence of higher fuel costs, one would need to consider how these costs are mitigated by reduced social security contributions and how additional costs may have occurred, e.g. due to the earlier updating of the vehicle fleet. The latter would require estimating vehicle fleet updating (e.g., [Jacobsen et al., 2023](#)) based on micro-data, which the German Federal Motor Transport Authority is not able to provide going back sufficiently in time.

tions relative to synthetic baselines of 15%, 25%, and 13%, respectively. The external validity of our findings on the average effectiveness of environmental fuel taxation is corroborated by an SDID approach that also leverages the staggered implementation of environmental taxes in Sweden and Finland. Using official governmental cost estimates, we show that the eco-tax internalized more than 100 billion Euros of externalities between 1999 and 2009. The majority of reductions in external costs relate to reduced air pollution and associated health benefits. We show that these pollution reduction benefits are distributed regressively, i.e. they accrue disproportionately to lower-income districts, which we corroborate using alternative emissions data.

We complement our quasi-experimental analysis with multi-country panel regressions to estimate price and tax elasticities. We show that the eco-tax elasticity is 3 to 5 times larger than the market price elasticity. We employ these elasticity estimates to simulate emission reductions and to highlight the importance of fuel substitution from gasoline to diesel for navigating the trade-off between attaining climate and pollution targets. We provide further complementary evidence on mechanisms, suggesting that the eco-tax has likely contributed to fostering fleet renewal of passenger cars and to reduced passenger-kilometers traveled, without having reduced economic activity. We also find evidence for an increased salience of the eco-tax driven fuel price increases in the news, which may have contributed to the much higher demand response to the eco-tax as compared to market-price changes. Finally, we document that the eco-tax has likely induced low-carbon innovation.

Overall, our results underscore the pivotal role of pollution-reduction co-benefits for the assessment of fuel and carbon pricing schemes, which falls substantially below recommended levels of stringency in most countries (e.g., [Drupp et al., 2024b](#)). First, a sole focus on carbon abatement—as is common in the literature (e.g., [Andersson, 2019](#); [Leroutier, 2022](#))—substantially underestimates the potential of (environmental) fuel taxes or carbon prices to reduce externalities (e.g., [Basaglia et al., 2024](#); [Hernandez-Cortes and Meng, 2023](#)).<sup>38</sup> Thus, accounting for reductions in pollution costs and associated health co-benefits is crucial when evaluating the benefits of carbon pricing. Accounting for such health co-benefits, which more immediately benefit those who bear the costs of higher fuel prices, may also be crucial for gathering support for fuel and climate policies (e.g., [Löschel et al., 2021](#)).

Second, it is important for evaluations of fuel and carbon pricing to consider the trade-offs that can arise between climate and air pollution targets (e.g., [Linn, 2019](#);

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<sup>38</sup>Our results likely still provide a lower-bound of eco-tax induced externality reductions, as the eco-tax may also have contributed to reducing congestion (e.g., [Hintermann et al., 2025](#)), fatality risk (e.g., [Anderson and Auffhammer, 2014](#)) or the reliance on fossil imports and related security concerns.

Parry et al., 2021). We show that this is particularly relevant in the context of price instruments based on the carbon content of fuels that can foster gasoline-to-diesel substitution. While this general feature of second-best taxation (Knittel and Sandler, 2018) is less important in the US context, due to a predominant share of gasoline-fueled cars, it is key when evaluating fuel pricing schemes in Europe (Zimmer and Koch, 2017; Linn, 2019). We show that relaxing the assumption that consumers respond similarly to fuel taxes as to other sources of fuel price variation (Linn, 2019) suggests that policymakers face a much larger trade-off between climate and pollution-reduction benefits.

Finally, we offer insights for the discussion on the distributional effects of environmental policies and environmental justice implication of fuel pricing (e.g., Banzhaf et al., 2019). While the consumer costs of fuel taxation tend to be either distributionally neutral or burden lower-income households disproportionately (e.g., Bento et al., 2009; Sterner, 2012; Jacobs et al., 2022; Känzig, 2023; Drupp et al., 2025), poorer households may also benefit disproportionately from better air quality (e.g., Banzhaf et al., 2019; Hernandez-Cortes and Meng, 2023). Consequently, the overall distributional effect of fuel taxation may be less regressive than as often suggested based on consumer cost incidence only (e.g., Drupp et al., 2025). Here, we shed light on the distribution of pollution reduction benefits delivered by the world largest environmental tax reform across 401 German districts and find that health co-benefits are distributed pro-poor and disproportionally occur districts with higher share of the population living in rural areas and with higher levels of baseline transport-related pollution. The eco-tax thereby reduces environmental justice concerns along a number of dimensions. Furthermore, when assessed along the income dimension by means of the Suits index, our estimate of the regressivity of benefits is between 4 and 6 times as large as the regressivity of higher fuel costs (Jacobs et al., 2022). The pro-poor health co-benefits may thus overturn the mildly regressive costs of fuel taxation and render the eco-tax a pro-poor policy. This suggests that it is more important to provide assessment of the full range of distributional effects of fuel taxation even before the crucial correcting level of revenue-recycling is devised (e.g., Bento et al., 2009). Furthermore, as perceived effectiveness and distributional outcomes are key considerations affecting climate policy support (e.g., Dechezleprêtre et al., 2025), communicating the substantial health co-benefits of environmental taxation and their pro-poor distribution may provide an important impetus for deliberations on more stringent fuel and carbon pricing.

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# Supplementary Online Appendix

## *Fuel taxation and environmental externalities: Evidence from the world's largest environmental tax reform*

Authors: Piero Basaglia, Sophie Behr, and Moritz Drupp

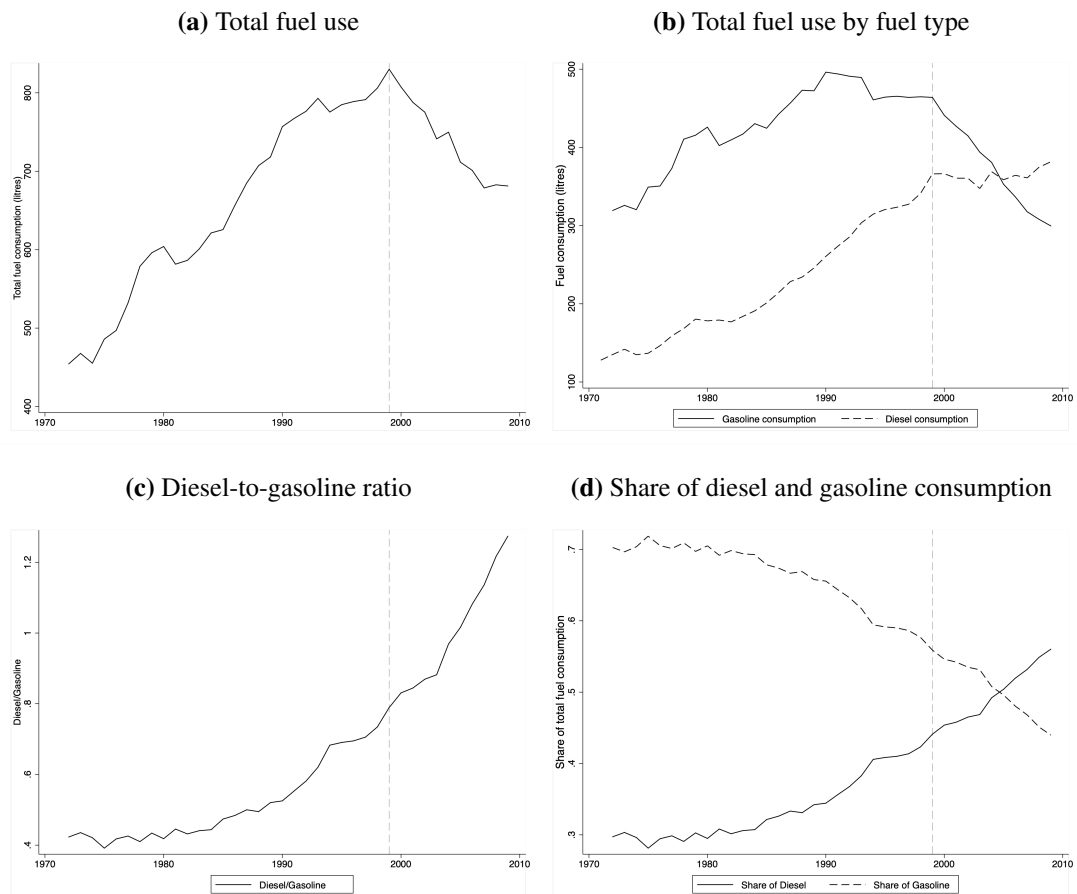
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## Appendix A Descriptive statistics and data sources

This section provides descriptive statistics referenced in the main text, details on the data sources, and additional information on the sample definitions used throughout the analysis.

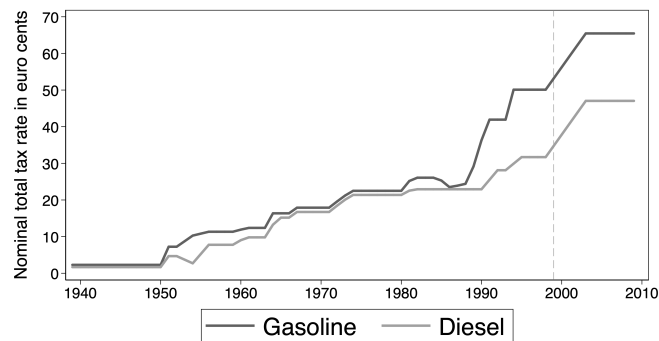
**Figure A.1: Fuel consumption over time in Germany**



*Notes:* Data on fuel consumption is expressed in liters per capita or percentage terms, as denoted on the y-axis.

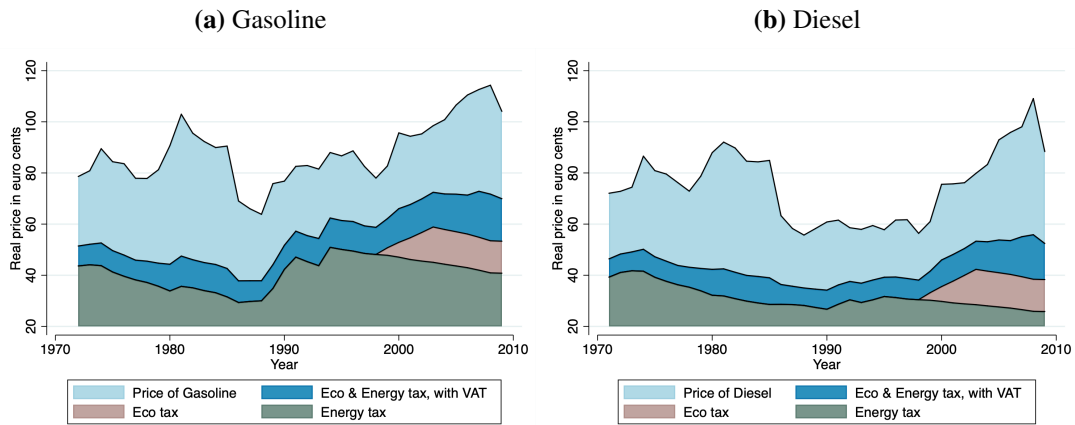
*Source:* World Bank (see Table A.1 for more details).

**Figure A.2:** Nominal taxes of gasoline and diesel over time



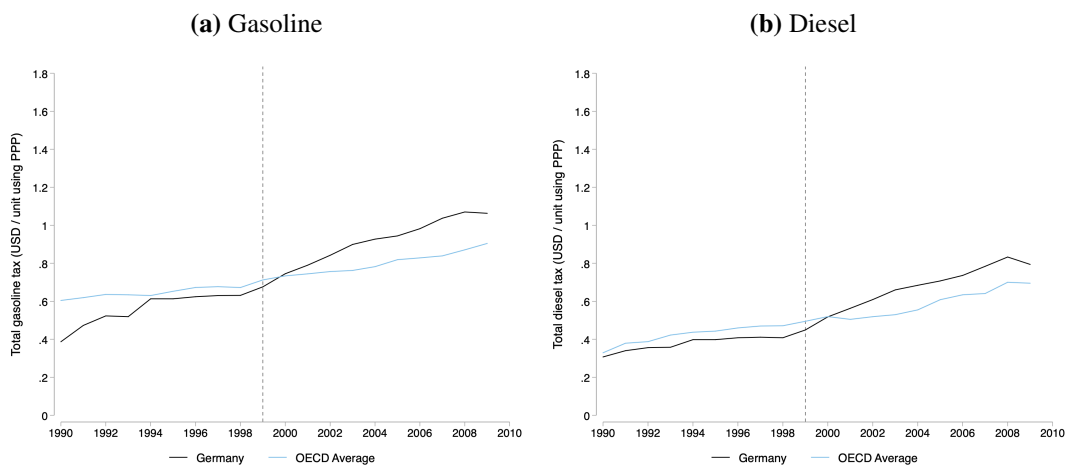
Notes: The figure above plots nominal taxes of gasoline and diesel from 1939 to 2009 as reported by the [Bundesministerium der Finanzen \(2014\)](#). Note that whenever a tax changes throughout a year, the average tax is calculated and shown here. Numbers are in cents.

**Figure A.3:** Real fuel prices and their tax components over time



Notes: Prices are in 1995€. Own calculations.

**Figure A.4:** Fuel taxes in Germany and the OECD average



Notes: Prices are in USD using PPP. Source: IEA Energy Prices and Taxes Statistics.

**Table A.1: Data Sources**

Variable	Source
Share of CO <sub>2</sub> emissions from transport	Data downloaded from <a href="#">World Bank</a>
CO <sub>2</sub> emissions from fuel combustion	<a href="#">IEA</a>
PM <sub>2.5</sub> and NO <sub>x</sub> emissions from EDGAR	<a href="#">EDGAR</a>
Population	<a href="#">World Bank</a>
Expenditure-side real GDP at current PPPs (in mil. 2011 US\$)	<a href="#">Penn World Tables</a>
Urban population (% of total population)	<a href="#">World Bank</a>
Road sector diesel (1) and gasoline (2) fuel consumption per capita (kg of oil equivalent)	<a href="#">World Bank (1)</a> , <a href="#">World Bank (2)</a> ,
Road sector gasoline fuel consumption per capita (kg of oil equivalent)	<a href="#">Mineralwirtschaftsverband</a>
Consumer price index for Germany (1995=100)	<a href="#">Statistisches Bundesamt (Destatis)</a>
Strategic Reserve for Gasoline and Diesel in DM/t	<a href="#">Erdölbevorratungsverband</a>
Energy Tax for diesel and gasoline in cents per litre	<a href="#">Bundesministerium für Finanzen</a>
Eco Tax for diesel and gasoline in cents per litre	<a href="#">Bundesministerium für Finanzen</a>
Value-added tax rate	<a href="#">Statista</a>
Fuel prices and taxes for OECD countries	<a href="#">IEA Energy Prices and Taxes Statistics</a> (Commercial data)
Unemployment Rate	<a href="#">Bundesagentur für Arbeit</a>
U.S. Crude Oil First Purchase Price (Dollars/Barrel)	<a href="#">EIA</a>
Euro/ECU exchange rates - annual data	<a href="#">Eurostat</a>
Vehicles ownership per 1,000 people	Received from Professor Gately ( <a href="#">Dargay et al., 2007</a> ).
Low-carbon patents related to transportation: triadic patent families and total	<a href="#">OECD</a>
Newspaper-specific article frequency counts	<a href="#">Factiva</a> (Commercial data)
Road passenger transport (pkm)	<a href="#">OECD</a>
Vehicle registrations by age	<a href="#">UNECE</a>
Road casualties	<a href="#">OECD</a>

**Definition of restricted sample.** Table [A.2](#) below summarizes the list of countries excluded from our estimation sample whenever we refer to the “*restricted sample*” (also denoted as *restr.*) throughout the paper. We include the rationale and references to justify each exclusion.

**Table A.2: Restrictions in the donor pool**

Country	Restricted	Rationale	Reference
Finland	✓	Carbon tax	<a href="#">Kossoy et al. (2015)</a> ; <a href="#">Mideksa (2024)</a>
Sweden	✓	Carbon tax	<a href="#">Kossoy et al. (2015)</a> ; <a href="#">Andersson (2019)</a>
Norway	✓	Carbon tax	<a href="#">Kossoy et al. (2015)</a>
The Netherlands	✓	Environmental reform	<a href="#">Kossoy et al. (2015)</a>
Italy	✓	Fuel tax	<a href="#">OECD (2001)</a>
Spain	✓	Fuel tax	<a href="#">Bosch (2001)</a>
UK	✓	Fuel tax	<a href="#">OECD (2001)</a>
Japan	✓	Fuel efficiency standards	<a href="#">Osamu (2012)</a>
Austria	✓	Fuel tourism	<a href="#">Dings (2004)</a>
Luxembourg	✓	Fuel tourism	<a href="#">Dings (2004)</a>
Ireland	✓	Economic boom	<a href="#">Andersson (2019)</a>

## Appendix B Alternative causal inference methods

This section of the Online Appendix presents additional supporting material and results for the synthetic control method (SCM) and its generalized version (GSCM). Unlike the main paper, which focuses on more granular units, these analyses are conducted at the country level. To maximize the number of observations, we use a donor pool of OECD countries while applying the restrictions detailed in Table A.2 to reduce potential confounders, following the approach of Andersson (2019).

### B.1 The Synthetic Control Method

This section introduces the synthetic control method (SCM) (e.g., Abadie and Gardeazabal, 2003; Abadie, 2021) and explains how we leverage this approach to corroborate our estimations of the causal effects of environmental taxation on carbon and air pollutant emissions presented in the main paper.

**The SCM estimator.** Suppose there are  $J + 1$  countries. Each country is indexed by  $j$ , where  $j = 1$  denotes the *treated* country (i.e., Germany), while  $j = 2, \dots, J + 1$  are *untreated* countries (the *donor pool*), which may be used to construct a control group. The  $T$  time periods are divided into pre-treatment and post-treatment (i.e., after the eco-tax reform in 1999) with  $T_0$  as the period prior to the policy ( $t = t_0, t_{-1}, \dots, T_0$ ). Denoting the intervention as  $I$ , the SCM considers that the observed outcome,  $y_{jt}$ , is the effect from the treatment,  $\alpha_{jt}I_{jt}$ , and the counterfactual outcome,  $y_{jt}^J$ :

$$y_{jt} = \alpha_{jt}I_{jt} + y_{jt}^J. \quad (16)$$

The idea of the SCM is to construct a vector of weights over  $J$  donor countries such that their weighted combination mimics the pre-treatment outcome of the treated country. This weighted combination of donor units is called a synthetic Germany. Defining  $X_1$  as the  $k \times 1$  vector of the  $k$  characteristics of Germany in the pre-intervention period, and  $X_0$  as the  $k \times J$  vector with the same pre-treatment characteristics for donors, the SCM algorithm identifies non-negative donor weights  $W$ , such that  $\sum_{j=2}^{J+1} w_j = 1$ , to minimize the divergence between pre-treatment characteristics  $X_1$  and  $X_0$  of the treated country and the untreated donors. More formally, the vector  $W^*$  is chosen to minimize the mean square prediction error (MSPE) over  $k$  pre-treatment characteristics:

$$MSPE = \sum_{m=1}^k v_m (X_{1m} - X_{0m} W)^2, \quad (17)$$

where  $V$  is a matrix of non-negative components measuring the relative importance of each predictor,  $v_m$ . Given optimal weights  $w_j^*$  for each  $j = 2, \dots, J + 1$  donor country, the synthetic control at any time  $t$  is the weighted combination of the outcome variable (e.g., CO<sub>2</sub> emissions in the transport sector) in the donor countries,  $\sum_{j=2}^{J+1} w_j^* y_{jt}$ . The treatment effect  $\alpha_{1t}$  is then the difference between emissions in the treated country  $y_{1t}$

**Table B.1:** Overview of the specification choices for the SCMs

Specification	Lagged outcome variable	Selected literature examples
<b>Baseline</b>	Lagged outcome in 1998 ( $t_0$ )	<a href="#">Andersson, 2019</a> ; <a href="#">Kaul et al., 2022</a> ; <a href="#">Leroutier, 2022</a>
<b>Lags (Mean)</b>	Pre-treatment outcome mean	<a href="#">Abadie and Gardeazabal, 2003</a> ; <a href="#">DeAngelo and Hansen, 2014</a>
<b>Lags (All)</b>	Lagged pre-treatment outcome ( $t_0, t_{-1}, \dots, T_0$ )	<a href="#">Bohn et al., 2014</a> ; <a href="#">Dustmann et al., 2017</a> ; <a href="#">Isaksen, 2020</a>
<b>Lags (Selected)</b>	Lagged outcome in 1971, 1980, 1991, 1998	<a href="#">Cavallo et al., 2013</a> ; <a href="#">Cunningham and Shah, 2018</a>
<b>Reunification</b>	Lagged outcome in 1991 and 1998	<i>Specific to the German case</i> (cf. <a href="#">Abadie et al., 2015</a> )
<b>Tax anticipation</b>	Lagged outcome in 1999 ( $t_1$ )	<a href="#">Abbring and Van den Berg, 2003</a> ; <a href="#">Coglianese et al., 2017</a>
<b>No covariates</b>	Lagged pre-treatment outcome ( $t_0, t_{-1}, \dots, T_0$ )	<a href="#">Gobillon and Magnac, 2016</a> ; <a href="#">Lindo and Packham, 2017</a>

*Notes:* Summary of SCM specifications. *Specification* denotes the name that we use for SCM specification henceforth. *Lagged outcome variable* specifies the number and years of the pre-treatment outcome lags. All except *No Covariates* include as predictors (i) GDP per capita (PPP, in mio 2011 USD), (ii) gasoline and (iii) diesel consumption per capita, (iv) the share of the urban population, and (v) the number of vehicles per 1000 people. SCM specifications for  $\text{NO}_x$  emissions also include (vi)  $\text{PM}_{2.5}$  emissions in the transport sector as a general proxy for air pollution to account for the impact of unilateral policies affecting emission levels. We refer to the specification used by [Andersson \(2019\)](#) as the *Baseline* model. We start the post-treatment period in 1999 even if the first fully treated year is 2000 to capture anticipation effects (cf. Section A in the OA for details). Our *Tax anticipation* specification provides results when we set  $t_1$  in the year 2000 for comparison.

and emissions in the synthetic counterfactual in the post-treatment period,  $t > T_0$ :

$$\hat{\alpha}_{1t} = y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jt}.^{39} \quad (18)$$

**Choice of SCM predictors.** There are various methods for choosing the relative importance of predictors ( $v_m$ ) ([Abadie and Gardeazabal, 2003](#); [Abadie et al., 2010](#)). The standard approach selects the matrix  $V$  along weights  $W$  to minimize the pre-treatment difference between actual and synthetic Germany’s emissions, using the *synth* package in STATA by [Abadie et al. \(2010\)](#). Despite being a primarily data-driven approach, there is some discretion in specifying the SCM, which may lead to “cherry picking” combinations of predictors to influence the result (e.g., [Ferman et al., 2020](#)).<sup>40</sup> Given a lack of consensus on how to choose the best specification, we report results for a range of specifications used in previous SCM evaluations (see Table B.1).

**Statistical inference for the SCM.** A key advantage of the SCM is that it offers an approach to causal analysis that does not rely on parallel pre-intervention trends like difference in difference methods. Yet, it does not allow to employ standard (large-sample) inferential methods, primarily because the number of suitable donors and time periods are usually very limited. [Abadie et al. \(2010, 2015\)](#) and [Abadie \(2021\)](#) suggest using placebo experiments using permutation techniques to make inferences. We implement cross-sectional placebo tests by sequentially applying the SCM algorithm to every potential donor country and compare estimated placebo effects with the baseline results for Germany, after accounting for the quality of the pre-treatment match, which we do by scaling effects by the relevant pre-treatment root MSPE (RMSPE). Examining whether potential comparison countries show larger treatment effects helps assess the

<sup>39</sup>The average treatment effect is thus given by:  $\hat{\beta}_{1T} = \frac{1}{T} \sum_{t=T_1}^T (y_{1t} - \sum_{j=2}^{J+1} w_j^* y_{jt})$ .

<sup>40</sup>While [Kaul et al. \(2022\)](#) point out that including the entire pre-treatment periods of the outcome variable as a predictor causes all other covariates to be obsolete, [Ferman et al. \(2020\)](#) advise using all pre-treatment periods as it is less arbitrary.

robustness of our results. A p-value is then computed as the proportion of control units that have an estimated effect at least as large as Germany's. Suppose that the estimated standardized effect for some post-treatment period is  $\hat{\alpha}_{1t}$  and that the distribution of in-place placebo is  $\hat{\alpha}_{jt}^{PL} = \{\hat{\alpha}_{jt} : j \neq 1\}$ , the one-sided and two-sided p-values are then:

$$p = Pr(\hat{\alpha}_{jt}^{PL} \geq \hat{\alpha}_{1t}) \quad \text{and} \quad p = Pr(\hat{\alpha}_{jt}^{PL} \leq \hat{\alpha}_{1t}), \quad (19)$$

$$p = Pr(|\hat{\alpha}_{jt}^{PL}| \geq |\hat{\alpha}_{1t}|) = \frac{\sum_{j \neq 1} 1(|\hat{\alpha}_{jt}^{PL}| \geq |\hat{\alpha}_{1t}|)}{J}. \quad (20)$$

Following [Firpo and Possebom \(2018\)](#) and [Abadie and L'hour \(2021\)](#), we implement a one-sided test, which allows constructing p-values based on placebo effects,  $\hat{\alpha}_{jt}^{PL}$ , that yield reductions in post-treatment emissions, as only reductions in emissions due to fuel taxes are of interest for the rank statistics (we also report two-sided p-values). To evaluate how the significance of the effects unfolds over time—as the eco-tax rate increased in yearly steps from 1999 to 2003 (see [Figure B.3](#))—we apply the permutation-based inference procedure for each post-treatment year.

## B.2 Emissions reductions according to SCMs

We, first, focus on examining emission reductions according to the SCM, performing inference using permutation tests and assessing their robustness using standard sensitivity and placebo tests (cf. [Section B.2](#)) before turning to the GSCM (cf. [Section B.7](#)).

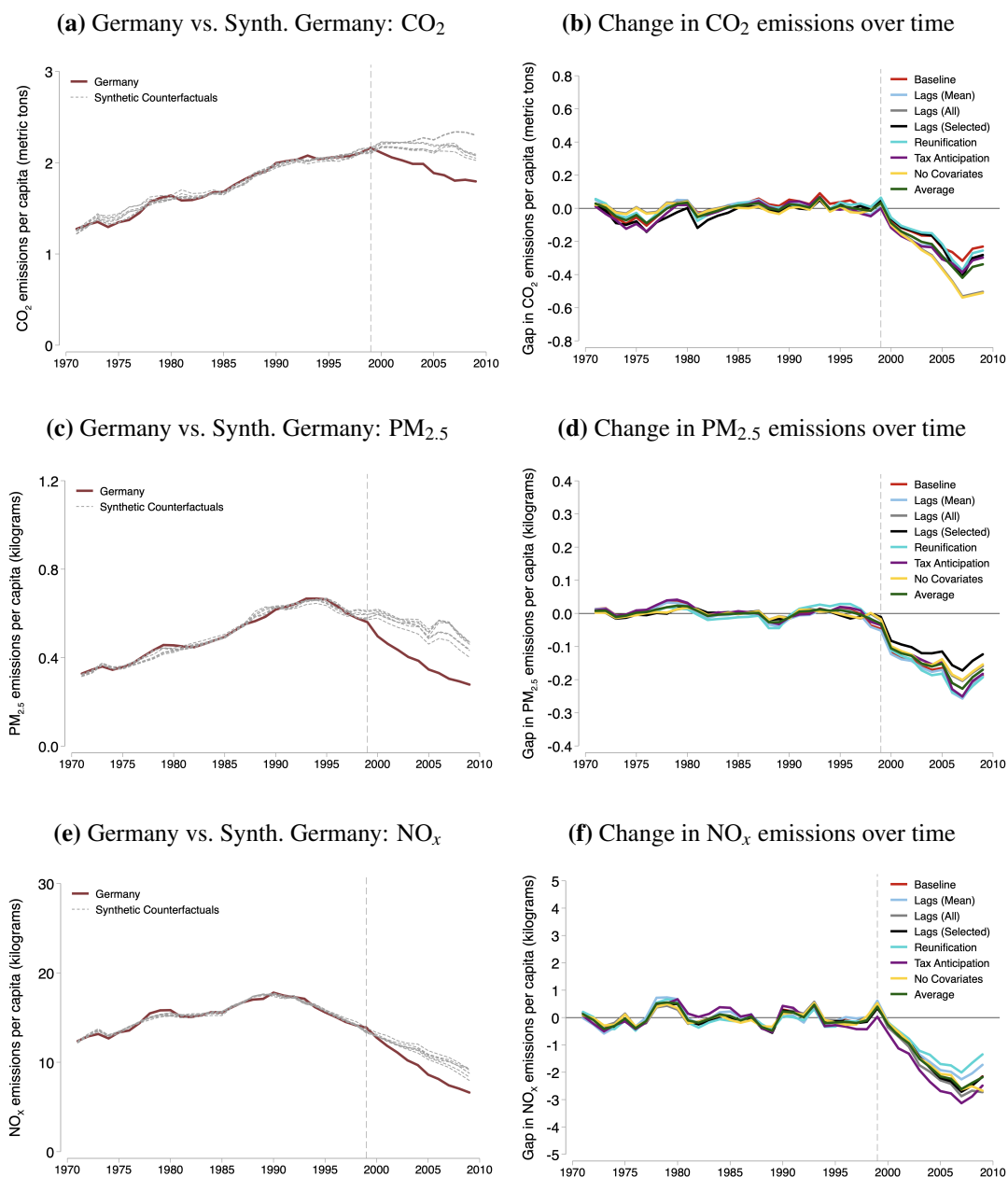
Panels (a), (c) and (e) in [Figure B.1](#) plot the path of CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions in the German transport sector (solid line) and in synthetic Germanies (dashed lines) across specifications (cf. [Table B.1](#)) from 1971 to 2009. The overlap between the solid and dashed line before 1999 captures the quality of the SCM pre-treatment fit; the same comparison after 1999 plots the dynamic treatment effects for the eleven years that followed. All panels reveal sizable emission reductions following the eco-tax reform.

The validity of SCM effects depends on synthetic Germany's ability to replicate emissions from the German transportation sector prior to the eco-tax introduction. Panels (a) and (b) show that prior to the treatment, emissions from transportation in Germany and its synthetic counterpart exhibit a high degree of similarity, with an average absolute difference of slightly more than 0.02 metric tons of CO<sub>2</sub>, less than 0.01 kg of PM<sub>2.5</sub> and around 0.22 kg of NO<sub>x</sub>. [Figure B.4](#) in the OA plots the distribution of country-specific weights across all specifications and shows that the composition of our synthetic Germanies varies considerably across outcomes and specifications. [Tables B.2 - B.4](#) in the OA compares the values of key predictors for Germany prior to 1999 with those for our baseline synthetic Germany (cf. [Section 4](#)). Overall, synthetic Germany exhibits a much more refined fit compared with the donor pool average.

Panels (b), (d) and (e) of [Figure B.1](#) report the estimated gap in metric tons of CO<sub>2</sub> and kg of PM<sub>2.5</sub> and NO<sub>x</sub> emissions across the seven SCM specifications (colored lines), where *Average* refers to the average estimated emission gap (green line). All specifications point to sizable decreases in CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions due to the eco-tax. Panel (b) shows that the distance between Germany and the synthetic Germanies is steadily growing between 1999 and 2007.<sup>41</sup> In 2007, this distance was on average -0.42

<sup>41</sup>There are different possible explanations for the convergence in emissions after 2007. An obvious

**Figure B.1: Synthetic Control Method results for emissions**



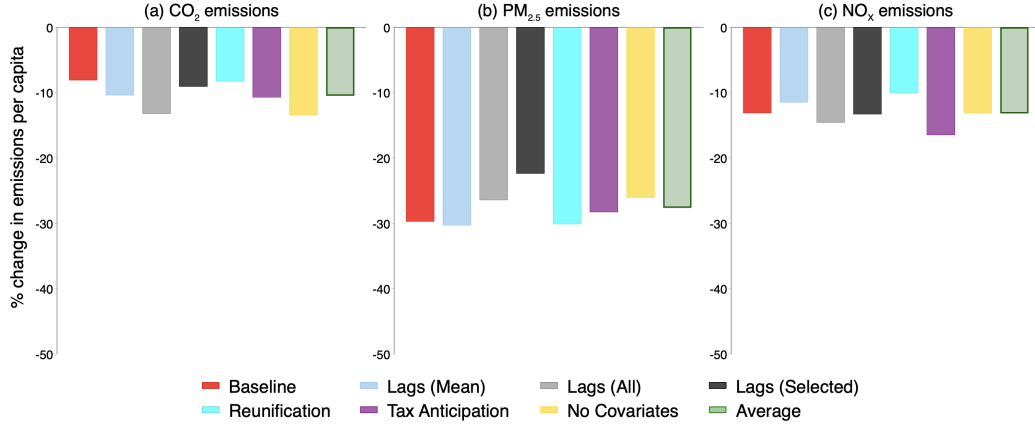
*Notes:* The figure plots the estimated reductions in CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions relative to (synthetic) counterfactuals. Panels (a) and (b) refer to reductions in CO<sub>2</sub> emissions per capita in metric tons or percentage terms. Panels (c) - (f) refer to reductions in PM<sub>2.5</sub> and NO<sub>x</sub> emissions per capita expressed in kg. Panels (a), (c) and (e) plot the absolute paths of emissions in Germany and Synthetic Germanies for our specifications (see Table B.1). Panels (b), (d) and (f) report gaps in emissions over time relative to synthetic Germanies, estimated by our seven different SCM specifications and their average.

metric tons of CO<sub>2</sub> per capita, equivalent to a 19 percent reduction. Between 1999 and 2009, annual emission reduction amounted to 0.23 metric tons of CO<sub>2</sub> per capita on

one is the financial crisis, which evolved into an economic crisis across the EU in 2008, which likely affected German transport differently than that of donor countries, implying that synthetic Germany may not describe the counterfactual after 2007/2008 as accurately as before. Another explanation is decreasing fuel taxes in real terms. As the last increase of the eco-tax took place in 2003, the real fuel tax on gasoline and diesel has been decreasing ever since then due to inflation.

average, which cumulatively sums up to 208,216,572 tons of CO<sub>2</sub>. Panel (d) presents the emission gap over time for PM<sub>2.5</sub>. On average, 0.15 kg of per capita PM<sub>2.5</sub> less were emitted each year in comparison to a scenario with no eco-tax, which amounts to total PM<sub>2.5</sub> savings of around 135,632 tons. Finally, Panel (f) displays emission gaps for NO<sub>x</sub>. Following the eco-tax reform, per capita NO<sub>x</sub> emissions were lower by 1.5 kg, on average, with a cumulative reduction in NO<sub>x</sub> of 1,347,190 tons.

**Figure B.2:** Mean annual percentage gap in CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions



Notes: The figure plots the average annual percentage gap for each specification in CO<sub>2</sub>, PM<sub>2.5</sub> and NO<sub>x</sub> emissions between Germany and a synthetic counterfactual development reported in Figure B.1.

Figure B.2 plots mean annual changes in emissions in percentage terms to put into perspective the distribution of the effect magnitudes from different specifications. CO<sub>2</sub> per capita emissions decrease, on average, from 8.1% to 13.4% between 1999 and 2009, conditional on the specification used, while PM<sub>2.5</sub> and NO<sub>x</sub> per capita emission reductions range between 22.4% - 30.3% and 10% - 16.5%, respectively. Our finding that emission reductions due to the eco-tax are sizable is thus robust across a range of specifications.

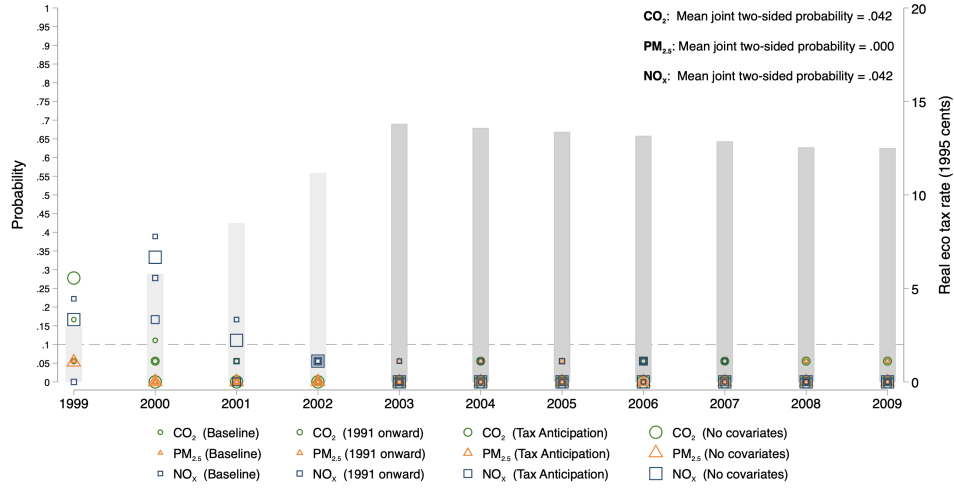
### B.2.1 Inference from permutation tests for the SCM

We rely on permutation tests to gauge the significance of our treatment effects. Figure B.3 plots estimated one-sided p-values in each post-intervention year. We report yearly permutations for a number of SCM specifications: (i) *Baseline*, (ii) *Baseline* restricting the pre-intervention period after German reunification in 1991, (iii) *Tax Anticipation*, and (iv) *No covariates* following Ferman et al. (2020). Overall, the distribution of the estimated p-values is centered well below a 10% threshold level, and generally below a 5% threshold, particularly after the last eco-tax rate increase in 2003. The mean joint two-sided p-values are below 5% for CO<sub>2</sub> and NO<sub>x</sub> and below 1% for PM<sub>2.5</sub> (see Figure B.3).

### B.2.2 Additional sensitivity and placebo tests for the SCM

Our SCM findings are robust to a host of standard sensitivity and placebo tests, including in-time placebos and the use of alternative donor pools.

**Figure B.3: Inference results for the Synthetic Control Method**



*Notes:* The figure plots estimated one-sided p-values (primary left-hand side y-axis) computed as the proportion of effects from control units as great as the treated unit in each post-intervention period, after scaling it by the relevant pre-treatment RMSPE (Abadie, 2021). Joint two-sided p-values represent the proportion of placebos that have a ratio of post-treatment RMSPE over pre-treatment RMSPE at least as large as the average ratio for Germany. The gray bars plot the annual real eco-tax rate in 1995 cents (secondary right-hand side y-axis). The darker gray bars indicate the post-treatment periods where the full nominal eco-tax rate increase fuel was in place.

**In-time tests.** For the in-time placebos, the year of treatment is shifted to a number of years prior to the actual eco-tax reform. Any sizable and enduring placebo effect would cast doubt on the validity of the results from Figure B.1. Figure B.5 in the OA shows that the synthetic control closely resembles the actual emission trajectories in Germany after the placebo treatment and that no significant divergence is detected.

**Alternative donor pools.** To investigate the sensitivity of our emission results to the composition of the donor pool, we perform the following tests: (i) implementing the SCM without any sample restriction either with the inclusion of covariates as predictors or solely based pre-treatment lags, (ii) excluding only countries that implemented carbon taxes, and (iii) “leave-one-out” tests (cf., Abadie et al., 2015), where we sequentially exclude from the restricted donor pool all control countries with a weight larger than 0.001 (0.1%). The results (see Figures B.6 and B.7 in the OA) show that none of the possible alternative donor pool compositions yield a consistent non-negative post-intervention gap.

### B.3 Standard SCM diagnostics

This section contains the following material: Tables B.2 - B.4 report country-specific weights used for the construction of our synthetic counterfactuals in Figure B.1. The three panels in Figure B.5 plot in-time placebo tests when we assign a placebo treatment to Germany in 1995. Figure B.6 reports SCM results when we do not impose any of the sample restrictions discussed in Section 4. Figure B.7 reports leave-one-out tests (cf. Abadie et al., 2015) for our *Baseline* (i.e., Panels a, c and e) and *No covariates* specifications (i.e., Panels b, d and f). The former is in line with the recommendations in Kaul et al. (2022), while the latter follows Ferman et al. (2020).

**Table B.2: SCM for CO<sub>2</sub>: Pre-Treatment Predictor Means for Germany, Baseline Synthetic Germany and the Sample Average**

Variables	Germany	Synthetic	Sample Mean
GDP per capita	22,197.42	23,615.94	17,972.24
Diesel consumption per capita	185.23	185.27	130.29
Gasoline consumption per capita	332.55	332.77	343.23
Share of urban population	0.73	0.73	0.73
Number of vehicles per 1,000 people	410.34	410.48	290.14
CO <sub>2</sub> from transport in 1998	2.10	2.10	2.12

All variables except lagged CO<sub>2</sub> per capita are averaged from 1971-1998. GDP per capita is measured at current PPPs in million 2011 USD. Gasoline and diesel consumption is measured in kg of oil equivalent. Share of urban population is measured as a percentage of total population. CO<sub>2</sub> emissions are measured in metric tons per capita and are retrieved from the IEA.

**Table B.3: SCM for PM<sub>2.5</sub>: Pre-Treatment Predictor Means for Germany, Baseline Synthetic Germany and the Sample Average**

Variables	Germany	Synthetic	Sample Mean
GDP per capita	22,197.42	22,346.93	17,972.24
Diesel consumption per capita	185.23	170.25	130.29
Gasoline consumption per capita	332.55	367.82	343.23
Share of urban population	0.73	0.75	0.73
Number of vehicles per 1,000 people	410.34	410.39	290.14
PM <sub>2.5</sub> from transport in 1998	0.58	0.61	0.58

All variables except lagged PM<sub>2.5</sub> per capita are averaged from 1971-1998. GDP per capita is measured at current PPPs in million 2011 USD. Gasoline and diesel consumption is measured in kg of oil equivalent. Share of urban population is measured as a percentage of total population. PM<sub>2.5</sub> emissions are measured in kg per capita and are retrieved from the EDGAR v6.1 database.

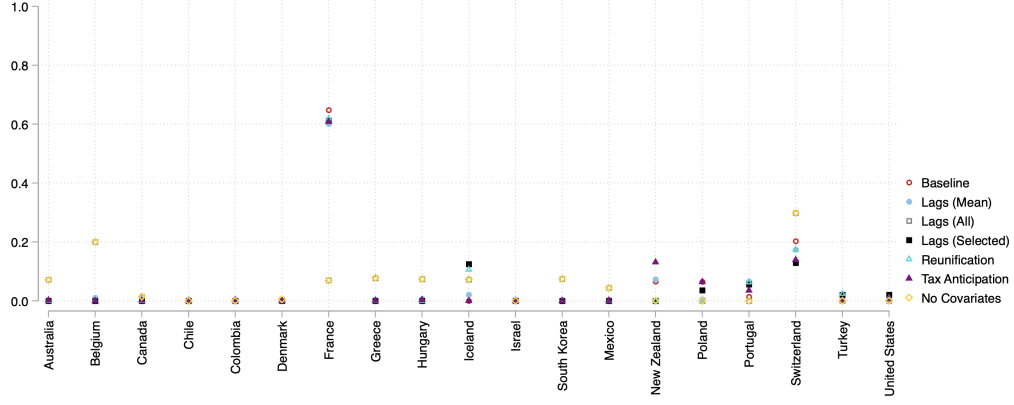
**Table B.4: SCM for NO<sub>x</sub>: Pre-Treatment Predictor Means for Germany, Baseline Synthetic Germany and the Sample Average**

Variables	Germany	Synthetic	Sample Mean
GDP per capita	22,197.42	22,199.20	17,972.24
Diesel consumption per capita	185.23	179.35	130.29
Gasoline consumption per capita	332.55	303.51	343.23
Share of urban population	0.73	0.76	0.73
Number of vehicles per 1,000 people	410.34	360.88	290.14
PM <sub>2.5</sub> from transport	0.50	0.50	0.42
NO <sub>x</sub> from transport in 1998	14.13	14.26	16.72

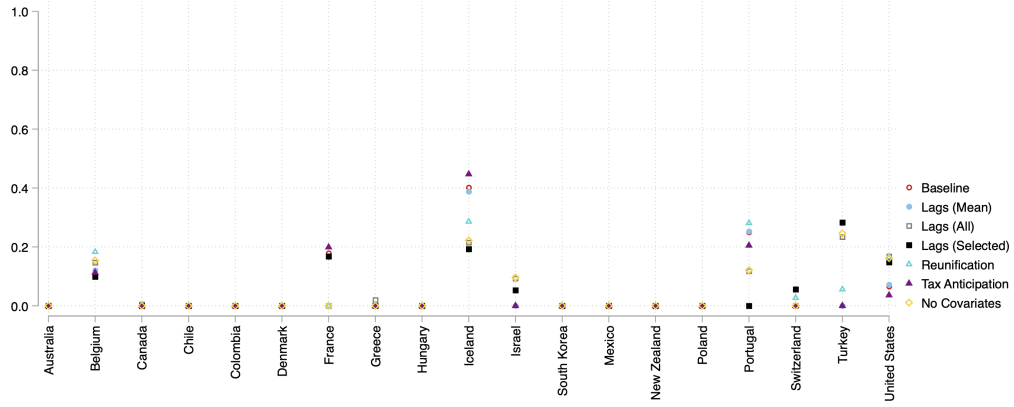
All variables except lagged NO<sub>x</sub> per capita are averaged from 1971-1998. GDP per capita is measured at current PPPs in million 2011 USD. Gasoline and diesel consumption is measured in kg of oil equivalent. Share of urban population is measured as a percentage of total population. NO<sub>x</sub> emissions are measured in kg per capita and are retrieved from the EDGAR v6.1 database.

**Figure B.4:** Comparing donor pool weights across SCM specifications

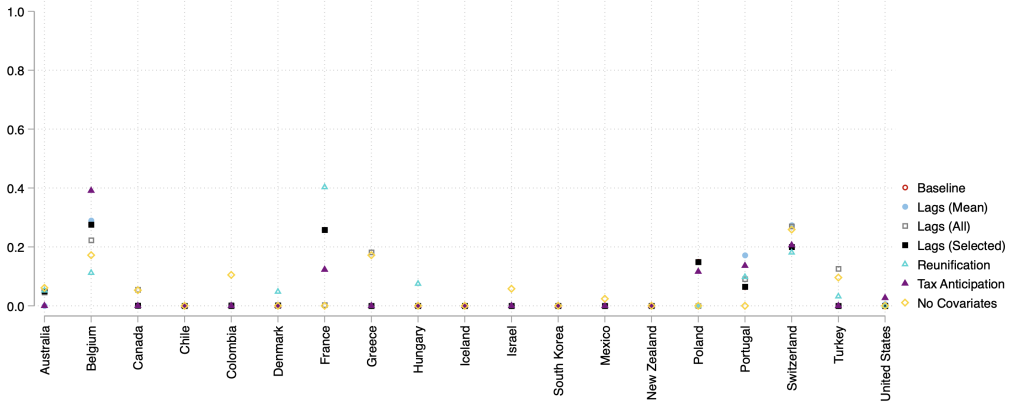
**(a) Synthetic Germany: CO<sub>2</sub>**



**(b) Synthetic Germany: PM<sub>2.5</sub>**



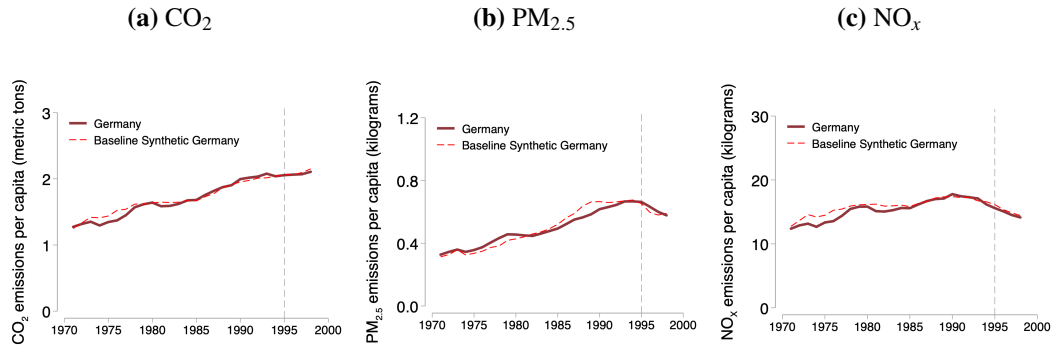
**(c) Synthetic Germany: NO<sub>x</sub>**



*Notes:* The figure plots the estimated country-specific weights assigned by the synthetic control algorithms across our set of SCM specifications (cf. Table B.1).

## B.4 Placebo in time

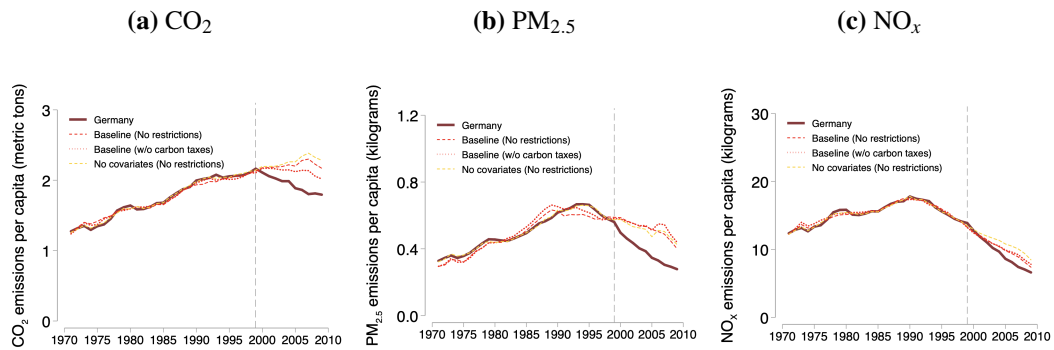
**Figure B.5:** In-time placebos



*Notes:* The figure plots the in-time placebo for our results on (a)  $\text{CO}_2$ , (b)  $\text{PM}_{2.5}$ , and (c)  $\text{NO}_x$  emissions where a placebo treatment is assigned in 1995.

## B.5 No sample restrictions

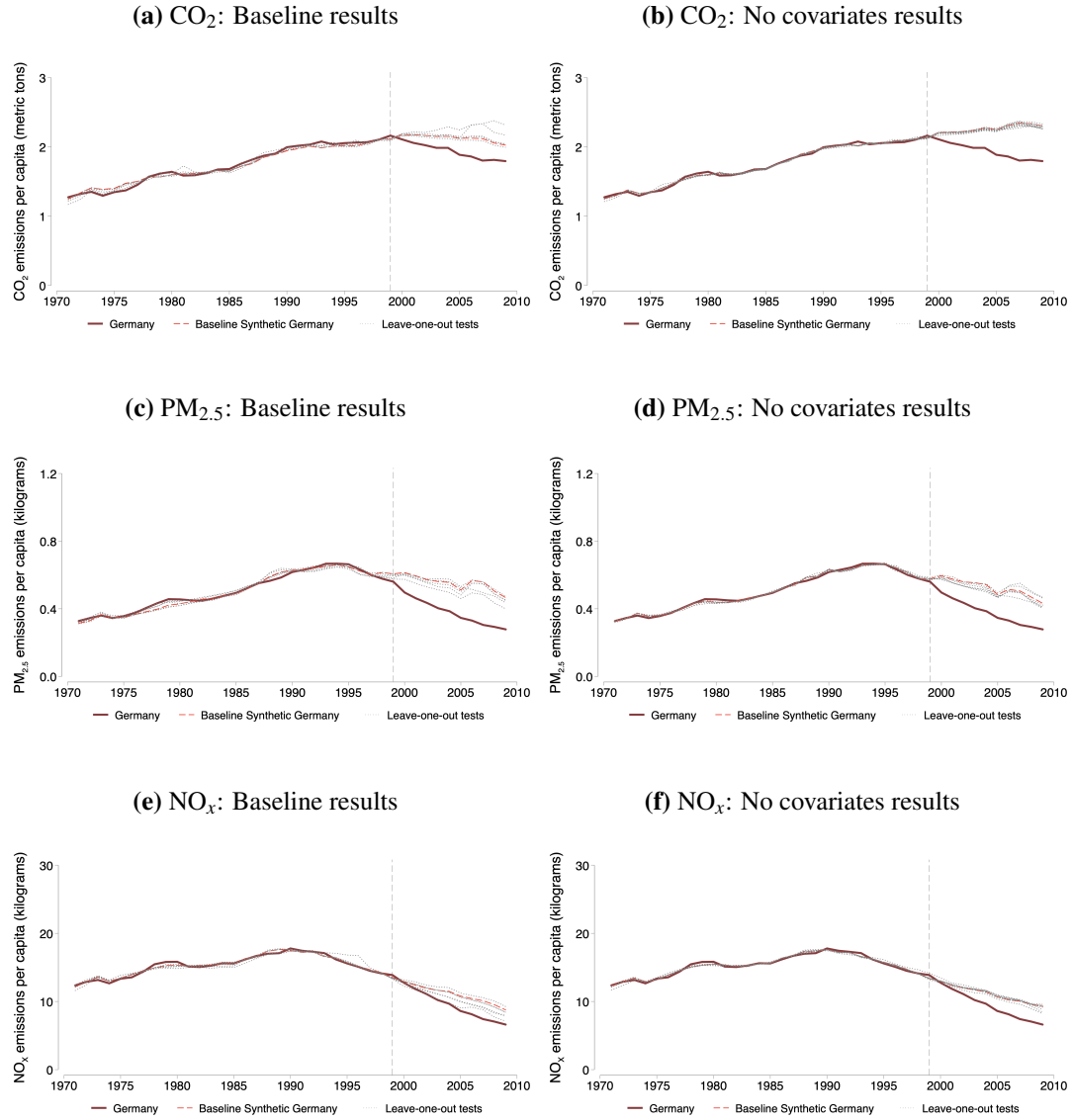
**Figure B.6:** Results with no donor pool restrictions



*Notes:* The figure plots our Baseline SCM results without applying the sample description described in Section 4 and summarised in Table A.2.

## B.6 Leave-one-out tests

**Figure B.7: Leave-one-out tests**



*Notes:* The figure plots leave-one-out tests following [Abadie et al. \(2015\)](#) where we iteratively exclude countries that receive at least a 1% in the construction of the synthetic counterfactual. More details can be found in Section B.2.2.

## B.7 Emissions reductions according to generalized SCMs

We next construct GSCM counterfactuals by modeling emissions of countries with interactive fixed effects (IFE) models following [Xu \(2017\)](#). For our GSCM analysis, we assume that each outcome ( $y$ ), i.e., emissions of CO<sub>2</sub>, PM<sub>2.5</sub>, or NO<sub>x</sub>, can be explained by a corresponding factor model of the form:

$$y_{it} = \tau_{it} Eco_{it} + X'_{it}\beta + \lambda'_i F_t + \varepsilon_{it}, \quad (21)$$

where  $t = \{1970, \dots, 2009\}$  corresponds to the time period and  $i$  represents a country. The sets  $\mathcal{T}$  and  $\mathcal{C}$  contain Germany and unregulated countries, respectively.  $Eco_{it}$  refers to the binary treatment indicator and equals 1 for treated units in the post-treatment period (i.e.,  $i \in \mathcal{T}$  and  $t \geq t^{Eco}$ ;  $t^{Eco} = 1999$ ). The main parameter of interest is  $\tau_{it}$ , the treatment effect at time  $t$ .  $X_{it}$  and  $\beta$  are vectors of observed covariates and their parameters, respectively.  $F_t$  and  $\lambda_i$  correspond to vectors of unobserved time-varying latent factors and their unit-specific factor loadings. Finally,  $\varepsilon_{it}$  refers to idiosyncratic shocks. The ATTs in periods  $t \geq t^{Eco}$  are given by  $\tau_{it}$  which is equal to  $Y_{it}(1) - Y_{it}(0)$ , i.e., the difference between the observed outcome of unit  $i$  at time  $t$  and its counterfactual outcome. As  $Y_{it}(0)$  is by definition unobserved for treated units, we employ the three-step GSCM estimation ([Xu, 2017](#)) to obtain the counterfactual:

$$Y_{it} = X'_{it}\beta + \lambda'_i F_t + \varepsilon_{it}, \quad i \in \mathcal{C} \quad (22)$$

$$Y_{it} = X'_{it}\hat{\beta} + \lambda'_i \hat{F}_t + \eta_{it}, \quad i \in \mathcal{T}, t < t^{Eco} \quad (23)$$

$$\hat{Y}_{it}(0) = X'_{it}\hat{\beta} + \hat{\lambda}'_i \hat{F}_t, \quad i \in \mathcal{T}, t \geq t^{Eco} \quad (24)$$

First, leveraging data on control units, Eq. 22 is estimated to retrieve the coefficient on the observed covariates,  $\hat{\beta}$ , and time-varying factors,  $\hat{F}_t$ . Second, the GSCM algorithms select factor loadings  $\hat{\lambda}_i$  for treated units by minimizing the mean squared prediction error (MSPE) in pre-treatment years (Eq. 23). Third, it imputes the predicted counterfactual outcome  $\hat{Y}_{it}(0)$  utilizing  $\hat{\beta}$ ,  $\hat{F}_t$ , and  $\hat{\lambda}_i$  (Eq. 24). The GSCM selects the number of factors,  $F_t$ , and their loadings,  $\lambda_i$ , based on a data-driven cross-validation algorithm, which limits arbitrariness and reduces risks of over-fitting. With predicted counterfactual outcomes for treated units, we estimate the ATT. Finally, to construct confidence intervals, we apply the parametric bootstrapping scheme from [Xu \(2017\)](#).

We provide three different model specifications. First, we include controls to explicitly account for the impacts of EU membership, namely a binary EU member indicator and a dummy identifying EU member countries after 2005 (denoted *IFE only*). We include this dummy to control for potential spillovers due to the EU Emissions Trading Scheme (EU ETS), introduced in 2005, and the EU-wide PM<sub>10</sub> limits in cities, also introduced in 2005. These spillovers are likely not substantial, as transport emissions were not covered by the EU ETS and have not decreased due to the scheme ([Bayer and Aklin, 2020](#)). Further, Germany failed to meet the 2005 PM<sub>10</sub> limits, triggering infringement proceedings in 2009, and EU-wide PM<sub>10</sub> limits on were not very effective initially, with 70% of all cities with larger populations than 250,000 having exceeded the limits at some point as of 2007 ([Wolff and Perry, 2010](#)). Some German municipalities responded by implementing low-emission zones from 2008 onward, limiting access

for highly-polluting vehicles within city centers.

Second, we additionally model each country's emissions as a function of their economic activity (*Economic activity*), proxied by GDP per capita (Bayer and Aklin, 2020). Finally, we restrict the donor pool to EU countries (*EU only*) to further address concerns that effects may be partly driven by EU-wide regulation (e.g., Reynaert, 2021).

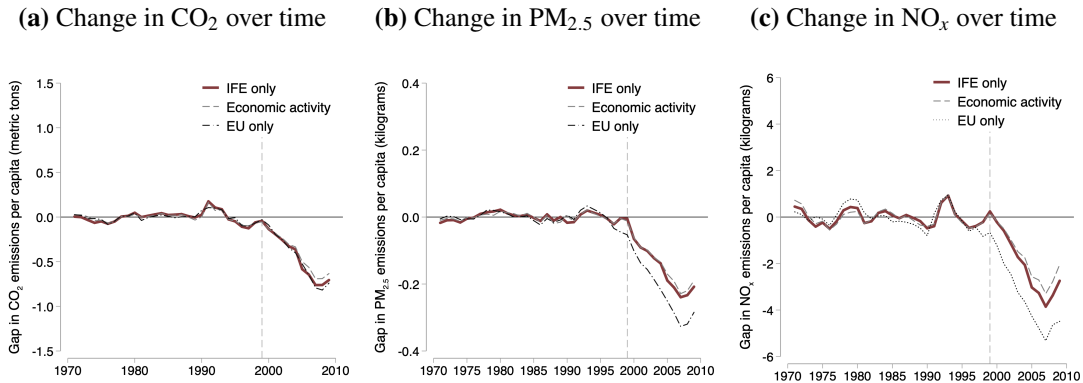
Wald tests for pre-treatment fitting checks show that all the different models capture the variability in the data well prior to the eco-tax reform, validating the main identification assumption. Table B.5 summarizes our GSCM results. We report mean reductions of emissions due to the eco-tax with bootstrapped 95% confidence intervals. Figure B.8 plots the dynamic treatment effects estimated for each of our GSCM specifications. Our GSCM results are comparable in magnitude to the average SCM results reported in Figure B.1, pointing towards slightly larger magnitudes in carbon reductions and almost identical average reductions in air pollution. Figure C.3 in the OA further compares the dynamic treatment effects across all empirical strategies at the country level, highlighting the consistency of our findings.

**Table B.5:** Effects of the eco-tax with a Generalized Synthetic Control

	IFE only	Economic activity	EU only
<b>Panel A: CO<sub>2</sub> (t)</b>			
Mean [95% CI]	-0.43 [-0.53; -0.34]	-0.39 [-0.50; -0.25]	-0.44 [-0.57; -0.29]
<b>Panel B: PM<sub>2.5</sub> (kg)</b>			
Mean [95% CI]	-0.15 [-0.26; -0.04]	-0.14 [-0.25; -0.07]	-0.21 [-0.27; -0.13]
<b>Panel C: NO<sub>x</sub> (kg)</b>			
Mean [95% CI]	-1.98 [-3.32; -0.24]	-1.65 [-3.09; -0.14]	-3.34 [-5.33; -0.26]
Observations	1053	939	451
Countries	27	27	14
Wald test p-value	<0.001	<0.001	<0.001

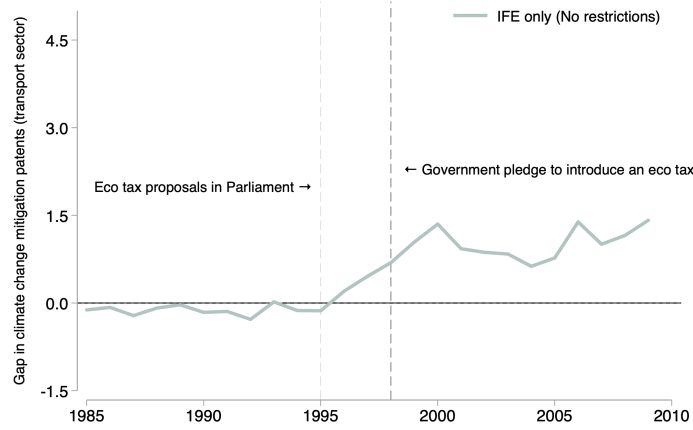
Notes: Summary of average treatment effects and 95% confidence intervals for different GSCM specifications. Wald test p-values refer to pre-treatment fitting tests (cf. Xu, 2017); for each specification, we report the highest p-values across panels. All models include IFE and a binary indicator for German reunification and post-intervention. *IFE only* includes a dummy for EU membership and for EU member countries after 2005. *Economic activity* also controls for GDP per capita, while *EU only* restricts the donor pool to EU countries.

**Figure B.8:** GSCM with Interactive Fixed Effects Models



Notes: The figure plots the estimated gaps in emissions relative to a synthetic counterfactual development based on a Generalized Synthetic Control Method with interactive fixed effects models Xu (2017). More details on the GSCM specifications can be found in Section B.7.

**Figure B.9:** Effects of the eco-tax with the GSCM on low-carbon patents



Notes: The figure plots the estimated gaps in emissions relative to a synthetic counterfactual development based on a Generalized Synthetic Control Method with interactive fixed effects models and no sample restrictions (Xu, 2017). More details on the GSCM specifications can be found in Section B.7.

## Appendix C Elasticities

This Section is structured as follows. First, we provide evidence of tax pass-through to prove that taxes are noticeable to consumers. Second, Tables C.1a - C.1b provide a host of robustness tests for our real and eco-tax elasticity results presented in Section 6. Figure C.1 plots our elasticity results when using a distributed lag model with one lead to account for anticipatory behavior (Coglianese et al., 2017; Kilian and Zhou, 2024).<sup>42</sup> Table C.3a and C.3b provides evidence of gasoline-to-diesel substitution in our setting again leveraging the semi-elasticity models presented in Section 3.2. Figure C.2 displays predicted NO<sub>x</sub> emissions under different taxation scenarios complementing Figure 5 in the main text. Figure C.3 compares the dynamic treatment effects across all supplementary empirical strategies employed in our study, namely the (a) SCM, (b) the GSCM and (c) the simulation approach.<sup>43</sup> Finally, Figure C.4 leverages again the semi-elasticity models to provide complementary suggestive evidence on the average effects of the eco-tax on road casualties (i.e., considering fatalities and injuries).

**Tax pass-through.** Before computing fuel-specific price and tax elasticities, we check if the tax increases get effectively passed through to the retail price of fuel to ensure that changes in taxation are noticeable to consumers (c.f. Andersson, 2019). We use first-differencing to regress the crude oil price  $i$  and the combined nominal energy and eco tax  $\tau^{eco,energy}$  on the retail fuel price  $p^*$  of gasoline and diesel, respectively:

$$\Delta p_t^* = \alpha_0 + \alpha_1 \Delta \sigma_t + \alpha_2 \Delta \tau_t^{eco,energy} + \varepsilon_t \quad (25)$$

<sup>42</sup>We also run first-differences models including different sets of leads and lags of the normalized tax change (c.f., Kilian and Zhou, 2024). We produce a distribution of p-values for testing the null of equal effects between tax-exclusive and eco-tax price changes, which we reject across all specifications. Results are available upon request.

<sup>43</sup>Note that simulated PM<sub>2.5</sub> emissions are not directly comparable to our SCMs results as the former do not account for non-exhaust emissions.

**Table C.1:** Comparing real price, aggregate tax and eco-tax elasticities by fuel

(a) Gasoline consumption				(b) Diesel consumption			
	Real price	Aggregate tax	Eco-tax		Real price	Aggregate tax	Eco-tax
Real price of Gasoline	-0.00603** (0.00278)			Real price of Diesel	-0.00440*** (0.00103)		
Raw price of Gasoline (only VAT)		-0.00584* (0.00331)	-0.00357* (0.00204)	Raw price of Diesel (only VAT)		-0.00384*** (0.000908)	-0.00346*** (0.00104)
Energy + Eco Tax		-0.00798** (0.00375)		Energy + Eco Tax		-0.0111*** (0.00141)	
Energy Tax on Gasoline			-0.00242 (0.00497)	Energy Tax on Diesel			-0.00729** (0.00292)
Eco Tax on Gasoline			-0.0306*** (0.00773)	Eco Tax on Diesel			-0.0143*** (0.00359)
Dummy Eco Tax	-0.154 (0.131)	-0.144 (0.126)	0.104** (0.0393)	Dummy Eco Tax	-0.0205 (0.0564)	0.0574* (0.0315)	0.0794*** (0.0174)
Trend	0.00158 (0.0138)	-0.00328 (0.0118)	0.0240 (0.0210)	Trend	0.0189*** (0.00587)	0.0104** (0.00456)	0.0187** (0.00774)
GDP per capita	0.000174 (0.0116)	0.00893 (0.0168)	-0.0245 (0.0318)	GDP per capita	0.0177*** (0.00528)	0.0287*** (0.00702)	0.0201** (0.00753)
Unemployment rate	0.0292 (0.0176)	0.0311* (0.0177)	0.00902 (0.0239)	Unemployment rate	0.0107* (0.00558)	0.0104* (0.00538)	0.00651 (0.00816)
Observations	38	38	38	Observations	39	39	39

Notes: The dependent variable is the log of fuel consumption in liters per capita, which refers to total fuel consumption or either gasoline or diesel consumption (as indicated by the column heading). Prices are in 1995€. Results for gasoline consumption refer to 1972-2009 due to missing price data prior to 1972. Unemployment is measured as percentage of total labor force. Newey-West standard errors in parentheses are heteroskedasticity and autocorrelation robust. Standard errors are calculated relying on the automatic bandwidth selection procedure following Newey and West (1994). \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

**Table C.2:** Real price elasticities for transport fuels after 1991

(a) Gasoline consumption					(b) Diesel consumption				
	(1) OLS	(2) OLS	(3) OLS	(4) IV: Brent Crude		(1) OLS	(2) OLS	(3) OLS	(4) IV: Brent Crude
Real price of Gasoline	-0.00698*** (0.00142)	-0.00693*** (0.00150)	-0.00510*** (0.000592)	-0.00531*** (0.000640)	Real price of Diesel	-0.00404** (0.00161)	-0.00456*** (0.00112)	-0.00358*** (0.000318)	-0.00317*** (0.000315)
Dummy Eco Tax	0.105** (0.0371)	0.106*** (0.0354)	0.106*** (0.0164)	0.106*** (0.0135)	Dummy Eco Tax	0.0687*** (0.0151)	0.0635*** (0.0167)	0.0634*** (0.0111)	0.0632*** (0.00961)
Trend	-0.0237*** (0.00703)	-0.0217* (0.0111)	-0.0336*** (0.00544)	-0.0332*** (0.00505)	Trend	0.0206*** (0.00596)	0.0108 (0.00670)	0.00457 (0.00264)	0.00384* (0.00227)
GDP per capita		-0.00311 (0.00686)	0.00795 (0.00636)	0.00793 (0.00575)	GDP per capita		0.0172*** (0.00388)	0.0217*** (0.00355)	0.0211*** (0.00235)
Unemployment rate			0.0181*** (0.00309)	0.0178*** (0.00268)	Unemployment rate			0.0104** (0.00388)	0.0113*** (0.00378)
N	19	19	19	19	N	19	19	19	19

Notes: The dependent variable is the log of fuel consumption in liters per capita, which refers to total fuel consumption or either gasoline or diesel consumption (as indicated by the column heading). Columns (4) use the Brent crude oil price as an instrumental variable for the real fuel price. Prices are in 1995€. Unemployment is measured as percentage of total labor force. Newey-West standard errors in parentheses are heteroskedasticity and autocorrelation robust. Standard errors are calculated relying on the automatic bandwidth selection procedure following Newey and West (1994). \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

The p-values of a linear Wald test show that for both regressions, the tax coefficient  $\alpha_2$  is not significantly different from unity.<sup>44</sup> For gasoline,  $\alpha_2$  equals 0.94 (with a 95% confidence interval of [0.79; 1.08]). The result is comparable for diesel, where the coefficient is 0.86 [0.54; 1.17]. We repeat the estimation with the tax rates being formally separated into energy and eco-tax in the model:

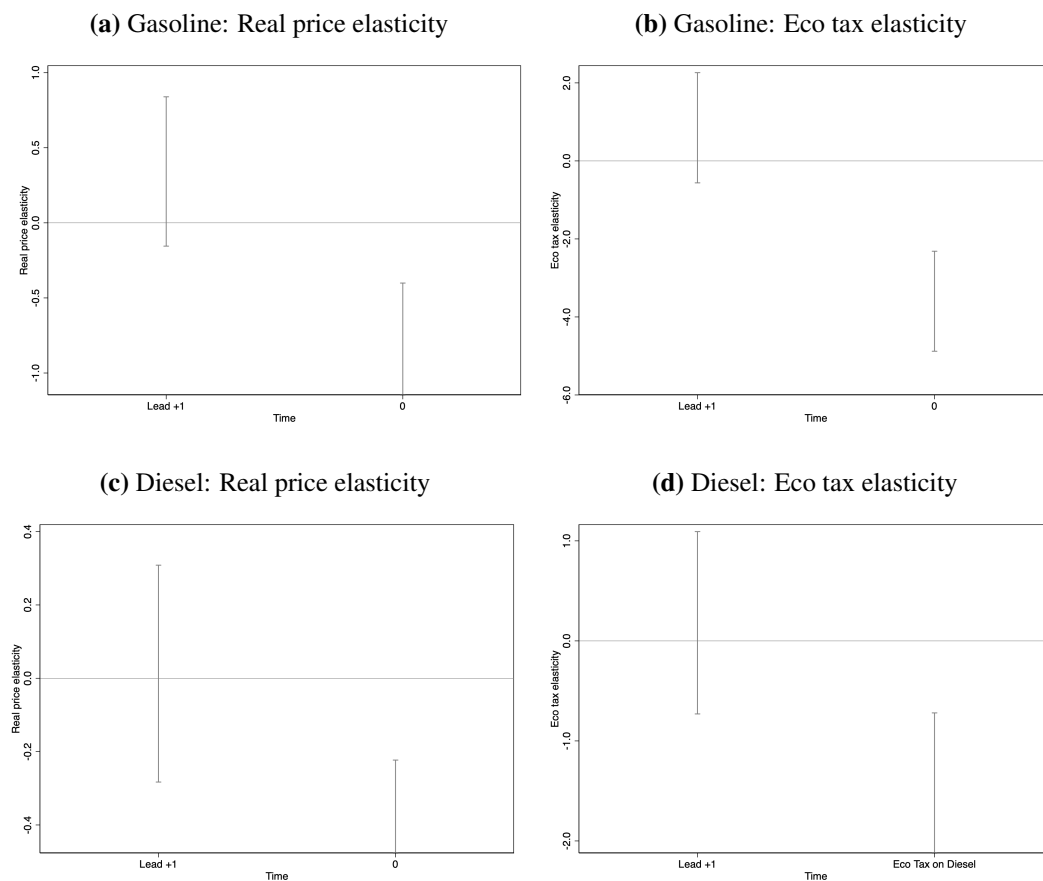
$$\Delta p_t^* = \alpha_0 + \alpha_1 \Delta \sigma_t + \alpha_3 \Delta \tau_t^{\text{energy}, \text{VAT}} + \alpha_4 \Delta \tau_t^{\text{eco}, \text{VAT}} + \varepsilon_t \quad (26)$$

<sup>44</sup>The p-value of the linear Wald test for  $\Delta \alpha_2 = 1$  is equal to 0.38 for gasoline and 0.34 for diesel.

Again, we are not able to reject the hypothesis that there is full pass-through.<sup>45</sup> This indicates that fuel taxes have been noticeable for consumers and that we can interpret our estimates of fuel-specific tax elasticities as price elasticities of demand.

## C.1 Time-series elasticities with a distributed lag model

**Figure C.1:** Fuel-specific real price and eco tax elasticities with a lead

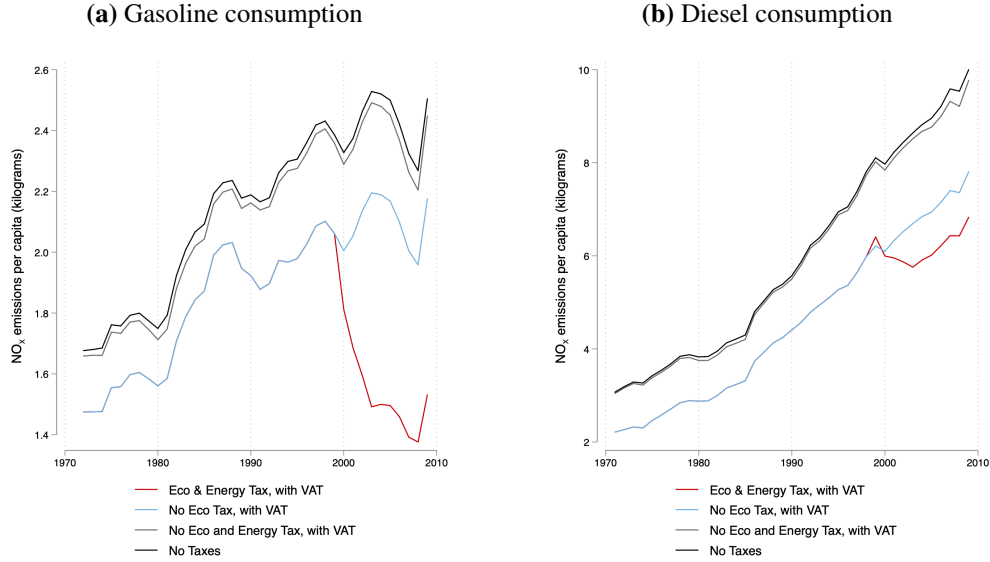


*Notes:* The figure plots the estimated fuel-specific elasticities of gasoline and diesel demand by amending our log-level semi-elasticity models with the introduction of a lead (c.f. Section 3.2). Specifically, Panel (a) and (c) show the real price elasticity of gasoline and diesel demand respectively (c.f. Table 2b and 2a). Panel (b) and (d) display the gasoline and diesel eco tax elasticities (c.f. Table 3b and 3a). Prices are in 1995€. Results for gasoline consumption refer to 1972-2009 due to missing price data prior to 1972. Unemployment is measured as percentage of total labor force. Confidence intervals are based on Newey-West standard errors are heteroskedasticity and autocorrelation robust. Standard errors are calculated relying on the automatic bandwidth selection procedure following Newey and West (1994). \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*

<sup>45</sup>For gasoline,  $\alpha_3$  equals 0.92 [0.75; 1.09] and  $\alpha_4$  1.02 [0.83; 1.20]. While the eco-tax coefficient for diesel is similar at 0.96 [0.49; 1.43], the energy tax one is lower at 0.64 [0.02; 1.25]. The p-values of the linear Wald tests for  $\Delta\alpha_3 = 1$  are 0.34 for gasoline and 0.24 for diesel, and 0.84 and 0.87 for  $\Delta\alpha_4 = 1$ .

## C.2 NO<sub>x</sub> emission under different taxation regimes

**Figure C.2:** Predicted NO<sub>x</sub> emissions by fuel under different tax scenarios



*Notes:* The figures above plot predicted emissions from the eco-tax specification of our log-level semi-elasticity models (c.f. Section 3.2) under different taxation scenarios. We rely the estimated fuel-specific price and tax elasticities computed from our estimates from column (3) in Tables 3a and 3b. Panel (a) refers to predicted emissions from gasoline consumption, while Panel (b) covers diesel consumption. In each panel the y-axis refers to per capita NO<sub>x</sub> in kilograms. The top black line displays predicted emissions when the eco and energy tax elasticities are set to zero, and VAT is deducted from the fuel price. For the gray line, the eco and energy tax elasticities are set to zero but VAT is included. The light blue line shows how predicted emissions change when the eco tax is set to zero, but we include the energy tax and VAT. The red line provides predicted emissions using the full model.

## C.3 Fuel substitution due to the eco-tax

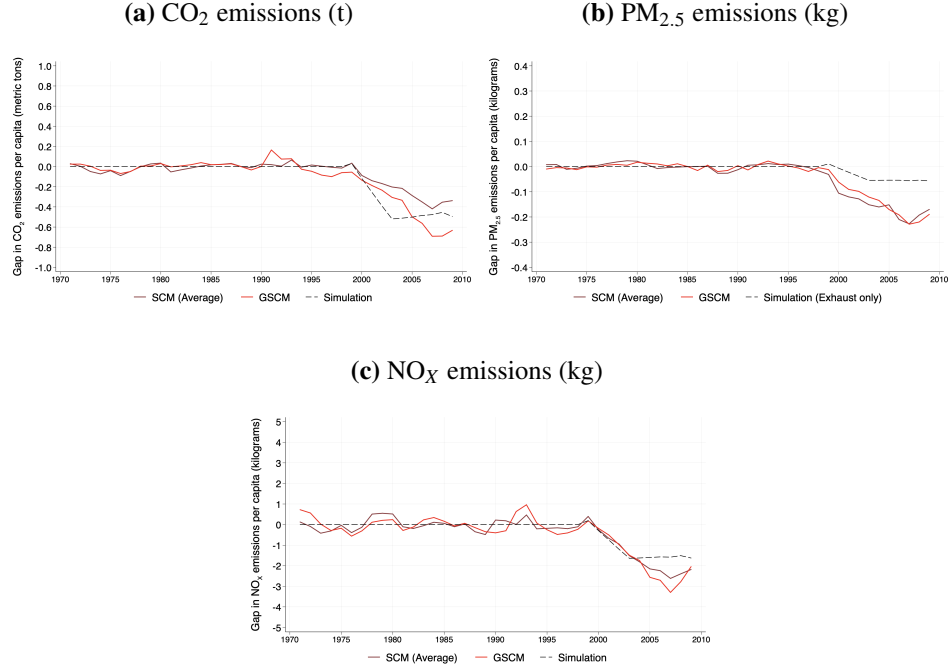
**Table C.3:** Fuel substitution

(a) Diesel-to-Gasoline ratio				(b) Share of Diesel			
	(1)	(2)	(3)		(1)	(2)	(3)
	Diesel/Gasoline	Diesel/Gasoline	Diesel/Gasoline		Share of Diesel	Share of Diesel	Share of Diesel
Raw price of Gasoline (only VAT)	0.00187 (0.00241)	0.00185 (0.00124)	0.00184 (0.00126)	Raw price of Gasoline (only VAT)	0.000255 (0.000565)	0.000250 (0.000314)	0.000248 (0.000317)
Energy Tax on Gasoline	0.00471*** (0.00123)	-0.000316 (0.00263)	0.000991 (0.00237)	Energy Tax on Gasoline	0.00179*** (0.000396)	0.000697 (0.000658)	0.000917 (0.000721)
Eco Tax on Gasoline	0.0175*** (0.00634)	0.0157*** (0.00465)	0.0126** (0.00482)	Eco Tax on Gasoline	0.00415*** (0.00144)	0.00376*** (0.00110)	0.00325*** (0.00108)
Dummy Eco Tax	-0.0108 (0.0276)	-0.0619** (0.0296)	-0.0377 (0.0242)	Dummy Eco Tax	0.00367 (0.00645)	-0.00746 (0.00747)	-0.00339 (0.00630)
Trend	0.0126*** (0.00306)	-0.00700 (0.00700)	0.00671 (0.0152)	Trend	0.00482*** (0.000731)	0.000554 (0.00168)	0.00286 (0.00378)
GDP per capita		0.0372** (0.0149)	0.0214 (0.0187)	GDP per capita		0.00810** (0.00352)	0.00546 (0.00491)
Unemployment rate			-0.0142	Unemployment rate			-0.00239 (0.00420)
Observations	38	38	38	Observations	38	38	38

*Notes:* The dependent variable is either (a) the ratio of diesel-to-gasoline consumption in litres per capita or (b) the share of diesel of total fuel consumption in percentage terms (as indicated by the column heading). Prices are in 1995€. Results for gasoline consumption refer to 1972-2009 due to missing price data prior to 1972. Unemployment is measured as percentage of total labor force. Newey-West standard errors in parentheses are heteroskedasticity and autocorrelation robust. Standard errors are calculated relying on the automatic bandwidth selection procedure following Newey and West (1994). \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

## C.4 SCMs and the Simulation Approach

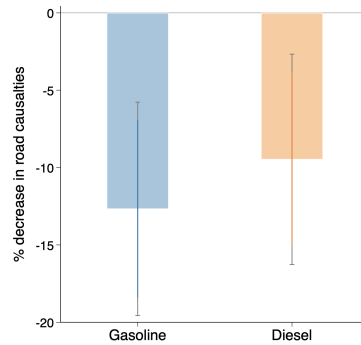
**Figure C.3:** Gap in per capita emissions: SCMs vs Simulation Approach



*Notes:* The figures above plot the estimated average gap in per capita emissions from our synthetic control experiments (c.f. Section B.1) and the simulation approach based on our log-level semi-elasticity models (c.f. Section 3.2). Nationwide reductions in emissions in the simulation approach have been computed by accounting for predicted emission reductions from both gasoline and diesel. Note that simulated PM<sub>2.5</sub> emissions are not directly comparable to our SCMs results as the former do not account for non-exhaust emissions.

## C.5 Impacts of the eco-tax on road casualties

**Figure C.4:** Effects of the eco-tax on road casualties



*Notes:* The dependent variable is the number of road casualties (i.e., including fatalities and injuries) in logarithmic terms. The estimated effects refer to the average eco-tax rate of 13 cents. All regressions control for the fuel raw price, the energy tax rate, GDP per capita (in 1995€), the unemployment rate, and include a time trend as well as a dummy for the post-treatment period (i.e., equal to 1 after 1999). We use Newey-West standard errors that are heteroskedasticity and autocorrelation robust following [Newey and West \(1994\)](#).

## Appendix D Staggered adoption setting

This section provides additional information on the staggered synthetic difference-in-differences approach from Section 5.1. To isolate the impact of fuel taxation, we identify other European countries where environmental taxes were implemented without reinvesting their revenue into climate mitigation programs, namely Finland in 1990 and Sweden in 1991 (Sumner et al., 2011).

**Table D.1:** Average effects of environmental taxes with staggered adoption

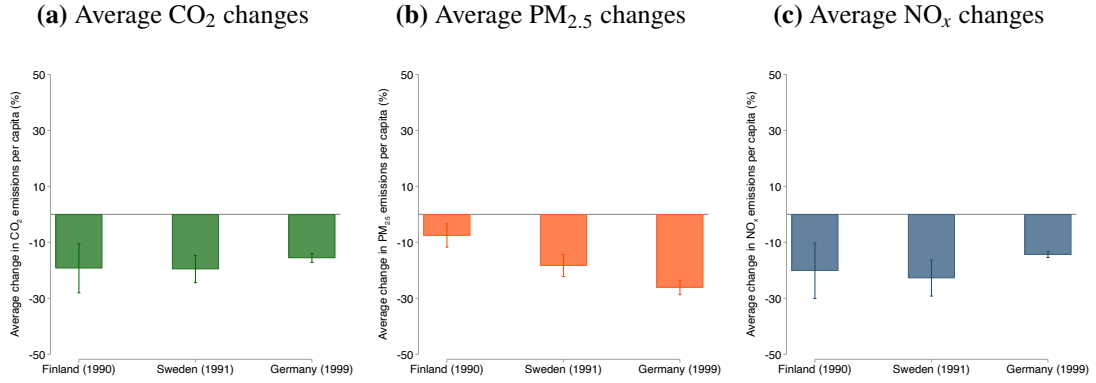
	CO <sub>2</sub> emissions (t)	PM <sub>2.5</sub> emissions (kg)	NO <sub>x</sub> emissions (kg)
Mean estimate ( $\hat{\tau}^{\text{sdid}}$ from Eq. 6)	-0.385	-0.164	-2.943
Standard error ( $\sqrt{\widehat{V}_{\tau}}$ from Eq. 4)	(0.019)	(0.008)	(0.149)
Observations	45440	45440	45440
Countries	EU-27	EU-27	EU-27

*Notes:* All outcome variables are expressed in per capita terms and the unit of measurement is indicated in the column heading. The table displays the estimated average effects of the eco-tax on CO<sub>2</sub>, PM<sub>2.5</sub>, and NO<sub>x</sub> emissions leveraging the SDID estimation procedure introduced in Section 3.1.

Overall, the average estimates for emission reductions presented here are comparable in magnitude to our baseline specification (cf. Table 1) based on Germany only. In Figure D.1, we further report average effects in percentage terms (scaled by baseline emissions) by country to compare the relative magnitude of emission reductions. We observe greater average reductions in CO<sub>2</sub> and NO<sub>x</sub> emissions for Sweden and Finland, but lower decreases in PM<sub>2.5</sub>. Several factors are expected to contribute to the estimated heterogeneity across countries. First, while Sweden had a higher tax rate, which we would expect to reasonably translate into larger effects, the magnitude of the effects for Finland—despite its lower tax rate—may be, partly, explained by two factors: (i) a period of economic recession during the 1990s which had deep and persistent repercussions on the Finnish economy and labor market, plausibly affecting fuel demand (cf. Mideksa, 2024) and (ii) a concurrent nationwide tax relief scheme on the registration of cars with catalytic converters which might have contributed to shape and accelerate the fleet renewal rate towards more efficient and less-polluting vehicles (Ministry of the Environment, 1995). By contrast, Germany and Sweden did not levy registration taxes on new vehicles (aside from VAT) but imposed considerably higher and more comparable fuel taxes (ACEA, 2022). Second, since PM emissions primarily stem from diesel, variations in the composition of the vehicle fleet (e.g., a larger base of diesel use) could explain the heterogeneous reductions observed in PM<sub>2.5</sub> emissions. At the time when the eco-tax had been fully phased in, approximately 40% of new car registrations in Germany were diesel vehicles. By contrast, Sweden and Finland exhibited considerably lower percentages, at around 1% and 5% respectively, when they introduced a carbon tax in the transport sector. These differences shed light on the underlying mechanisms behind the differences in emission reductions.

Finally, Table D.2 presents an alternative specification of our staggered approach at the country level. The results remain qualitatively similar to our baseline findings in Table D and the innovation results described in Section 7 of the paper (cf. Figure 7).

**Figure D.1:** Percentage changes relative to baseline in each country



Notes: Panels (a) - (c) plot percentage changes which were calculated as the ratio of country-specific mean estimates ( $\hat{\tau}_a^{sdid}$  from Eq. 6) to baseline emissions in each country in the year before the implementation of the environmental fuel tax.

**Table D.2:** Effects of environmental taxes (SDID with staggered adoption)

	CO <sub>2</sub> emissions (t)	PM <sub>2.5</sub> emissions (kg)	NO <sub>x</sub> emissions (kg)	Low-carbon patents
Environmental fuel taxation	-0.245*** (0.057)	-0.099** (0.039)	-2.771** (1.104)	0.643*** (0.246)
Observations	858	858	858	550
Countries	22	22	22	22

Notes: All outcome variables are expressed in per capita terms. Patents are expressed in per million population terms. Standard errors are computed using the bootstrap variance estimation algorithm outlined in Arkhangelsky et al. (2021), which requires multiple treated units. All regressions control for GDP per capita and include unit-specific and time-specific fixed effects as well as a binary variable indicating whether a country was regulated by EU-wide regulations after 2005. Emissions reductions are estimated by additionally controlling for pre-treatment diesel and gasoline consumption. For low-carbon innovation, we control for pre-treatment triadic patents per capita.

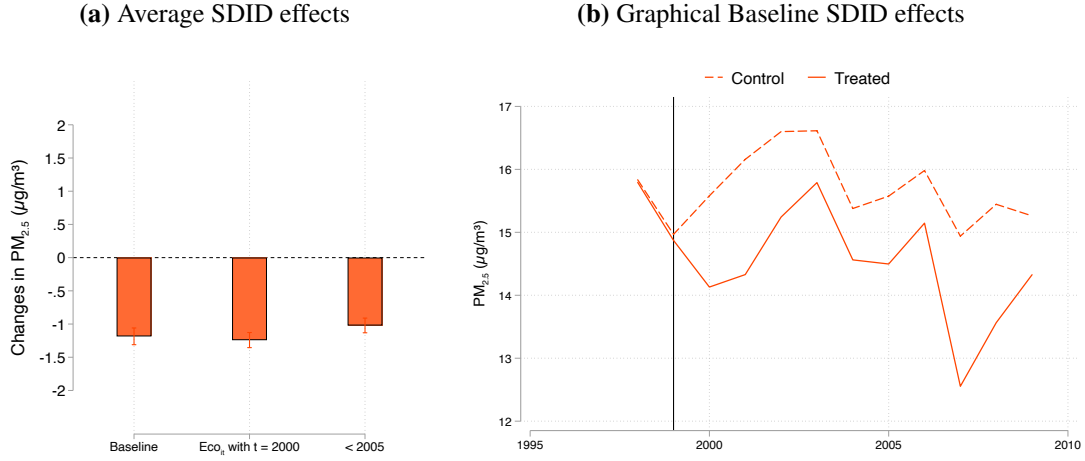
## Appendix E Results with PM concentration data

As discussed in Section 4, we validate our main findings on air pollution using an alternative dataset from Shen et al. (2024). This dataset provides annual estimates of PM<sub>2.5</sub> concentrations at a 0.1°×0.1° resolution, constructed via a deep learning algorithm combining satellite imagery, ground-based monitoring, and chemical transport models. We aggregate these data to the NUTS-3 level to construct a balanced panel covering the period 1998–2022, and compute yearly mean concentrations of PM<sub>2.5</sub> for each region.

Compared to the EDGAR dataset used in the main analysis, this alternative source differs in three important ways. First, it provides information only on PM<sub>2.5</sub>, whereas EDGAR includes a wider range of pollutants. Second, it does not allow for source-specific decomposition of emissions, so we cannot isolate pollution from the transport sector-potentially introducing measurement error if other sources were simultaneously affected by the eco-tax reform. Third, the dataset starts in 1998, providing a shorter pre-treatment window-particularly relevant since the eco-tax was implemented in April 1999. To partially address this, we treat 2000 as the first post-treatment year in a complementary specification, thereby gaining at least one pre-treatment observation.

Despite these limitations, the key advantage of the Shen et al. data is that it captures ambient concentration levels rather than emissions in absolute terms. This allows us to assess whether our main findings hold when using a different pollution metric and to

**Figure E.1: Average SDID effects on PM<sub>2.5</sub> concentration**



Notes: Panel (a) plots the mean estimates ( $\hat{\tau}^{sdid}$ ) of the SDID specifications described above. Panel (b) plots average trends in air emissions over time for German districts and the relevant weighted average of control European NUTS-3 regions in the Baseline (see text above for more details).

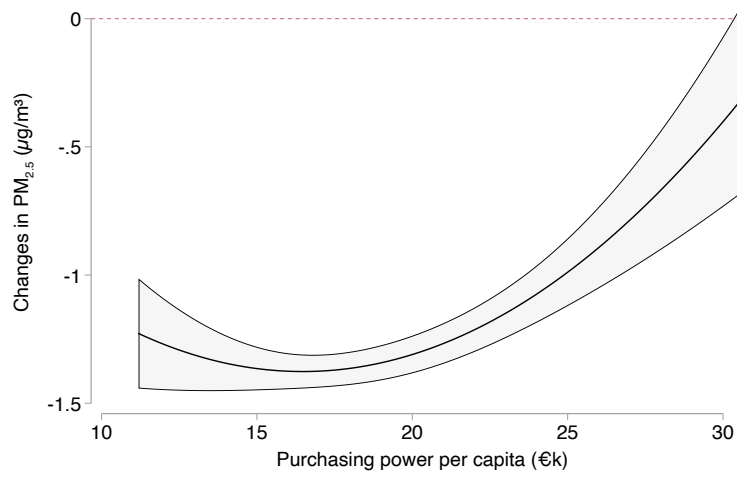
test the robustness of the pro-poor pattern in pollution reductions discussed in Section 8.

Panel (a) of Figure E.1 summarizes our main SDID results on the effects of the eco-tax on PM<sub>2.5</sub> concentrations, while Panel (b) provides a graphical representation of each specification. We present evidence from three different model setups. First, a baseline specification simply compares German Kreise to other European NUTS-3 regions. Second, we adopt an alternative timing assumption by shifting the first post-treatment period to 2000 (following the notation from Equation 1), which allows us to gain an additional pre-treatment observation. Third, we restrict the sample to the period up to 2005. This restriction is motivated by the introduction of the EU Emissions Trading System (EU ETS) in 2005, which-although it did not directly regulate the transport sector-could act as a potential confounder when using economy-wide pollution concentration data. This concern does not apply to our main analyses based on the EDGAR dataset, which allows for sector-specific emissions (see Section 4).

Across all three specifications, we find a significant reduction in PM<sub>2.5</sub> concentrations of approximately 1 microgram per cubic meter. For context, this effect size exceeds that of the British Columbia carbon tax, which was associated with a reduction of 0.62 g/m<sup>3</sup> in PM<sub>2.5</sub> concentrations (cf. Sileci 2023). This reinforces the conclusion that the German eco-tax had substantial co-benefits in terms of air quality improvements.

We next examine the relationship between pollution concentration reductions and income levels across districts. To proxy income, we use high-resolution spatial data on purchasing power (total disposable income after taxes and transfers) from the RWI-GEO-GRID dataset (Breidenbach and Eilers, 2018; RWI microm, 2020) for the year 2005, which we aggregate to the district level. Following the approach outlined in Section 8, we combine this income measure with estimated reductions in PM<sub>2.5</sub> concentrations and fit a non-linear (quadratic) model. The results presented in Figure E.2 confirm that-even when using a different dataset-reductions in pollution are larger in lower-income districts, indicating that the poorer areas experienced the greatest air quality improvements.

**Figure E.2:** PM<sub>2.5</sub> concentration changes along income



Notes: The figure above plots the reductions PM<sub>2.5</sub> concentrations along purchasing power and overlays a quadratic fit. For more details on this approach see Section 8.

## Appendix F A newspaper-based proxy for salience

This section provides additional information on the salience analysis conducted in Section 7, and it is structured in two parts. First, we report the different search strategies that were used to extract frequency counts of newspapers' articles from Factiva. Second, we provide a detailed description of the construction of our newspaper-based index.

### F.1 Search strategies

Here below, we report the two different search strategies that were developed to download articles' count used in the construction of our indices. A brief description of each strategy will follow. *Strategy #1* extracts all articles published in a given newspaper within a specific year to provide an overview of publishing trends. *Strategy #2* restricts our search to articles talking about environmental/ecological taxation. The goal is to identify publishing trends directly related to environmental taxation, which will be used to proxy salience in the public debate on this topic.

**Strategy #1: Publishing trends.** Total number of articles published in a given newspaper. To do this, we use the word *und* – the German word for *and* – assuming that it appears in virtually every published text.

**Strategy #2: Environmental taxation trends.** (Ökosteuer\* or "Ökologische Steuerreform" or Umweltsteuer\* or "Ökologische Finanzreform" or Umweltabgabe\*)

### F.2 Using information in newspaper articles as an indicator of salience

For each newspaper, we separately downloaded the annual count of articles that are picked up by our search strategies. To account for publishing trends specific to the topic of environmental taxation, we begin by computing a simple newspaper-specific ratio of articles matching Strategy #2 over the frequency counts from Strategy #1. A

challenge with these raw article ratios is that the number of articles varies a lot across newspapers and time, making it difficult to simply average the ratios across several newspapers. We, therefore, apply the standardization approach of [Baker et al. \(2016\)](#) to obtain our salience index.

We begin with the simple ratio of articles matching Strategy #2 divided by the total article counts for Strategy #1 for each newspaper, and then divide this ratio by the newspaper-specific standard deviation across all years. This creates a newspaper-specific time series with a unit standard deviation across the entire time interval, which ensures that the volatility of the index is not driven by the higher volatility of a particular newspaper. We then average these standardized series across all newspapers within each year. Lastly, we normalize the yearly series to a mean of 100 over the entire time interval to develop our main salience index. This procedure allows us to explicitly capture variation over time in the salience of the topic of environmental taxation while accounting for newspaper-specific overall publishing trends.

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