De-fueling externalities

Causal effects of fuel taxation and mediating mechanisms for reducing climate and pollution costs

Piero Basaglia[1] Sophie M. Behr[2] Moritz A. Drupp[1,3]

[1]Universität Hamburg, Hamburg, Germany
[2]DIW Berlin, Climate Policy Department, Germany
[3]CESifo Munich, Germany

University of Leipzig (March 05)

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Motivation

- Fuel taxation is a key public policy instrument to reduce externalities
  - Climate change, air pollution, energy security, etc...
- Effects of fuel taxation are not yet well understood
  - Reviews show limited aggregate effects of carbon taxes on emissions of around 0% to 2% per year (Green, 2021, *ERL*)
  - Recent quasi-experimental studies suggests more sizable effects (e.g., Andersson 2019, *AEJ*, Colmer et al. 2024, *REStud*)
  - Recent work highlights the role of tax salience, implying stronger reactions to tax-induced price increases (Li et al., 2014, *AEJ*)
  - Yet, many assessments assume that demand responses to tax changes are equivalent to those of market-driven price variations

⇒ **This paper** provides a quasi-experimental evaluation of how the world's largest environmental tax reform has reduced externalities and investigates key mechanisms

The Ecological Tax Reform in Germany

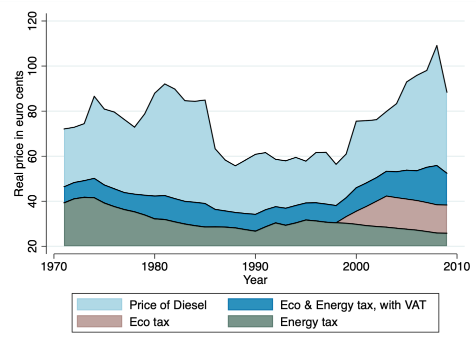
- Raised taxes on petrol, diesel, natural gas and heating oil and introducing a new duty on electricity; Used revenue to cut non-wage labor costs by reducing public pension contributions.
- Extensive sector-level exemptions (Knigge and Görlach, 2005)

  → We focus on the transport sector, as it was fully covered by the increase
- Fuel taxes were increased in yearly steps from 1999 to 2003 by 15.35 cents overall per liter on gasoline and diesel
  - An increase of EUR 58 for diesel and EUR 66 for gasoline per tCO2
  - Implicit carbon costs in 2003 were the second highest globally
- After 2003: planned eco tax rate increases were discontinued

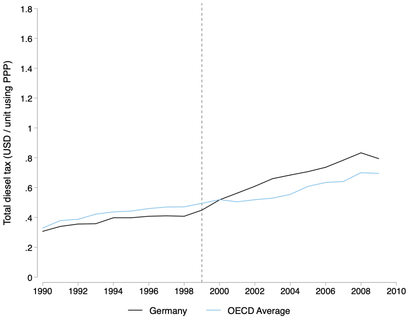
The Ecological Tax Reform in Germany: e.g., Diesel

Figure 1: Diesel price in Germany and the OECD

(a) Eco-tax



(b) Fuel price



Notes: Cross-country prices are in USD using PPP.
Source: IEA Energy Prices and Taxes Statistics.

Was the Ecological Tax Reform in Germany a Policy Flop?

WirtschaftsWoche

DIW BERLIN

Forscher: Ökosteuer-Reform war umweltpolitisch ein Flop

27. März 2019

This paper

- **Key questions**
  1. What are the climate benefits of the eco tax?
  2. What are the health co-benefits, and how are they distributed?
  3. What are the underlying mechanisms mediating the effectiveness of fuel pricing in reducing climate *and* pollution costs?

- **Primary outcomes**
  - Emissions of (i) CO_2, (ii) $PM_{2.5}$, and (iii) NO_X in the transport sector

- **Empirical strategies**
  (1) Quasi-experimental methods: SCM and SDID estimators
  (2) Fuel-specific elasticity models to disentangle behavioural responses

- **Main findings**
  - Large reductions in external damages. $\approx 3/4$ are health benefits
  - Fuel demand responds more to fuel taxes than market price changes
  - Tax salience and fuel substitution are key mediators

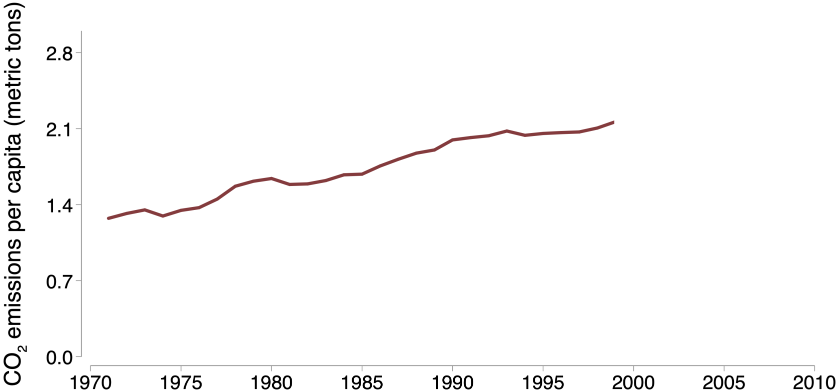
Outline

1. **Causal analysis**
   - Methodology
   - Aggregate results
   - Spatial results
2. **Non-causal supporting analyses**
3. **Summary**

Methodology

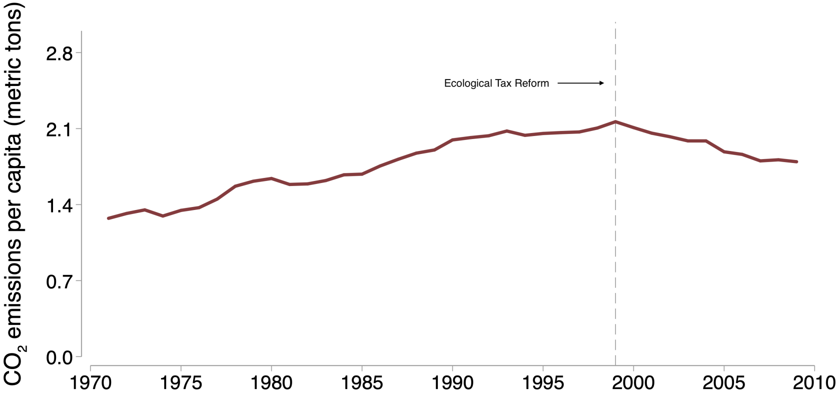
Empirical challenge: Absence of a counterfactual

Figure 2: Evolution of CO_2 emissions from the transport sector in Germany



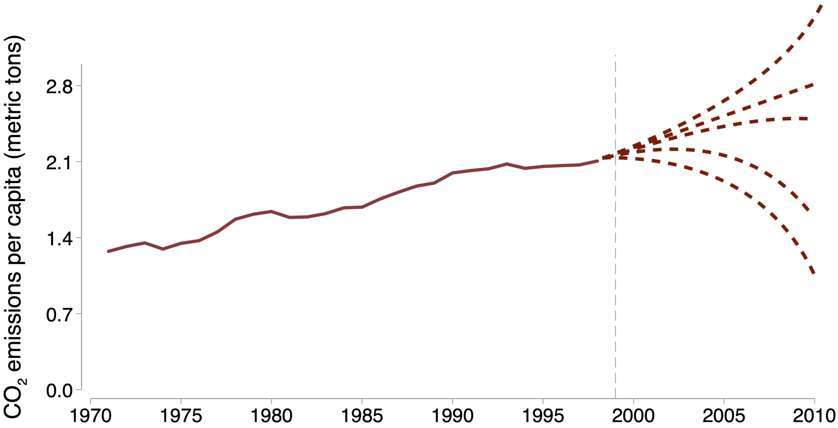
Empirical challenge: Absence of a counterfactual

Figure 3: Evolution of CO_2 emissions from the transport sector in Germany



Potential counterfactual scenarios **with no eco tax**

Figure 4: Counterfactual scenarios: CO_2 emissions from the transport sector in Germany



Quasi-experimental methods

- Aim. Construct a counterfactual for treated units, x, based on comparable untreated units, y (i.e., OECD countries w/o environmental taxes)
  - Intuition. Weighting control units based on their ability to align the (weighted) control group with the treatment group before the intervention
- Potential identification threat. Diverging pre-treatment trends in the outcome
  - A strong pre-treatment match facilitates the assumption that treated and control units would have trended similarly in absence of treatment

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1. Synthetic Control Method (SCM) (Abadie 2021 *JEL*):
   Construct counterfactual *synthetic German transport sector* from similar (OECD) donor countries using weights based on selection of covariates, including pre-treatment outcome lags (as used in Andersson 2019 *AEJ*)

SCM: Selecting predictors

Discretion in specifying the SCM may lead to *"cherry picking"* predictors to influence the result (e.g., Ferman et al., 2020). No consensus on this.

Table 1: Overview of the specification choices for the SCMs

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

Notes: The Table summarizes the different SCM specifications we consider. *Specification* denotes the name that we use for SCM specification henceforth. *Lagged outcome variable* specifies the number and the years of the pre-treatment outcome lags. All except *No Covariates* include as predictors (i) GDP per capita (PPP, in million 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.

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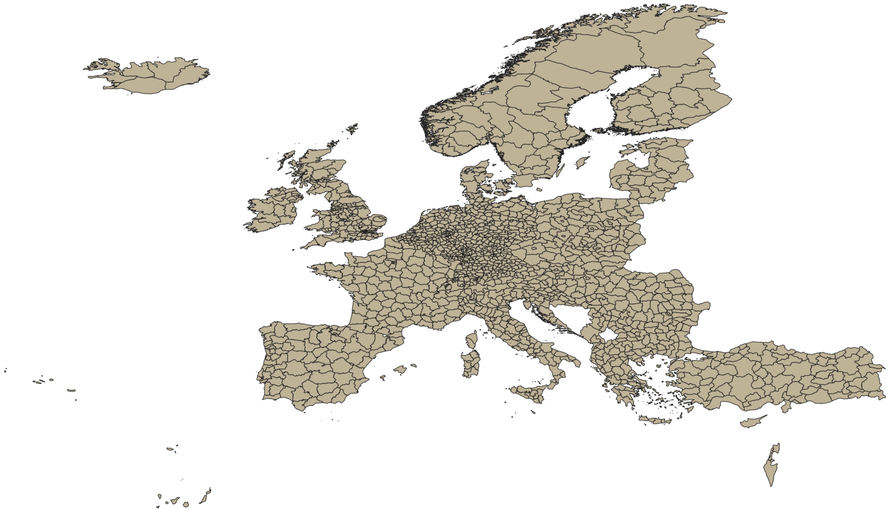
   Construct counterfactual *synthetic German transport sector* from similar (OECD) donor countries using weights based on selection of covariates, including pre-treatment outcome lags (as used in Andersson 2019 *AEJ*)
2. Synthetic Difference-in-Differences (SDID) (Arkhangelsky et al. 2021 *AER*):
   Combines SCM with traditional DID, includes both unit *and* time weights to allow for more closely matched pre-trends, has built-in inference and can easily leverage regional data (NUTS3 in Europe) to construct more robust controls

Emissions from transport sector in small regions (EDGAR)

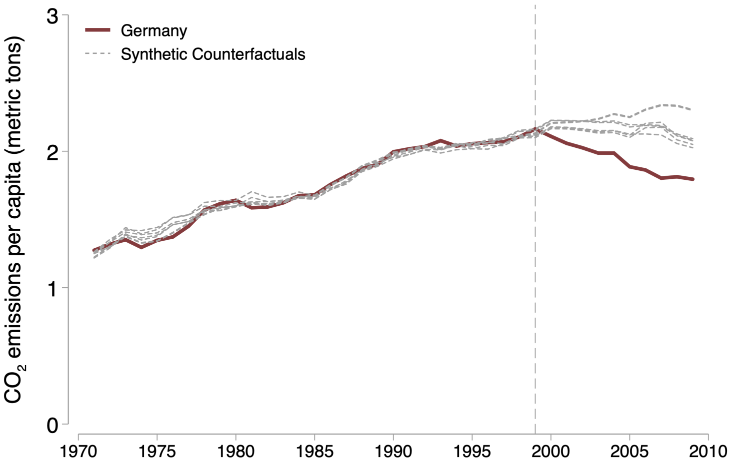
Figure 5: Small regions (NUTS3) in Europe



Aggregate results

SCM results on CO_2 emissions

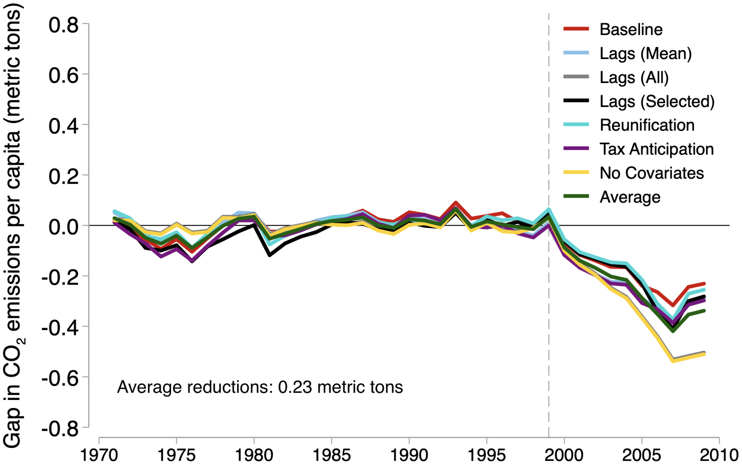
Figure 6: Germany vs. Synthetic Germany (transport sector): CO_2



SCM results on CO_2 emissions

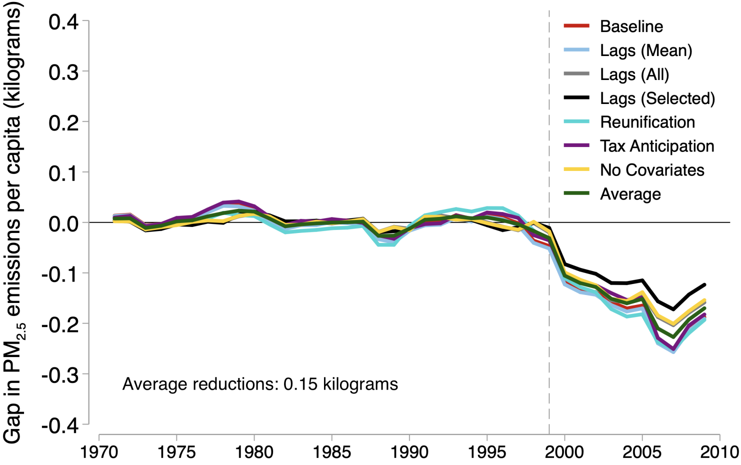
Inference After 1991

Figure 7: Change in CO_2 emissions over time



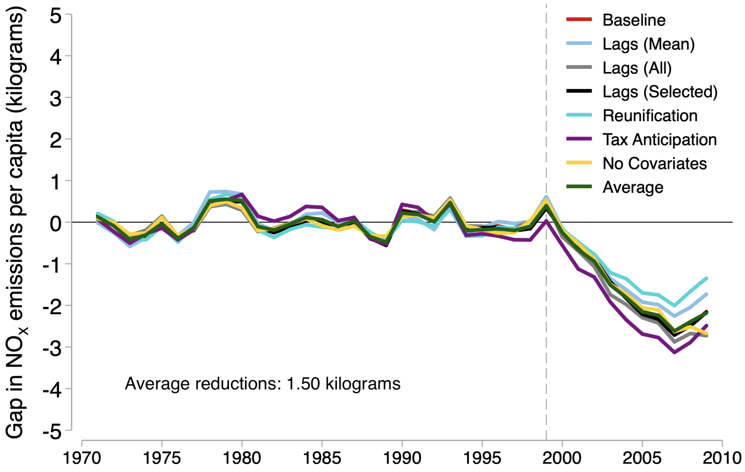
SCM results on $PM_{2.5}$ emissions Inference

Figure 8: Change in $PM_{2.5}$ emissions over time



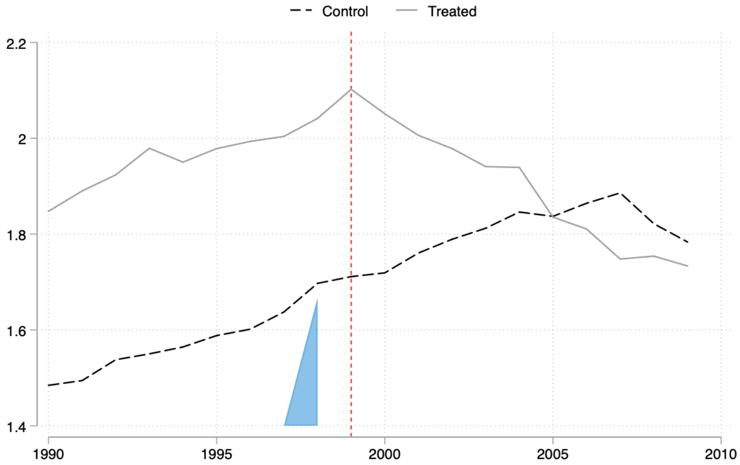
SCM results on NO_X emissions Inference

Figure 9: Change in NO_X emissions over time



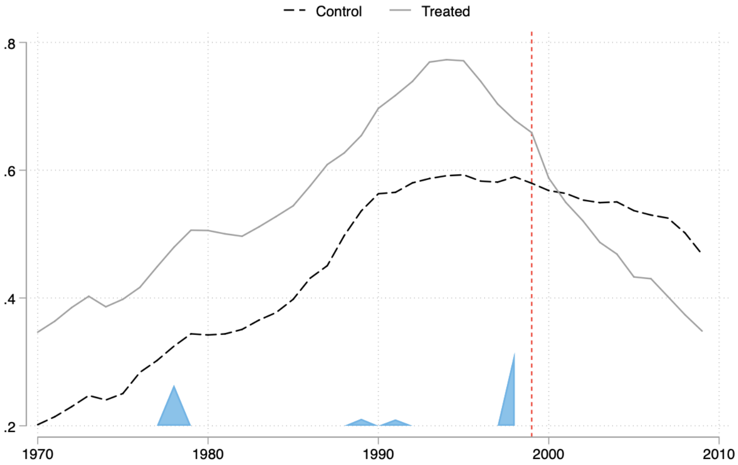
SDID example for CO_2 emissions

Figure 10: SDID trends and weights on CO_2 emissions



SDID example for $PM_{2.5}$ emissions

Figure 11: SDID trends and weights on $PM_{2.5}$ emissions

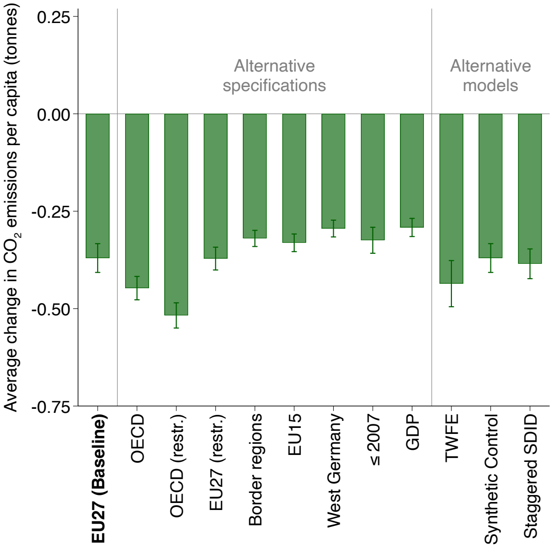


SDID: Results

	Carbon dioxide (tonnes)	Fine particulate matter (kg)	Nitrogen oxides (kg)
SCM	-0.23 t/capita	-0.15 kg/capita	-1.50 kg/capita
N	760	760	760
SDID	-0.30***	-0.16***	-2.57***
95-CI	-0.26 to -0.35	-0.15 to -0.17	-2.22 to -2.88
N	4760	75520	75520

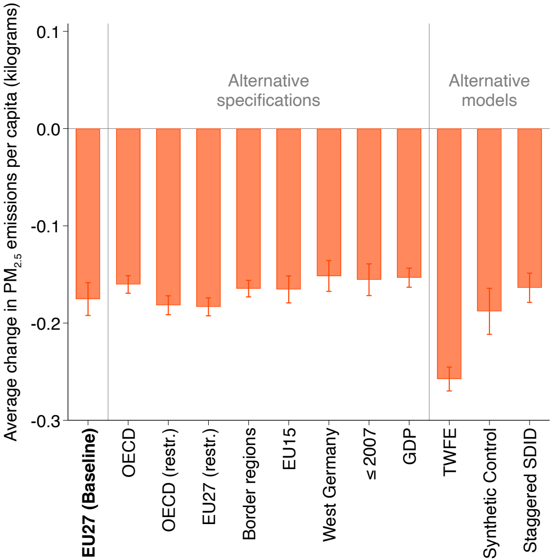
SDID: Results across specifications

Figure 12: SDID trends and weights on CO_2 emissions



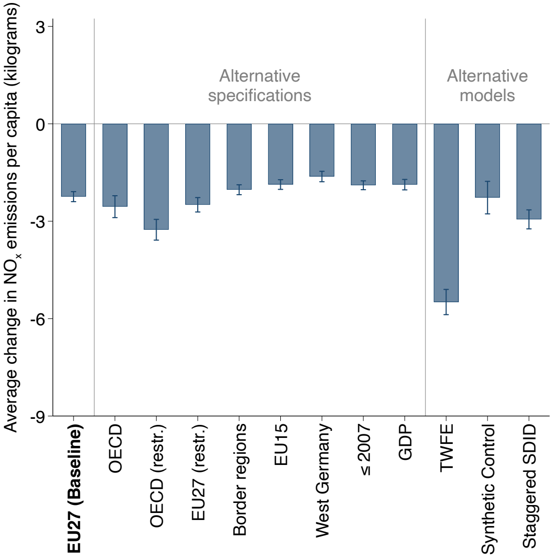
SDID: Results across specifications

Figure 13: SDID trends and weights on $PM_{2.5}$ emissions



SDID: Results across specifications

Figure 14: SDID trends and weights on NO_X emissions



Quantification of externality reductions

We use official, pollutant-specific average cost estimates from the German Umweltbundesamt (UBA, 2012) to quantify the reductions in climate and pollution externalities (1999-2009).

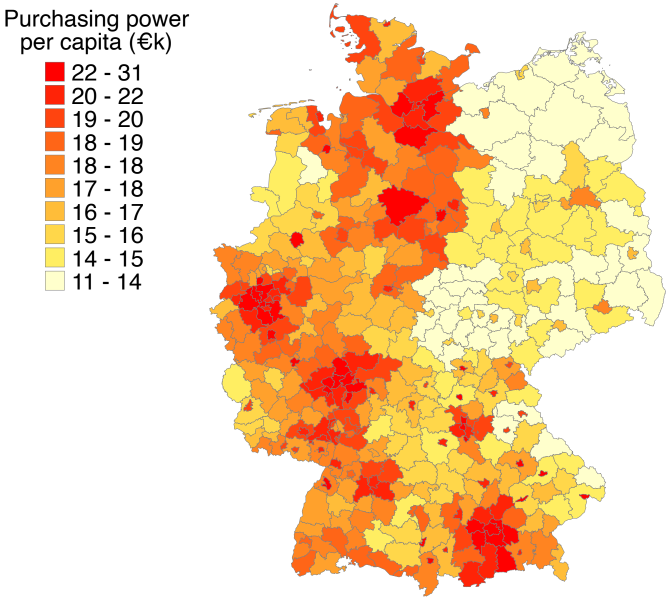
	average SCM	average SDID
Carbon costs	20.3	26.8
Pollution costs ($PM_{2.5}$ and NO_X)	60.6	78.8
Aggregate (bn EUR)	80.9	105.6

$\Rightarrow$ Reductions in health costs account for $\approx$3/4 of reduced damages

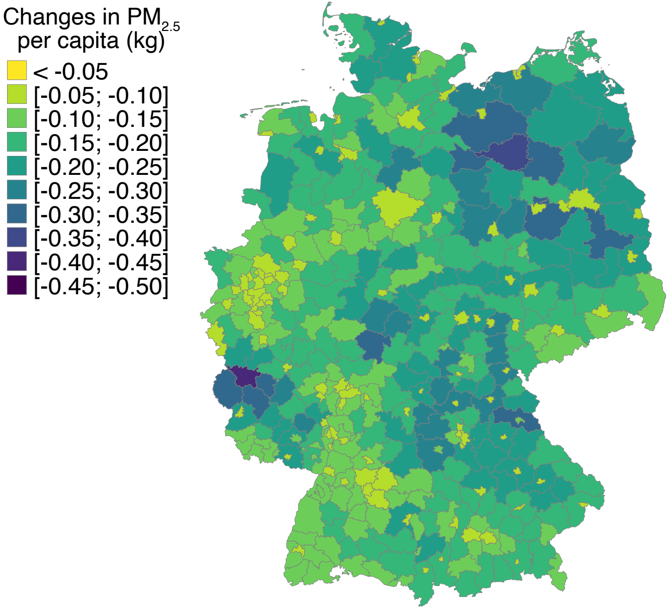
Spatial results

Who benefits from pollution reduction co-benefits?

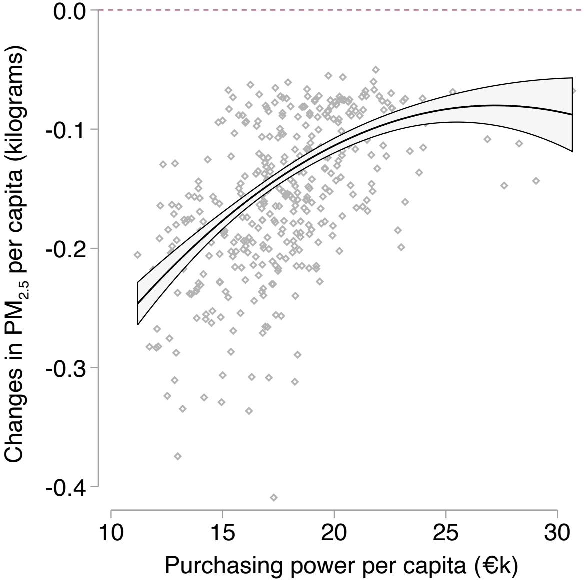
Purchasing power per capita in 2005 (based on RWI data)



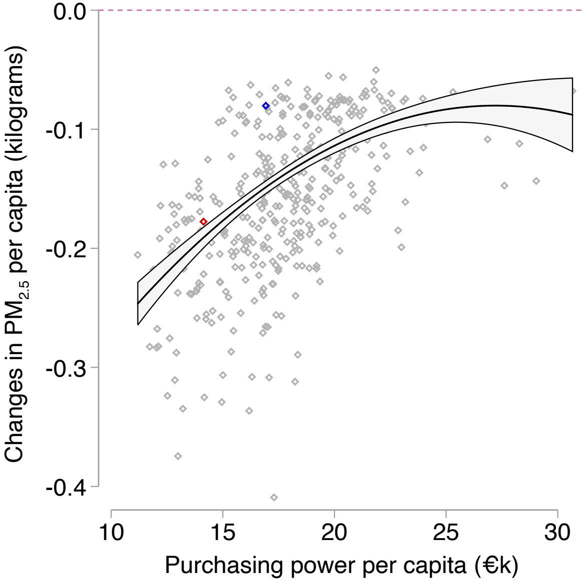
Local air pollution changes due to the eco-tax



Air pollution changes and purchasing power



Air pollution changes and purchasing power: Leipzig(s)



Supporting (non-causal) analyses of mechanisms

Underlying mechanisms Leads Real price elasticity Tax elasticity Simulated gaps

- We extend Li et al. (2014) and Andersson (2019) and estimate the following cross-country semi-elasticity models for both gasoline and diesel demand
- We additionally validate our *Real price elasticities* with an IV approach exploiting variation in the (brent) crude oil price

$$log(y_{it}) = \beta_0 + \varphi_1 p_{it}^{real} + \lambda' X_{it} + D_t^{eco} \times \phi_i + \epsilon_{it}$$

Real price elasticity

$$log(y_{it}) = \beta_0 + \varphi_2 p_{it}^{excl} + \varphi_3 p_{it}^{eco} + \varphi_4 p_{it}^{energy} + \lambda' X_{it} + D_t^{eco} \times \phi_i + \epsilon_{it}$$

Eco tax elasticity

- y_{it}^{p}: fuel (gasoline or diesel) consumption per capita in t (log terms)
- p_{it}^{real}: real fuel price in t
- p_{it}^{excl}: tax-exclusive real fuel price (including VAT only) in t
- p_{it}^{eco}: real eco tax rate in t
- p_{it}^{energy}: real energy tax rate in t
- D_t^{eco}: dummy variable that equals one after the Eco Tax Reform (in 1999)
- $\lambda' X_t$: vector of controls including time and unit effects
- ϕ_i: country-specific dummies to capture detailed (post-treatment) fixed effects
- ϵ_t: idiosyncratic error term

Eco tax elasticity: Gasoline

Table 2: Gasoline consumption

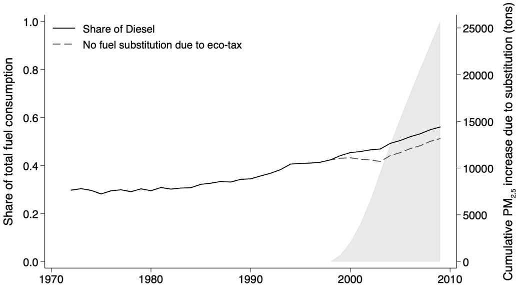
	(1) OLS: Baseline	(2) OLS: Fixed effects	(3) OLS: Fixed effects
Raw price of Gasoline	-0.00357*	-0.00256	-0.00427**
	(0.00179)	(0.00165)	(0.00163)
Energy Tax on Gasoline	-0.00242	-0.00485***	-0.00413***
	(0.00476)	(0.00128)	(0.000569)
Eco-tax on Gasoline	-0.0306***	-0.0296***	-0.0247***
	(0.00700)	(0.00479)	(0.00350)
Raw price = Eco-tax (p-value)	<0.001	<0.001	<0.001
Eco-tax elasticity	2.7	2.7	2.2
Sample	Germany	OECD	EU
Controls	✓	✓	✓
Observations	38	765	509

$\Rightarrow$ Eco-tax elasticity is $\approx$5 times larger than real price elasticity

Fuel substitution as a mediating mechanism Reductions by fuel

- Carbon emission rates per liter of Diesel and Gasoline vehicles are comparable
- But: Diesel vehicles are more fuel efficient (⇒ i.a. fewer CO2 emissions) yet their PM emission rates are much larger (Ntziachristos and Samaras, 2019)

Figure 15: Substitution towards diesel due to the eco-tax

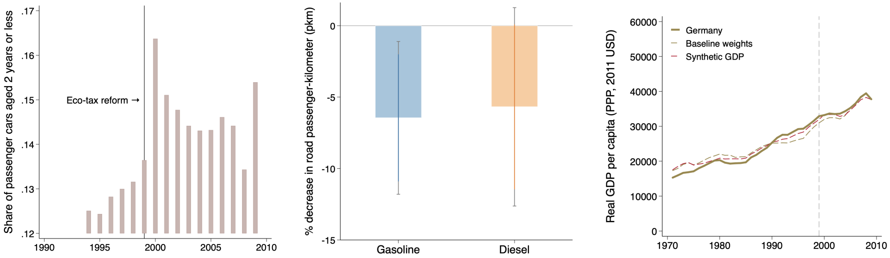


Notes: The figure plots the annual predicted substitution towards diesel from our semi-elasticity models.

Additional underlying mechanisms

Figure 16: Underlying mechanisms of reductions in emissions

(a) Fleet renewal (b) Passenger-kilometers (c) GDP per capita



Notes: Panel (a) plots the share of new passenger cars in the German fleet (aged 2 years or less) using data from the UNECE Statistical Database. Panel (b) plots the estimated percentage reductions in passenger-kilometers (pkm) by fuel for the average eco-tax rate of 13 cents. Data on pkm was retrieved from OECD Statistics. Panel (c) plots the evolution of GDP per capita in Germany and compares it with synthetic counterfactual developments.

Leveraging newspaper data: Tax salience

- Drawing on Baker et al. (2016), we develop a newspaper-based index to track the evolution of the eco tax salience based on textual analysis of German newspapers
- We rely on a set of text-based search strategies that identify around 5,700 unique articles in the Factiva database from *Der Spiegel*, *Die Welt*, *Die Zeit*, and *Focus*

Figure 17: An example of our text-based search strategy

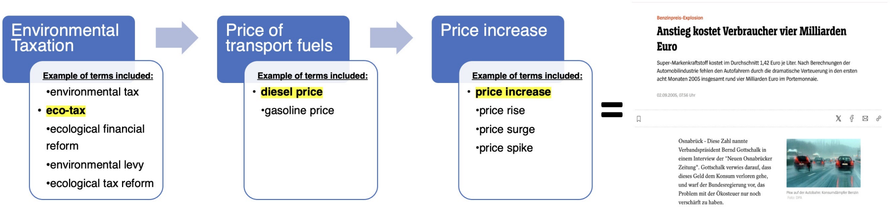


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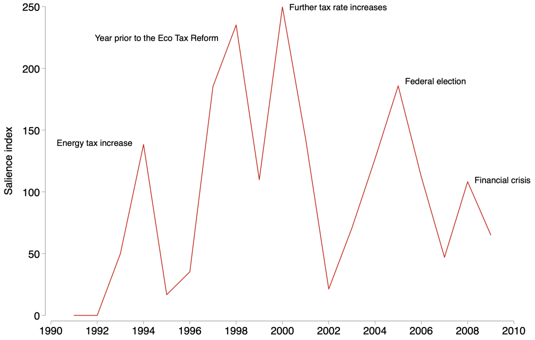
Figure 18: Evolution of the salience index over time



Leveraging newspaper data: Tax salience

Amended elasticity models

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- We rely on a set of text-based search strategies that identify around 5,700 unique articles in the Factiva database from *Der Spiegel*, *Die Welt*, *Die Zeit*, and *Focus*
- **Idea:** Capture the additional effect on fuel demand decrease (at a given tax rate) due to greater salience of the eco-tax induced price increases in the media
- **Approach:** We amend our semi-elasticity models by additionally interacting our (lagged) eco-tax price salience index with the annual real rate of the eco-tax.

Eco tax elasticity and salience: Gasoline

Table 3: Gasoline consumption

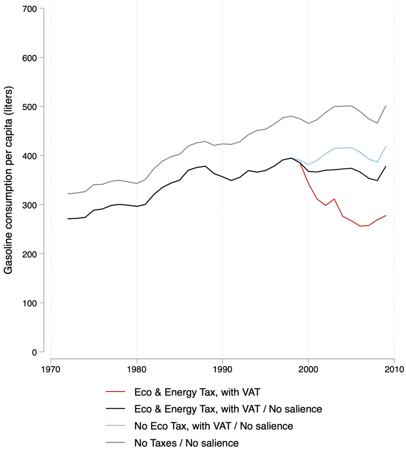
	(1) OLS: Baseline	(2) OLS: Fixed effects	(3) OLS: Fixed effects
Raw price of Gasoline	-0.00280	-0.00262	-0.00257
	(0.00176)	(0.00164)	(0.00164)
Energy Tax	-0.00338	-0.00489***	-0.00488***
	(0.00489)	(0.00128)	(0.00128)
Eco-tax	-0.00773	-0.00683***	-0.00594***
	(0.00557)	(0.00113)	(0.00145)
Eco-tax x Eco-tax price salience (lag)	-0.00441**	-0.00414***	-0.00467***
	(0.00190)	(0.000968)	(0.00101)
Environmental taxation (lag)			-0.0121**
			(0.00559)
Raw price = Eco-tax (p-value)	0.319	0.069	0.189
Non-salient eco-tax elasticity	0.70	0.62	0.54
Sample	Germany	OECD	OECD
Controls	✓	✓	✓
Observations	38	765	765

Predicted fuel consumption under different salience scenarios

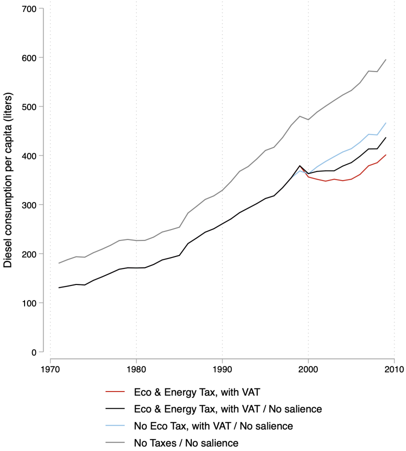
Salience accounts for ≈70% (55%) of reduction in gasoline (diesel) use

Figure 19: Estimated fuel consumption under different taxation and salience scenarios

(a) Gasoline consumption



(b) Diesel consumption



Summary

Summary

- Allocation: Eco-tax has substantially reduced externalities
  - Health benefits account for ≈3/4 of reduced damages
  - The demand response to an environmental tax is much larger than equivalent market-price effects, largely driven by tax salience
    - Simulation studies relying on real price elasticity estimates might severely underestimate the abatement potential of fuel taxation
- Distribution: Health co-benefits make fuel pricing less regressive

⇒ Public policy implications

- Policy has to navigate trade-offs between climate and pollution targets
- Policy communication is important:
  - Communicating health benefits may gather support for fuel pricing
  - Information campaigns to foster fuel/carbon price salience may help to reduce externalities (yet may also increase opposition)

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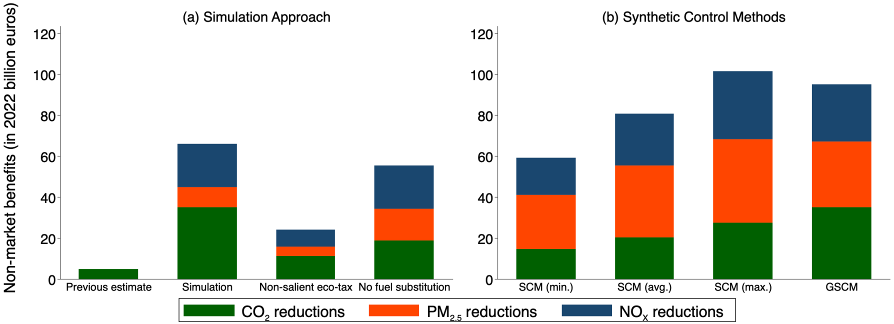
Appendix

Non-market benefits from emission reductions

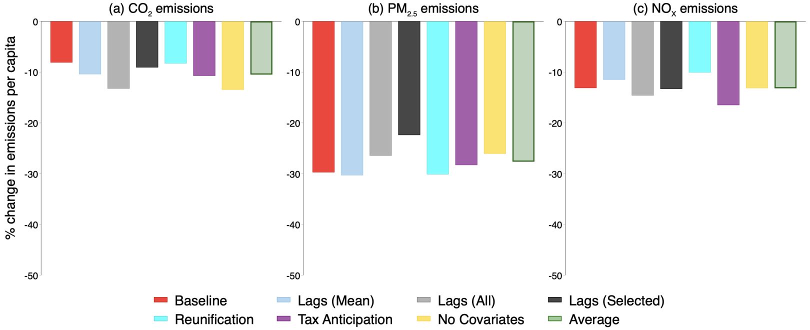
Figure 20: Non-market benefits of the eco tax



Notes: Estimated non-market benefits based on our estimates from (a) the Simulation Approach and (b) the Synthetic Control Method on CO_2, $PM_{2.5}$, and NO_x reductions and compares their magnitudes with the implied benefit estimate from Steiner and Cludius (2010). Aggregate benefits are computed relying on pollutant-specific official cost estimates provided by the Umweltbundesamt (2012) and expressed in 2022 euros. For comparison, SDID yields 91bn.

SCM results: Summary In-time placebos Leave-one-out

Figure 21: Estimated average annual percentage reductions in per capita emissions



Constructing a SCM synthetic counterfactual

- Suppose there are T time periods and $J+1$ countries
  - Each country is indexed by j where $j=1$ denotes Germany
  - T_0 indicates the period prior to the policy shock
- We identify a vector of predictors $\boldsymbol{W}^*$ to minimize the prediction error of pre-treatment values of our outcome variable ($\boldsymbol{Y}_0$)
- Counterfactual emissions, $\boldsymbol{Y}_1^*$, are given by $\boldsymbol{Y}_1^* = \boldsymbol{Y}_0\boldsymbol{W}^*$
- The treatment effect is equal to $\boldsymbol{Y}_0 - \boldsymbol{Y}_1^*$.

Selection of predictors (1)

Table 4: SCM for CO_2: Pre-Treatment predictor means for Germany, synthetic Germany and the sample

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
CO2 from transport in 1998	2.10	2.10	2.12

Selection of predictors (2)

Table 5: SCM for $PM_{2.5}$: Pre-Treatment predictor means for Germany, synthetic Germany and the sample

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
$PM_{2.5}$ from transport in 1998	0.58	0.61	0.42

Selection of predictors (3)

Table 6: SCM for NO_X: Pre-Treatment predictor means for Germany, synthetic Germany and the sample

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
$PM_{2.5}$ from transport	0.50	0.50	0.42
NO_X from transport in 1998	14.13	14.26	16.72

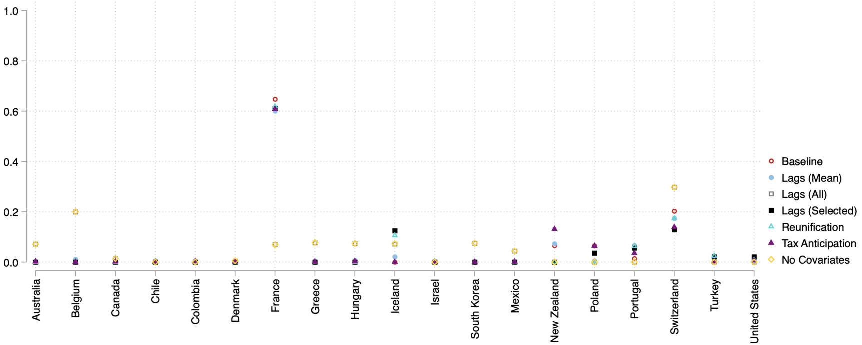
Donor pool

- We limit our dataset to countries that are part of the OECD
  - Desirable structural similarities with Germany in terms of their economic situation, emissions, and form of government (Abadie, 2021)
  - Additional restrictions: carbon pricing, data limitations

Country	Excluded	Rationale	Reference
Finland	✓	Carbon tax	Kossoy et al. (2015); Mideksa (2021)
Sweden	✓	Carbon tax	Kossoy et al. (2015); Andersson (2019)
Norway	✓	Carbon tax	Kossoy et al. (2015)
The Netherlands	✓	Carbon tax	Kossoy et al. (2015)
Italy	✓	Fuel tax	OECD (2001)
Spain	✓	Fuel tax	Bosch (2001)
UK	✓	Fuel tax	OECD (2001)
Japan	✓	Fuel efficiency standards	Osamu (2012)
Austria	✓	Fuel tourism	Dings (2004)
Luxembourg	✓	Fuel tourism	Dings (2004)
Czechia	✓	Sparse data before 1989	Dargay et al. (2007)
Slovakia	✓	Sparse data before 1989	Dargay et al. (2007)
Slovenia	✓	Sparse data before 1989	Dargay et al. (2007)

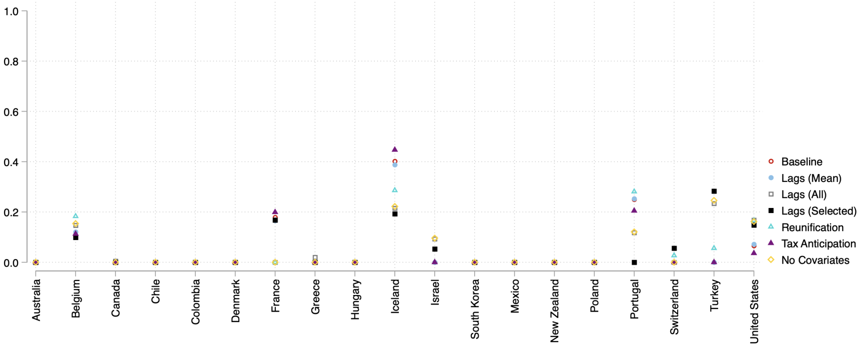
Country-specific weights in the SCM (1)

Figure 22: Synthetic Germany: CO_2



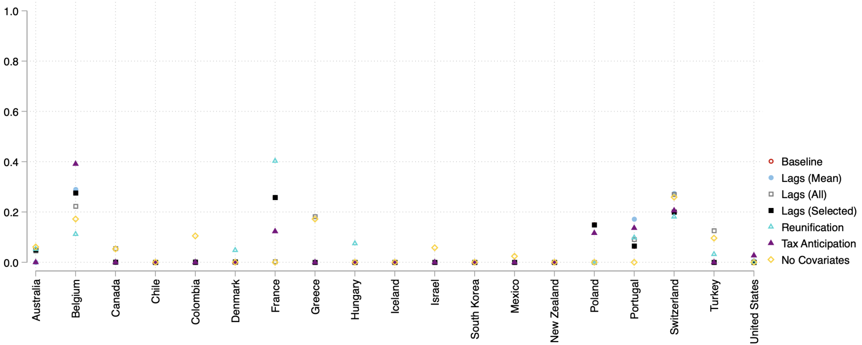
Country-specific weights in the SCM (2)

Figure 23: Synthetic Germany: $PM_{2.5}$



Country-specific weights in the SCM (3)

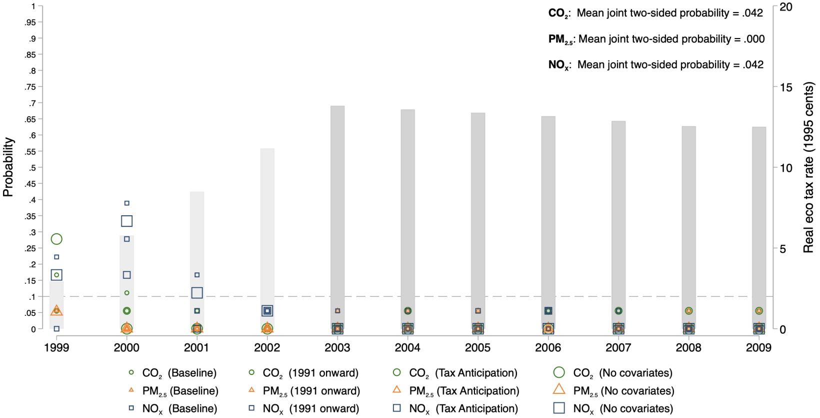
Figure 24: Synthetic Germany: NO_X



Inference for the Synthetic Control Method Back

We use placebo experiments using permutation techniques (Abadie, 2021), applying the SCM to all donors while accounting for pre-treatment fit

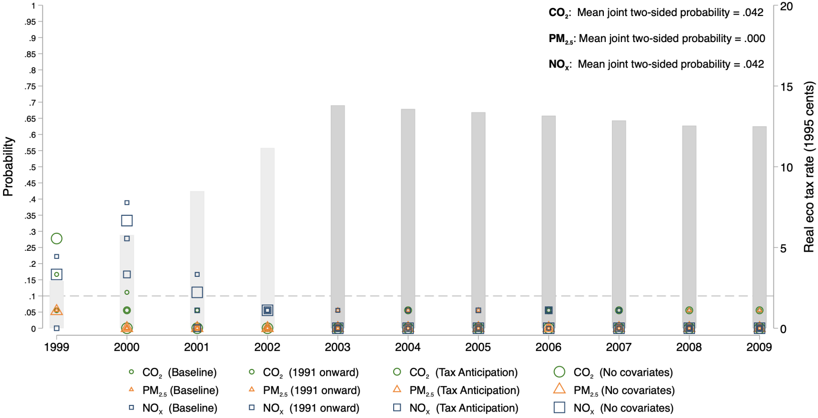
Figure 25: Annual significance levels of the results for carbon emissions



Inference for the Synthetic Control Method

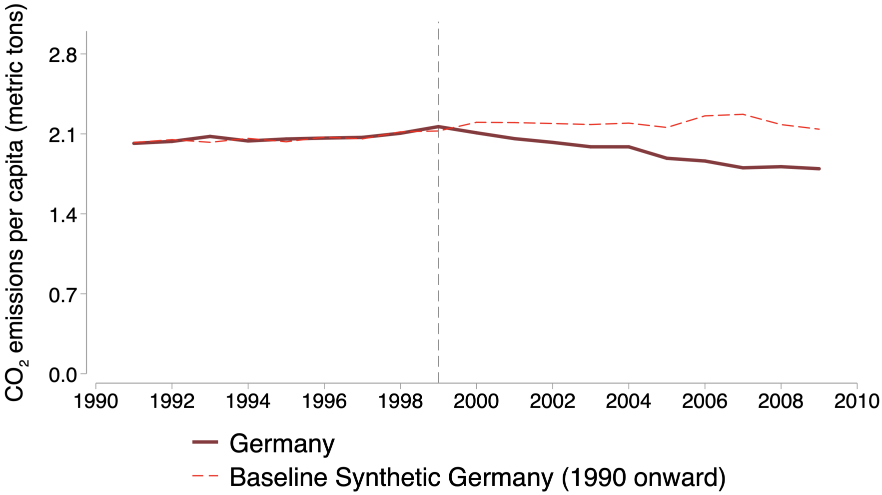
Back

Figure 26: Annual significance levels of the results for local air pollution



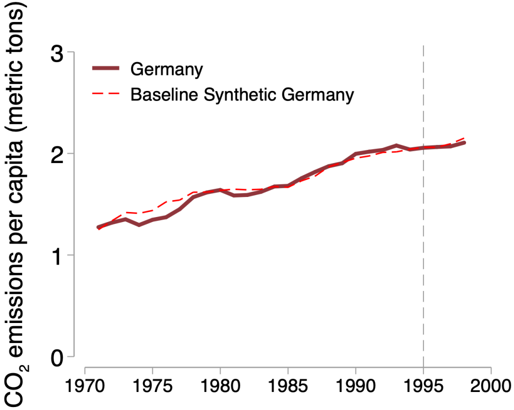
SCM results on CO_2 emissions after 1991 Back

Figure 27: Change in CO_2 emissions over time



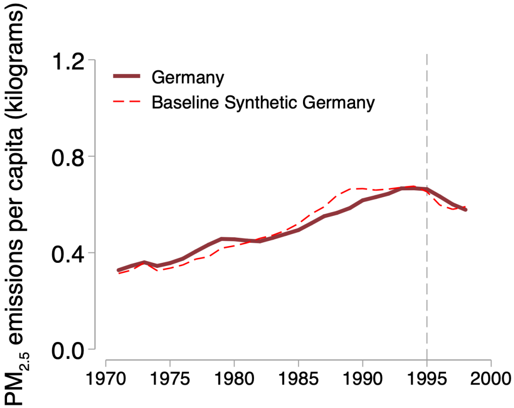
In-time placebo for CO_2 Back

Figure 28: CO_2: In-time placebo in 1995



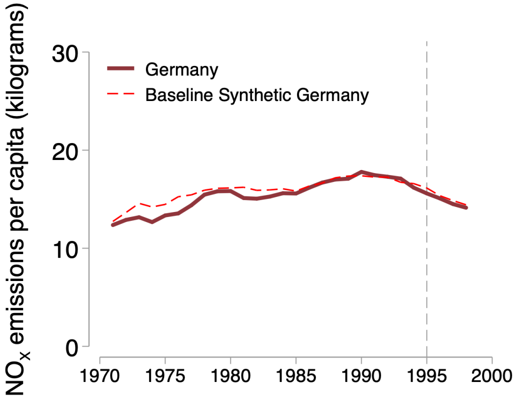
In-time placebo for $PM_{2.5}$ Back

Figure 29: $PM_{2.5}$: In-time placebo in 1995



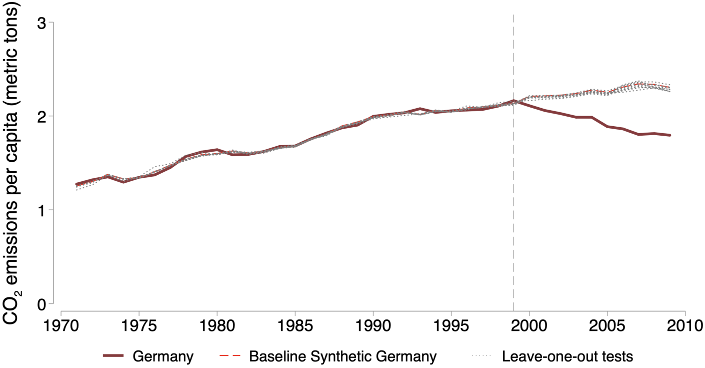
In-time placebo for NO_X Back

Figure 30: NO_X: In-time placebo in 1995



Leave-one-out tests for CO_2 Back

Figure 31: CO_2: Leave-one-out tests

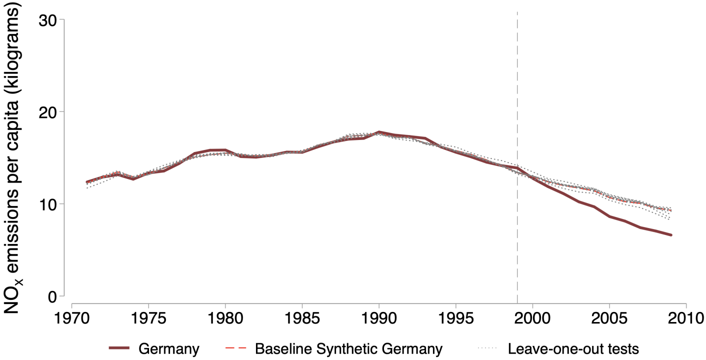


Leave-one-out tests for $PM_{2.5}$ Back

Figure 32: $PM_{2.5}$: Leave-one-out tests

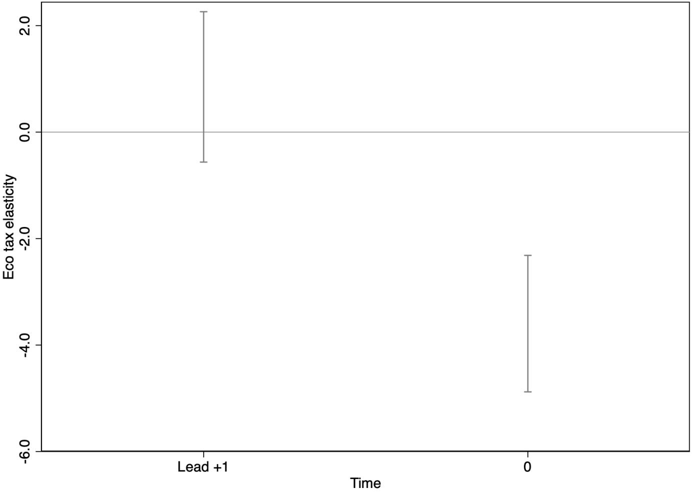
Leave-one-out tests for NO_X Back

Figure 33: NO_X: Leave-one-out tests



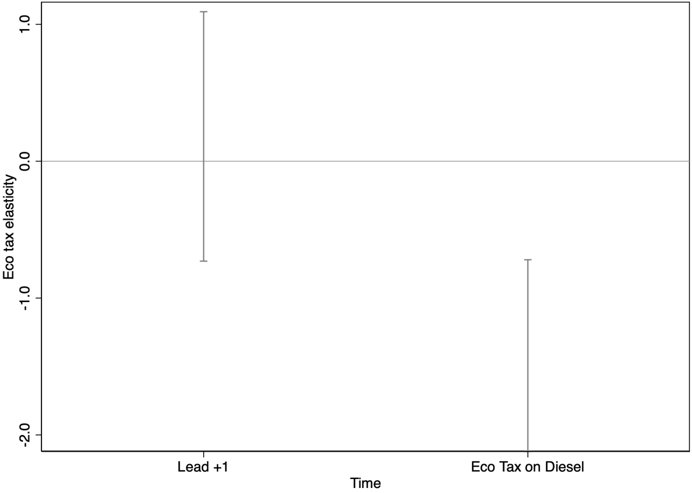
Accounting for anticipatory behaviour: Gasoline Back

Figure 34: Gasoline eco tax elasticities with a lead



Accounting for anticipatory behaviour: Diesel Back

Figure 35: Diesel eco tax elasticities with a lead



Real price elasticity: Gasoline Back

Table 7: Gasoline consumption

	(1) OLS: Baseline	(2) IV: Brent crude	(3) OLS: Fixed effects
Gasoline Price	-0.00603**	-0.00553*	-0.00553***
	(0.00278)	(0.00305)	(0.00103)
Instrument F-statistic		69.47	
Price elasticity	0.54	0.50	0.50
Sample	Germany	Germany	OECD
Controls	✓	✓	✓
Observations	38	38	765

Real price elasticity: Diesel Back

Table 8: Diesel consumption

	(1) OLS: Baseline	(2) IV: Brent crude	(3) OLS: Fixed effects
Diesel Price	-0.00440***	-0.00361***	-0.00454***
	(0.00103)	(0.000856)	(0.00147)
Instrument F-statistic		168.86	
Price elasticity	0.34	0.28	0.34
Sample	Germany	Germany	OECD
Controls	✓	✓	✓
Observations	39	39	574

Eco tax elasticity: Gasoline

Back

Table 9: Gasoline consumption

	(1) OLS: Baseline	(2) OLS: Fixed effects	(3) OLS: Fixed effects
Raw price of Gasoline	-0.00357*	-0.00256	-0.00427**
	(0.00179)	(0.00165)	(0.00163)
Energy Tax on Gasoline	-0.00242	-0.00485***	-0.00413***
	(0.00476)	(0.00128)	(0.000569)
Eco-tax on Gasoline	-0.0306***	-0.0296***	-0.0247***
	(0.00700)	(0.00479)	(0.00350)
Raw price = Eco-tax (p-value)	<0.001	<0.001	<0.001
Eco-tax elasticity	2.7	2.7	2.2
Sample	Germany	OECD	EU
Controls	✓	✓	✓
Observations	38	765	509

Eco tax elasticity: Diesel Back

Table 10: Diesel consumption

	(1) OLS: Baseline	(2) OLS: Fixed effects	(3) OLS: Fixed effects
Raw price of Diesel	-0.00346***	-0.00525***	-0.00506**
	(0.00104)	(0.00164)	(0.00187)
Energy Tax on Diesel	-0.00729**	0.000388	0.000937
	(0.00292)	(0.00152)	(0.00155)
Eco-tax on Diesel	-0.0143***	-0.0232***	-0.0197***
	(0.00359)	(0.00351)	(0.00328)
Raw price = Eco-tax (p-value)	$<$0.001	$<$0.001	$<$0.001
Eco-tax elasticity	1.1	1.7	1.5
Sample	Germany	OECD	EU
Controls	✓	✓	✓
Observations	39	574	415

Eco tax elasticity and salience: Gasoline Back

Table 11: Gasoline consumption

	(1) OLS: Baseline	(2) OLS: Fixed effects	(3) OLS: Fixed effects
Raw price of Gasoline	-0.00280	-0.00262	-0.00257
	(0.00176)	(0.00164)	(0.00164)
Energy Tax	-0.00338	-0.00489***	-0.00488***
	(0.00489)	(0.00128)	(0.00128)
Eco-tax	-0.00773	-0.00683***	-0.00594***
	(0.00557)	(0.00113)	(0.00145)
Eco-tax x Eco-tax price salience (lag)	-0.00441**	-0.00414***	-0.00467***
	(0.00190)	(0.000968)	(0.00101)
Environmental taxation (lag)			-0.0121**
			(0.00559)
Raw price = Eco-tax (p-value)	0.319	0.069	0.189
Non-salient eco-tax elasticity	0.70	0.62	0.54
Sample	Germany	OECD	OECD
Controls	✓	✓	✓
Observations	38	765	765

Eco tax elasticity and salience: Diesel Back

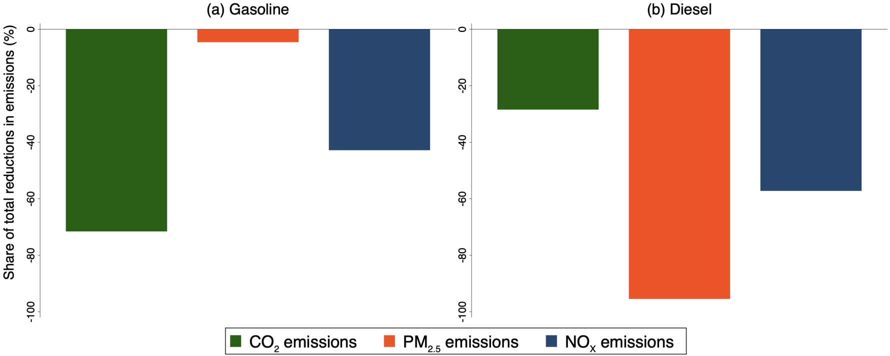
Table 12: Diesel consumption

	(1) OLS: Baseline	(2) OLS: Fixed effects	(3) OLS: Fixed effects
Raw price of Diesel	-0.00326***	-0.00533***	-0.00558***
	(0.000900)	(0.00163)	(0.00159)
Energy Tax	-0.00723**	0.000340	0.0000739
	(0.00348)	(0.00152)	(0.00137)
Eco-tax	-0.00818***	-0.00840***	-0.00647**
	(0.00275)	(0.00264)	(0.00304)
Eco-tax x Eco-tax price salience (lag)	-0.00120*	-0.00272***	-0.00359***
	(0.000689)	(0.000925)	(0.00106)
Environmental taxation (lag)			-0.0184**
			(0.00645)
Raw price = Eco-tax (p-value)	0.081	0.473	0.845
Non-salient eco-tax elasticity	0.62	0.63	0.49
Sample	Germany	OECD	OECD
Controls	✓	✓	✓
Observations	39	574	574

Share of abatement by fuel

Back CO2 gaps PM2.5 gaps NOx gaps

Figure 36: Share of total emission reductions by fuel due to the eco tax

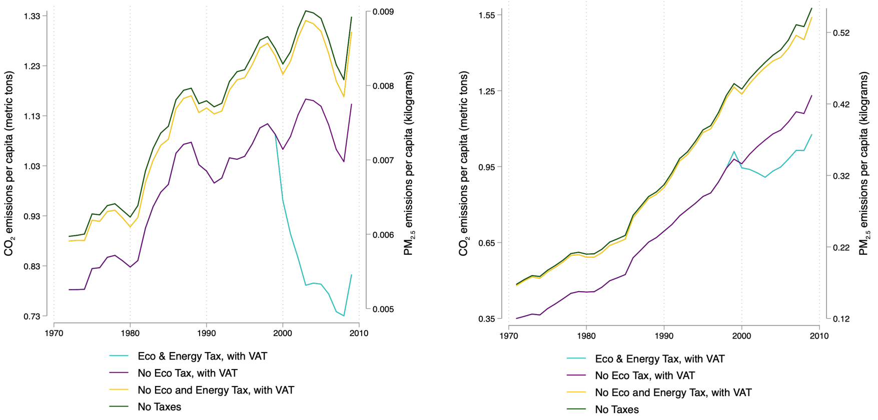


Predicted emissions by fuel in different tax scenarios NOx

Figure 37: Estimated emissions by fuel under different taxation scenarios

(a) Gasoline consumption

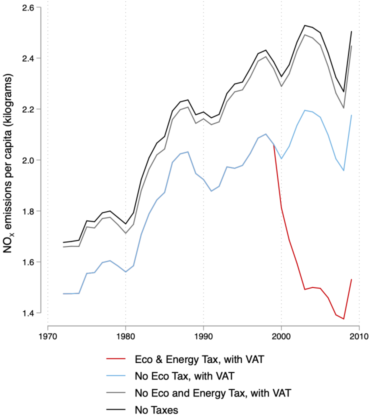
(b) Diesel consumption



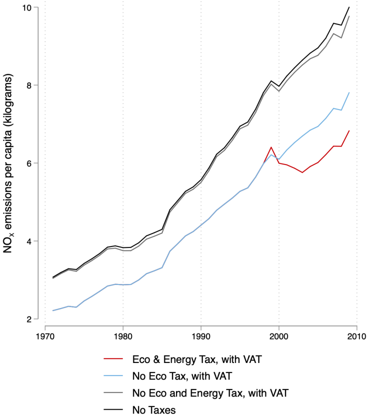
Predicted NO_X emissions in different tax scenarios Back

Figure 38: Estimated emissions by fuel under different taxation scenarios

(a) Gasoline consumption

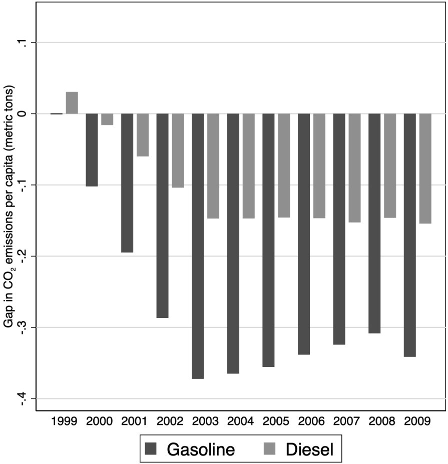


(b) Diesel consumption



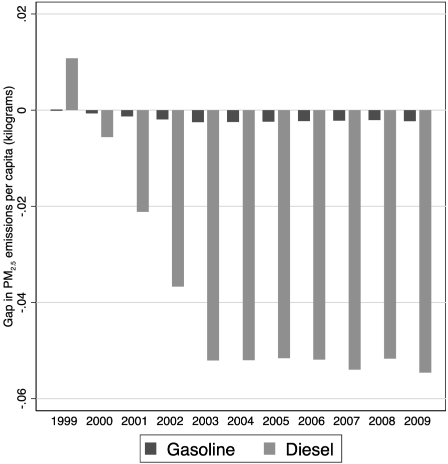
Predicted gaps in CO_2 by fuel Back

Figure 39: Predicted gaps in CO_2 by fuel over time



Predicted gaps in $PM_{2.5}$ by fuel Back

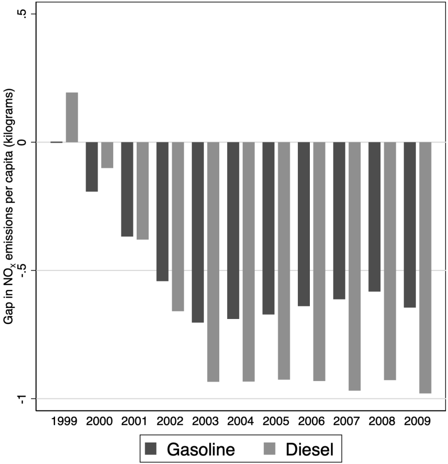
Figure 40: Predicted gaps in $PM_{2.5}$ by fuel over time



Predicted gaps in NO_X by fuel

Back

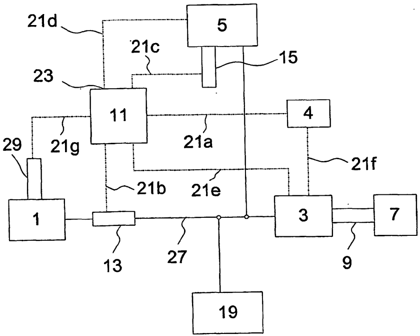
Figure 41: Predicted gaps in NO_X by fuel over time



Examples of low-carbon patents related to transport Back

Figure 42: Y02T patents filed by Bayerische Motoren Werke AG

(a) EP1410479B1: **Vehicle battery charging** (b) EP2065274B1: **Hybrid powertrain systems**



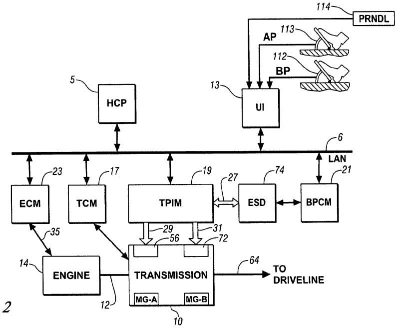


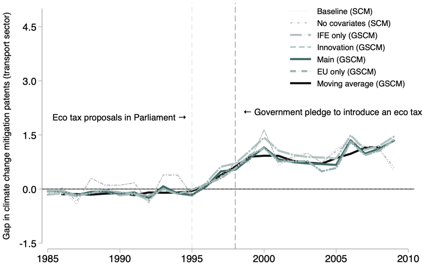
FIG. 2

Impacts on low-carbon innovation Examples

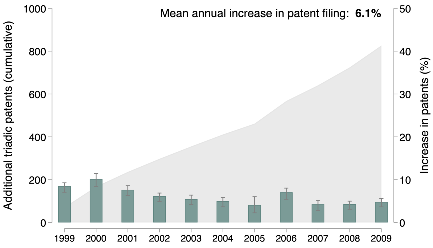
- Climate change mitigation triadic patents related to transportation (Y02T)
- Previous estimates find limited impacts of carbon pricing on low-carbon innovation $\rightarrow$ 1% increase due to the EU ETS (Calel and Dechezleprêtre, 2016)
- Economy-wide estimates. Unregulated companies, upstream equipment manufacturers, downstream suppliers and new entrants (c.f. Popp, 2019)

Figure 43: Effects of the eco-tax on low-carbon patented technologies

(a) Germany vs. Synthetic Germany



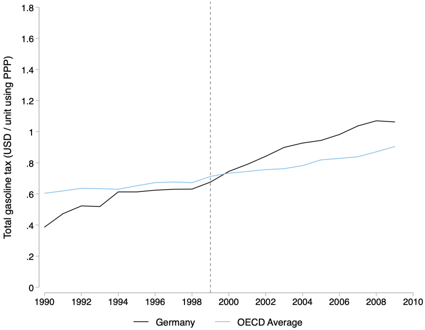
(b) Change in patents over time



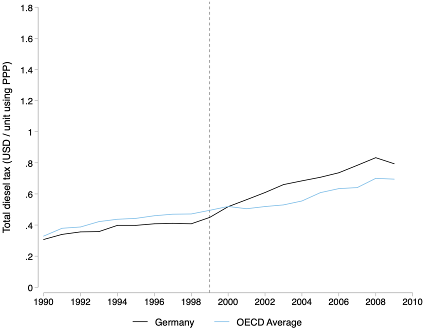
The Ecological Tax Reform in Germany

Figure 44: Fuel taxes in Germany and the OECD average

(a) Gasoline



(b) Diesel



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

GSCM results on carbon and co-pollutants

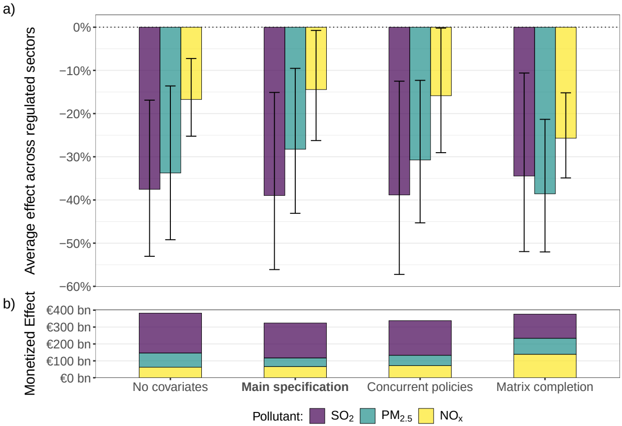
Table 13: Effects of the eco-tax with a Generalized Synthetic Control

	SCM	IFE only	Economic activity	EU only
Panel A: CO_2 (t)				
Mean [95% CI]	-0.23 t/capita	-0.43 [-0.53; -0.34]	-0.39 [-0.50; -0.25]	-0.44 [-0.57; -0.29]
Panel B: $PM_{2.5}$ (kg)				
Mean [95% CI]	-0.15 kg/capita	-0.15 [-0.26; -0.04]	-0.14 [-0.25; -0.07]	-0.21 [-0.27; -0.13]
Panel C: NO_X (kg)				
Mean [95% CI]	-1.50 kg/capita	-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 effect and 95% confidence intervals for different model specifications. Wald test p-values refer to a Wald test for pre-treatment fitting checks (c.f. Xu, 2017). For each specification, we report the highest p-values across all panels. All models include interactive fixed effects and a binary indicator for German reunification. *IFE only* includes a binary EU membership indicator and a dummy variable identifying EU member countries after 2005 *Economic activity* additionally controls for GDP per capita at current purchasing power parities (in million 2011 USD), while *EU only* simply restricts the donor pool to countries that are part of the European Union until the end of our sample.

Non-market benefits from emission reductions (2)

Figure 45: Non-market benefits of the EU ETS (Basaglia et al., 2024 R&R PNAS)



Notes: Estimated mean pollution reductions with 95-CI (Panel a) and monetized aggregate health co-benefits (Panel b) due to the EU ETS from 2005 to 2021.

SDID methodology

- SDID estimator of the average treatment effect on the treated (ATT) requires a balanced panel of N units or groups, over T time periods.

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

- The parameter $\hat{\tau}^{\mathrm{sdid}}$ is the ATT estimated in a TWFE regression with optimally chosen unit-specific ($\hat{\omega}_i^{\mathrm{sdid}}$) and time ($\hat{\lambda}_t^{\mathrm{sdid}}$) weights.
  - *unit-specific* weights allow to yield matching pre-intervention trends
    - Unit fixed effects (α_i) absorb any level differences and implies that the SDID estimator, by choosing unit weights ($\hat{\omega}_i$), will match treated and control units based on pre-treatment trends.
  - *time-specific* weights reduce influence of periods that significantly differ from post-treatment periods and increase model precision.
    - Time effects (β_t) allows for common temporal aggregate factors, e.g. 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.

Staggered adoption design with SDID

- We leverage the gradual roll-out of other environmentally-motivated fuel taxes in Finland (1990) and Sweden (1991)
- Staggered adoption. Further control for unobserved idiosyncratic shocks

Table 14: Effects of environmental taxes in Finland, Germany, and Sweden

	CO_2 emissions (t)	$PM_{2.5}$ emissions (kg)	NO_X emissions (kg)	Low-carbon patents
Environmental fuel taxation	-0.24***	-0.10***	-2.77***	0.64**
	(0.05)	(0.03)	(0.97)	(0.29)
Observations	858	858	858	550
Countries	22	22	22	22
Average point estimates by country				
Finland	-0.24	-0.10	-4.19	0.15
Sweden	-0.21	-0.07	-1.89	0.71
Germany	-0.32	-0.14	-1.75	1.14
German SCM effects for comparison				
Germany (SCM)	-0.23	-0.15	-1.50	0.99
Germany (GSCM)	-0.39	-0.14	-1.65	0.91

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) based on multiple treated units. All regressions include unit-specific and time-specific fixed effects and control for GDP per capita and a binary variable indicating whether a country was regulated by EU-wide regulations after 2005.

Air pollution changes