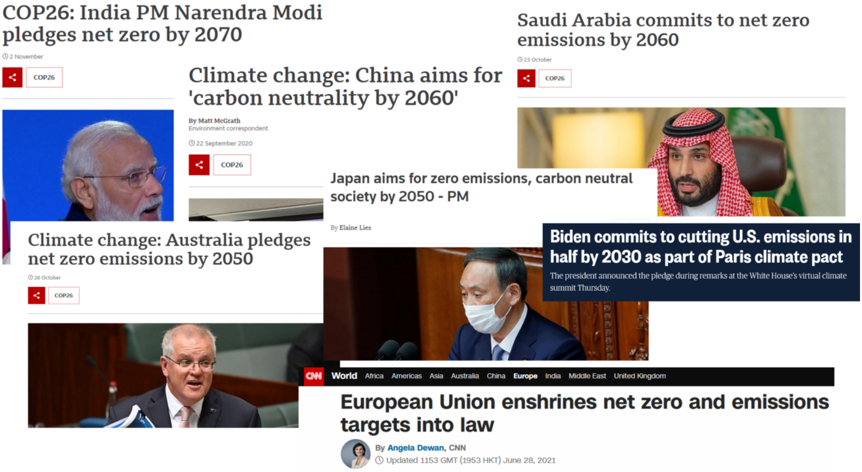
What reduces road CO_2 emissions? Policy attribution using break detection

Nicolas Koch Lennard Naumann Felix Pretis
Nolan Ritter **Moritz Schwarz**

Climate Econometrics Seminar Series

January 18, 2022

Ever more commitments to net zero



COP26: India PM Narendra Modi pledges net zero by 2070

2 November

COP26

Saudi Arabia commits to net zero emissions by 2060

23 October

COP26

Climate change: China aims for 'carbon neutrality by 2060'

By Matt McGrath
Environment correspondent

22 September 2020

COP26

Japan aims for zero emissions, carbon neutral society by 2050 - PM

By Elaine Lies

Climate change: Australia pledges net zero emissions by 2050

26 October

COP26

Biden commits to cutting U.S. emissions in half by 2030 as part of Paris climate pact

The president announced the pledge during remarks at the White House's virtual climate summit Thursday.

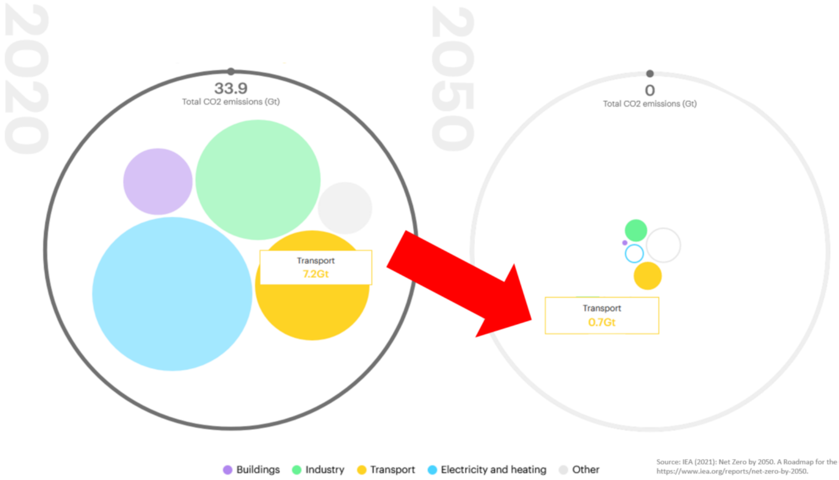
CNN World Africa Americas Asia Australia China Europe India Middle East United Kingdom

European Union enshrines net zero and emissions targets into law

By Angela Dewan, CNN

Updated 1153 GMT (1953 HKT) June 28, 2021

Transport Mitigation is indispensable for net zero



Source: IEA (2021): Net Zero by 2050. A Roadmap for the Global Energy Sector. https://www.iea.org/reports/net-zero-by-2050.

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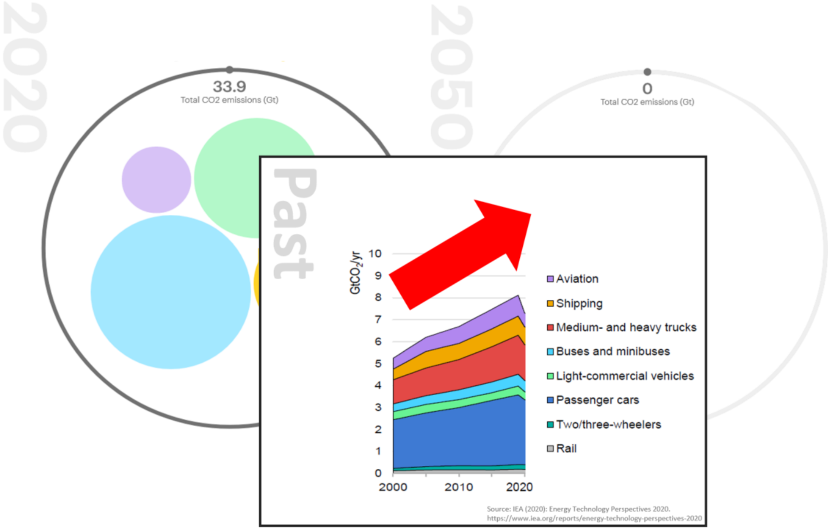

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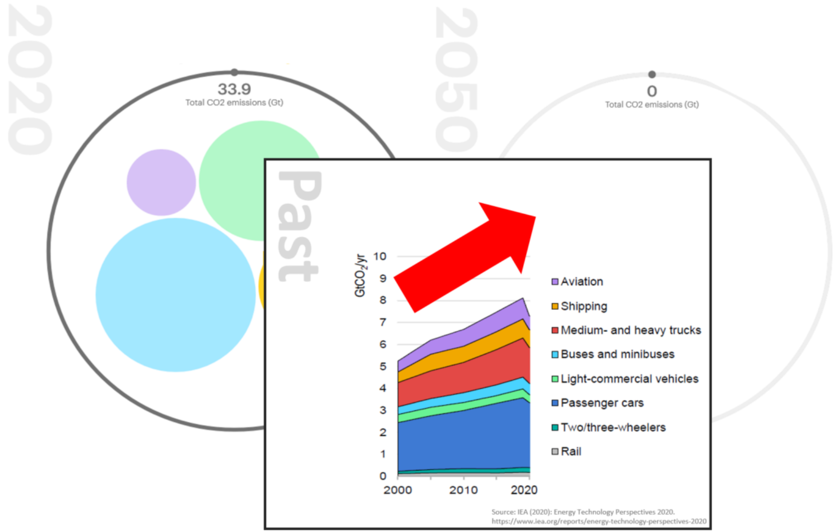

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How to effectively reduce emissions to net zero?

Range of possible policies

Carbon & fuel taxes

Road tolls

Vehicle purchase/ registration taxes

Subsidies & tax credits

Standards & labels

Bans & limits

How to effectively reduce emissions to net zero?

Which policy to choose?

- Many considerations relevant (costs, equity, etc.)
- Crucial in the context of Net-Zero challenge: policy effectiveness at reducing carbon emissions

Priority: Identify which policies have successfully reduced carbon emissions

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Actual policy approach

Policy makers almost exclusively legislate mixes of many simultaneously applied policy interventions

(Axsen et al. 2020; Eskander and Fankhauser 2020)

- Evaluating the causal effect of each individual policy in a legislative package is challenging if at all possible
- Simultaneously applied policies are a threat to identification
- Urgent need for better understanding of interacting policies

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Recent Examples

German Climate Change Policies in 2019 – 2021

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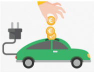
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includes: new sectoral targets (Climate Change Act), carbon pricing, subsidies, infrastructure investment, etc.

EU Fit for 55 Commission proposal

includes: CO_2 fuel standards, ICE bans (2035), Carbon Pricing (Revised EU ETS from 2026), public infrastructure investment (electric charging points), etc.

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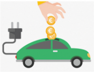
+ 
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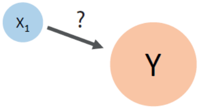
Forward and reverse causal questions

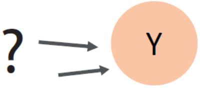
Empirical research mostly concerned with **"Forward Causal"** questions: **"Did X affect Y"**? e.g. Diff-in-Diff

- Effect of single, known policy interventions in isolation (e.g. carbon tax reform in 1991 on emissions)



Here: **"Reverse Causal"** question: **"What affected Y?"** (Gelman and Imbens, 2011, 2013)

- *'Searching for new variables that are not yet in the model.'*
- e.g. what caused emissions to fall since 2005?



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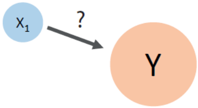

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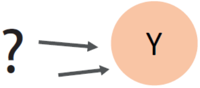

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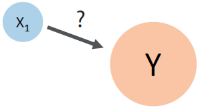

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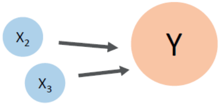

This paper

Viable data-driven approach to identify a-priori unknown policies or policy *mixes* that effectively reduce CO_2 emissions

Method: Operationalization of reverse-causal modeling within the domain of break detection in panel setting

1. Agnostically detect structural breaks in emissions relative to a control group
   - No a-prior knowledge: Any unit may be treated at any time with heterogeneous treatment effects
   - Machine learning to reduce the number of potential treatments
   - Post-selection model is equivalent to conventional DID
2. Attribution of emission breaks to single policy or policy mix

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Related literature

Policy evaluation literature

Policy evaluation literature predominantly focuses on **forward causal questions** using a range of time-tested, quasi-experimental tools

- DID (e.g. Klemetsen et al. 2020, Colmer et al. 2020); SCM (e.g. Andersson 2019, Bayer and Aklin 2020)
- Issues: (i) focus on tools-of-choice risks missing interventions that are a-priori unknown or underestimated; (ii) focus on single policies in isolation risks missing confounding or reinforcing policies
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Time series literature

Time series literature commonly links **structural breaks to policy**

- UK climate policy (Castle and Hendry 2021), Paris agreement on stock returns (Mukanjari and Sterner 2018), many others
- Issue: No control groups, does not identify treatment effects if there are trends
- Recent developments using LASSO in panel context (Okui and Wang 2021), but no focus on treatment evaluation
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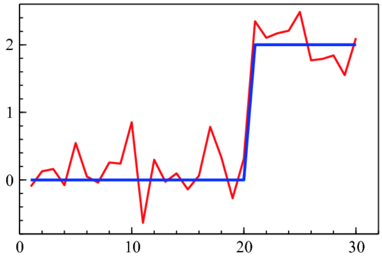
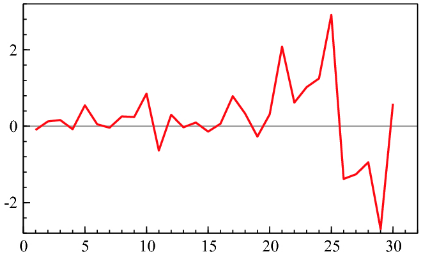
Structural Breaks

- Unexpected (often rapid) change in the stability of regression parameters (mean or variance)
- Many sudden changes, particularly when unanticipated, cause links between variables to shift
- Often breaks caused by events outside the analysis at hand (e.g., policy implementation, tipping points, wars, innovation)
- In time series dealt with by adjusting the intercept (e.g. Step-Indicator Saturation)



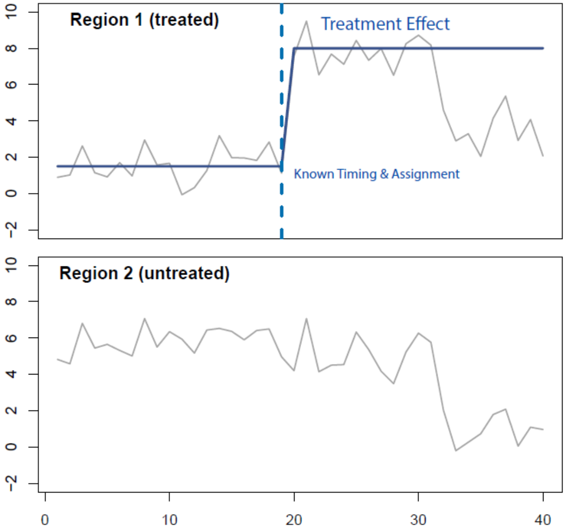
Location shift from a mean of zero to 2



Variance shift from 1 to 6 at observation 21

From Castle and Hendry, 2020

Method: Standard setting with known timing & assignment



Method: Standard setting with known timing & assignment

- Consistent treatment effect estimation with two-way fixed effects estimator (TWFE):

$$y_{i,t} = \alpha_i + \phi_t + \tau \times D_{i,t} + \varepsilon_{i,t}$$

- Note: binary treatment variables $D_{i,t}$ – denoting interactions of indicators $treat_i$ for treated & $post_t$ for post-treatment – are equivalent to breaks in the intercept of treated units

$$\begin{aligned} E\left[y_{i,t} \mid treat_i = 1\right] &= \alpha_i + \tau \times \mathbb{1}_{t \geq post} + \phi_t \\ &= \alpha_{i,t} + \phi_t \end{aligned}$$

$$\text{where } \alpha_{i,t} = \begin{cases} \alpha_i & \text{for } t < post \\ \alpha_i + \tau & \text{for } t \geq post \end{cases}$$

  - Step-shift τ in the treated units' intercepts when switching from pre- to post-treatment period

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Method: Unknown timing & assignment

General idea

- Equivalence between step-shifts in the unit-specific intercept (i.e. group fixed effect) and known treatment specification (e.g. when using DiD) suggests alternative approach to evaluate reverse causal questions
- Rather than exclusively evaluating known interventions, we estimate a TWFE estimator in search of potential structural breaks (step-shifts) in the unit-specific intercepts
- Once a break has been identified, it can be interpreted as a treatment for the relevant unit

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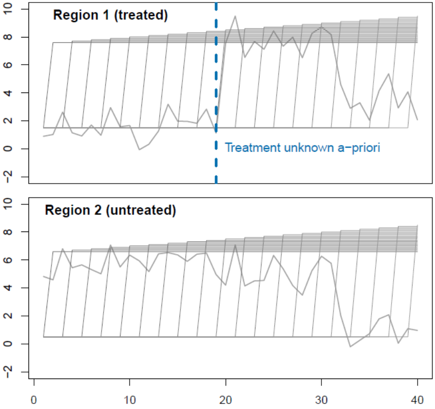
Method: Unknown timing & assignment

Step 1: Saturate a TWFE model with a full set of step-shifts



Step-shifts for every i and t:

$$y_{i,t} = \alpha_i + \phi_t + \sum_{j=1}^{N} \sum_{s=2}^{T} \tau_{j,s} \mathbb{1}_{\{i=j, t \geq s\}} + \varepsilon_{i,t}$$

- Operationalizes the notion of Gelman and Imbens (2013) that reverse causal questions require "*searching for new variables that are not yet in the model*"
- Nests "known treatments" as a special cases

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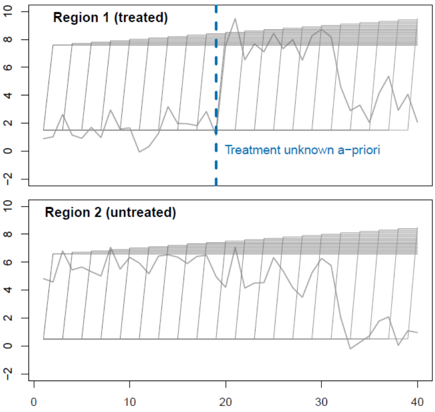

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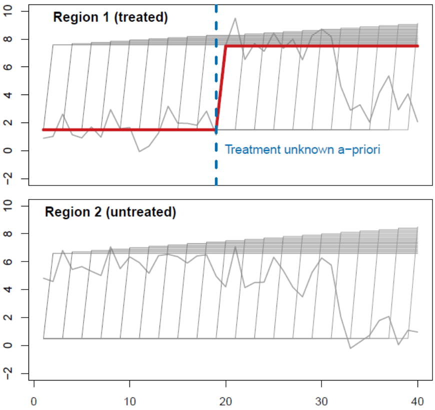
Step 2: Apply variable selection methods from machine learning



ML selection algorithm to move from general model that embeds all possible breaks to a sparse model w/ only relevant breaks

$$y_{i,t} = \alpha_i + \phi_t + \sum_{j \in \widehat{Tr}} \sum_{s \in \hat{T}_j} \hat{\tau}_{j,s} \mathbb{1}_{\{i=j, t \geq s\}} + \varepsilon_{i,t}$$

- where $\widehat{Tr}$ denotes set of detected treated units w/ treatment times $\hat{T}_j$

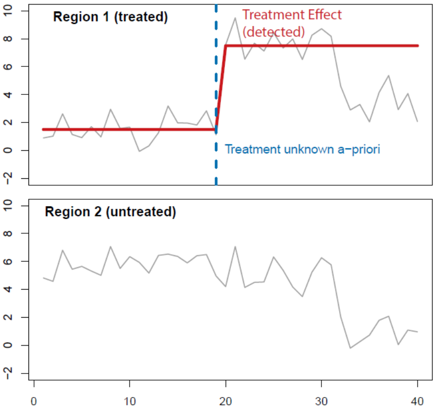
Here: "gets" algorithm

- Targets false positive rate γ_c
  $P\left(i \in \hat{Tr} | treat_i = 0\right) = 1 - (1 - \gamma_c)^T$

alternative machine learning algorithms

Method: Unknown timing & assignment

Step 3: Estimate post-selection model



- Identifies (possibly multiple) unit-specific treatment effects τ_i (averaged over time) conditional on treatment effects being non-zero
- Conditional on having detected treatment, resulting model is identical to imposing known intervention in TWFE with interactions

Method: Unknown timing & assignment

Step 4: Attribute detected treatment effects to policy interventions

- Confidence interval for the timing of each detected step-shift $\hat{T}_j$ to accommodate for timing uncertainty
- Resort to well-established policy databases to find policy measures implemented in the years in the confidence intervals
  - IEA's Policies and Measures Database
  - Climate Change Laws of the World
  - National Communications to the UNFCCC
  - ...

Method: More formal discussion

Discussion of this method, its properties and simulation results can be found in our newest **Working Paper** (Pretis and Schwarz, Working Paper)

Discovering What Mattered:
Answering Reverse Causal Questions by Detecting Unknown Treatment Assignment and Timing as Breaks in Panel Models

Felix Pretis[1,2] and Moritz Schwarz[2,3*]
[1]Department of Economics, University of Victoria
[2]Climate Econometrics, Nuffield College, University of Oxford
[3]Smith School of Enterprise and the Environment, University of Oxford

January 11th, 2022

Abstract

Implementation of this using the `gets` R-package as well as it's extension `getspanel`.

Application: EU transport emissions

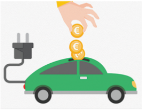
- Identical technological standards at EU level but largely varying national policy measures across Member States $\rightarrow$ **Unable to consider fuel standards, as set on the EU level** i.e. no variation across units.

Carbon & fuel taxes

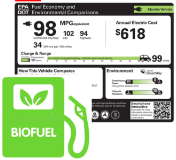
Road tolls

Vehicle purchase/ registration taxes

Subsidies & tax credits



~~Standards~~, mandates & labels



Bans & limits

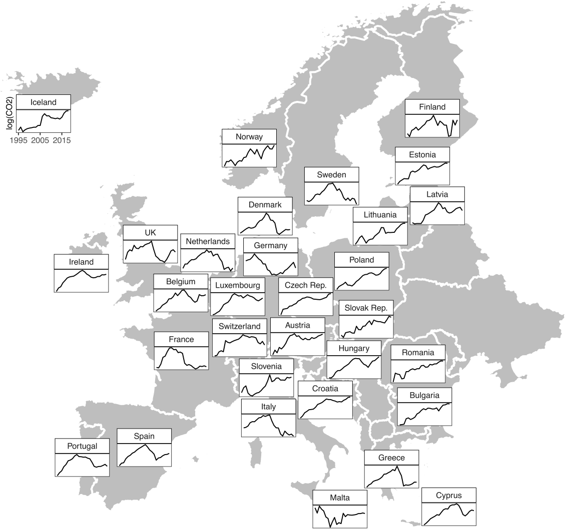
Application: EU transport emissions

Data

- **Emissions data** from Emissions Database for Global Atmospheric Research (EDGAR)
- Samples include **EU-15** and **EU-31** (incl. UK, Norway, Switzerland, Iceland)
- 1995 – 2018

Application: EU transport emissions

Data



Application: EU transport emissions
Model

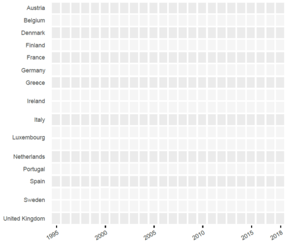
Saturated starting model

controlling for $x_{i,t} = \begin{pmatrix} log(GPD) \\ log(GDP)^2 \\ log(population) \end{pmatrix}$

For EU-15 sample:

$$log(CO_2)_{i,t} = \alpha_i + \phi_t + \sum_{j=1}^{N=15} \sum_{s=2}^{T=24} \tau_{j,s} \mathbb{1}_{\{i=j,t \geq s\}} + x'_{i,t}\beta + \varepsilon_{i,t}$$

Model selection over $N(T-1) = 345$ potential break variables

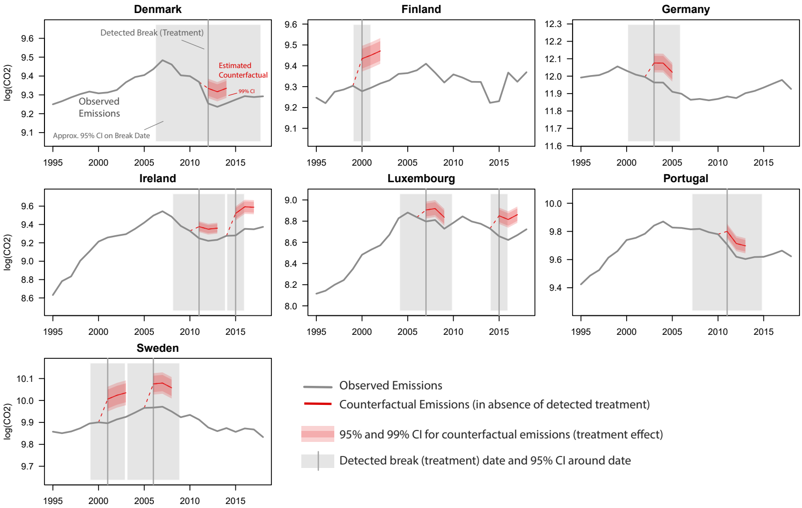


Results: Break detection

using "gets" with false-positive rate targets of 5%, 1%, or 0.1%

results table

Results: Treatment effects



Results: Attribution

Country	Break Year	Policy
Denmark	2012 ± 6	2008: Carbon tax increase 2010: "Green ownership tax": new taxes for light commercial vehicles 2010: Vehicle tax increase for cars without particle filters

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Finland	2000 ±2	1996-1999: Carbon tax increases
		2001: Car tax changed from total mass to CO_2 emissions

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Germany	2003 ± 3	1999-2003: "Ecological Tax Reform" increases motor fuel tax 2001: Harmonization of commuter tax deduction 2004: Mandatory fuel efficiency labelling for vehicles 2005: Road tolls for trucks

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		2010: Vehicle tax increase for cars without particle filters
Finland	2000 ±2	1996-1999: Carbon tax increases
		2001: Car tax changed from total mass to CO_2 emissions
Germany	2003 ±3	1999-2003: "Ecological Tax Reform" increases motor fuel tax
		2001: Harmonization of commuter tax deduction
		2004: Mandatory fuel efficiency labelling for vehicles
		2005: Road tolls for trucks
Ireland	2011 ±2	2008: Vehicle tax base shifts to CO_2 emissions
		2009: Tax incentives for purchase of bicycles
		2010: Introduction of carbon tax, increase in 2012
		2010: Bio-fuel obligations
Ireland	2015 ±2	2014: Carbon tax increase

Results: Attribution

Country	Break Year	Policy
Luxembourg	2007 ± 3	2007: Vehicle tax reform based on CO_2 emissions 2007: Subsidy for purchase of energy efficient vehicles 2007-2008: Fuel tax raised

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Portugal	2011 ±4	2007: Vehicle tax reform based on CO_2 emissions 2010: Incentives to purchase electric vehicles 2012: Introduction of nationwide road tolls

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Results: Attribution

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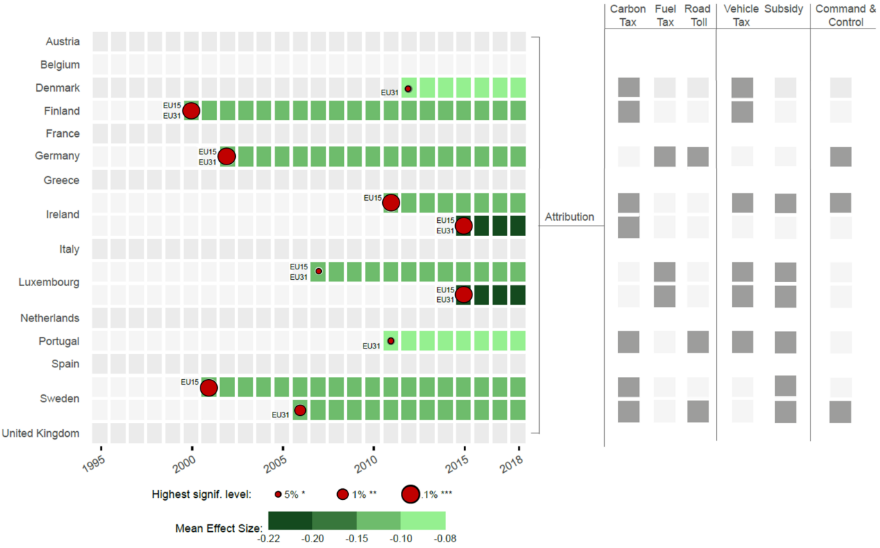
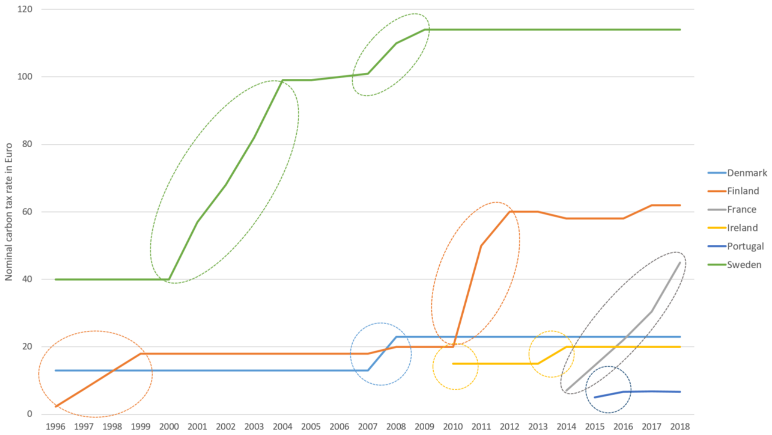
Results: Categorization of effective policies



"I don't buy it"

We repeatedly find that carbon and fuel taxes matter. But can we back this up with the data? (Data from Dolphin et al. (2020))



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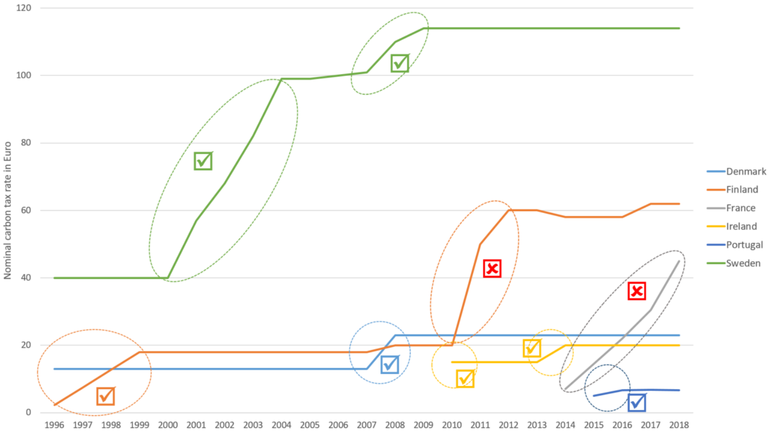

Our model finds carbon pricing changes, even though we did not feed it any information on it.

Results: Summary I

Detect 10 'large' interventions with -8% to -20% reductions in CO2 road emissions across 7 countries.

1. Treated (detected): 7
2. Control: 5 (EU15) or 24 (EU31)
3. Largest effects (Finland 2000, Germany 2002/03, Luxembourg 2015, Ireland 2015) linked to increases of existing but moderate carbon or fuel taxes.
4. Emission reductions linked to price interventions increasing cost of driving
   - Link 6 cases to carbon taxes and 2 cases each to fuel taxes and road tolls
   - Link 7 of the 10 unique breaks to policy mixes combining taxes with subsidies

Suggests that commitment to staggered, anticipated, and permanent tax increases over time can be particularly effective

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Results: Summary II

5. Only one detected emission reductions attributable to a single policy. Investigating a single policy therefore is likely to miss the effects of supplementary policies.
6. All detected emission reductions attributed to at least one tax intervention that increases the cost of driving
   - Indicates that carbon, fuel, or road use taxes are critical elements of effective policy mixes
7. Majority of emission reductions attributed to policy mixes that combine aforementioned taxes with vehicle taxes or subsidies
   - Suggests that policy mixes that simultaneously address the energy efficiency gap and rebound effects are effective

Results: Summary II

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Limitations

- Set-up does not allow identification of EU wide policies, such as Fuel Efficiency Standards. But same problem with DiD (Forward Causal)
- Appropriate judgement necessary for Attribution
- Further covariates enable testing attribution links further
- Currently only considering emission reducing breaks - positive breaks disregarded
- Risk to identification: Spillovers across countries (similar to forward causal studies)
- Differentiation between policies and structural breaks due to e.g. debt crisis not possible

Conclusion

- We propose a **complementary approach** to ex-post policy evaluation: Instead of estimating the effect of a single, known cause on emissions, we seek to **identify the multiple, known and unknown causes of an emissions effect**
- As policy makers implement ever more climate policy mixes to meet their net-zero targets, we believe our novel approach is policy relevant because it **enables drawing systematic inference on** the effectiveness of such **policy *mixes***
- Use case demonstrated for the EU transport sector – the key bottleneck for climate-neutrality in EU

Outlook

- Approach is readily applicable to many other contexts
- Both further country and sector (e.g. electricity or agriculture) applications in the pipeline
- More flexibility in the shape of step-indicators e.g., Smooth Policy Indicators that allow for a policy to phase-in and out
- Further robustness checks (e.g. excluding certain countries due to fuel tourism)

Thank You

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Appendix

Properties & Nuances

- Identify each treated unit with separate interaction – bypasses weighting problem in DiD (Goodman-Bacon, 2021; Callaway and Sant'anna 2020, etc.)
- Multiple breaks detected: equivalent to staggered treatment through interactions Wooldridge (2021)
- Time-varying Treatment effects
  - Piece-wise constant through linear combinations of step-functions.
  - Fully-time varying treatment effects through interactions (replace step-functions with impulse indicators)
- Detect treatment conditional on treatment effects being non-zero.
- Conditional on having detected treatment, resulting model is *identical* to imposing known intervention in TWFE with interactions
- Post-Detection Attribution: comparable to arguing 'as if random assignment' in 'known' treatment setting.

Machine learning selection algorithms

Range of machine learning algorithms available

1. Block search algorithm "gets"
   (Pretis et al. 2018; Schwarz and Pretis 2021)
   - Applies a near-exhaustive tree search over candidate variables
   - Targets false positive rate which converges to the chosen level of significance of selection γ_c as $n \to \infty$
   - Approximate break date uncertainty
2. Shrinkage-based methods such as the (adaptive) LASSO
   (Tibshirani 1996)
   - Do not target the false positive rate
   - Simulations suggest less power and less stable false-positive rate when compared "gets"

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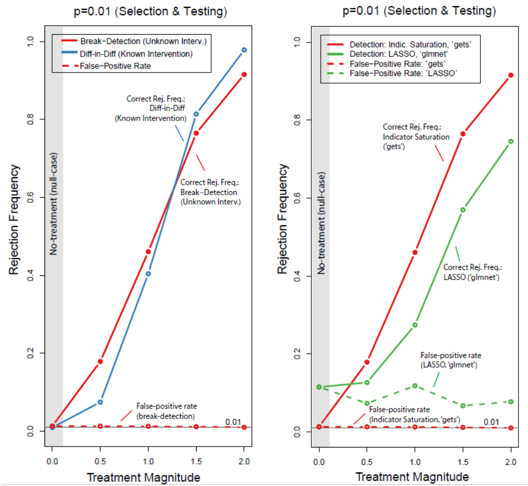
Machine learning selection algorithms

Simulation Performance (Pretis 2019)



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Results table

Country		Model					
		1	2	3	4	5	6
		EU-15	EU-15	EU-15	EU-31	EU-31	EU-31
		significance level for breaks					
	5%	1%	0.1%	5%	1%	0.1%	
Denmark	effect				−0.080		
	se				(0.020)		
	year				2012		
	95% CI				± 6		
Finland	effect	−0.103	−0.123	−0.128	−0.156	−0.171	
	se	(0.020)	(0.022)	(0.024)	(0.024)	(0.028)	
	year	2000	2000	2000	2000	2000	
	95% CI	± 2	± 2	± 2	± 1	± 2	
Germany	effect	−0.105	−0.131	−0.108	−0.112	−0.112	
	se	(0.018)	(0.020)	(0.022)	(0.021)	(0.025)	
	year	2002	2002	2002	2003	2003	
	95% CI	± 2	± 1	± 3	± 3	± 4	
Ireland (1st break)	effect	−0.087		−0.127			
	se	(0.020)		(0.023)			
	year	2011		2011			
	95% CI	± 3		± 2			
Ireland (2nd break)	effect	−0.148	−0.192		−0.247	−0.244	−0.229
	se	(0.028)	(0.028)		(0.030)	(0.034)	(0.037)
	year	2015	2015		2015	2015	2015
	95% CI	± 1	± 1		± 0	± 1	± 1

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Results table

Country		Model					
		1	2	3	4	5	6
		EU-15	EU-15	EU-15	EU-31	EU-31	EU-31
		significance level for breaks					
	5%	1%	0.1%	5%	1%	0.1%	
Luxembourg (1st break)	effect	−0.136			−0.108		
	se	(0.024)			(0.031)		
	year	2007			2007		
	95% CI	± 1			± 3		
Luxembourg (2nd break)	effect			−0.214	−0.193	−0.227	−0.262
	se			(0.031)	(0.030)	(0.035)	(0.038)
	year			2015	2015	2015	2015
	95% CI			± 1	± 1	± 1	± 1
Portugal	effect				−0.094		
	se				(0.021)		
	year				2011		
	95% CI				± 4		
Sweden (1st break)	effect	−0.095	−0.103	−0.110			
	se	(0.017)	(0.019)	(0.022)			
	year	2001	2001	2001			
	95% CI	± 2	± 2	± 3			
Sweden (2nd break)	effect				−0.108	−0.115	
	se				(0.019)	(0.022)	
	year				2006	2006	
	95% CI				± 3	± 4	

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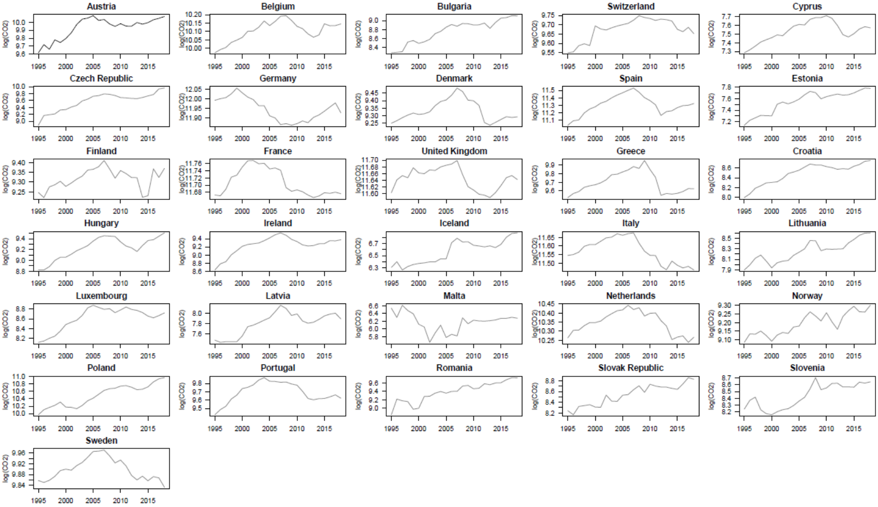
Emissions data



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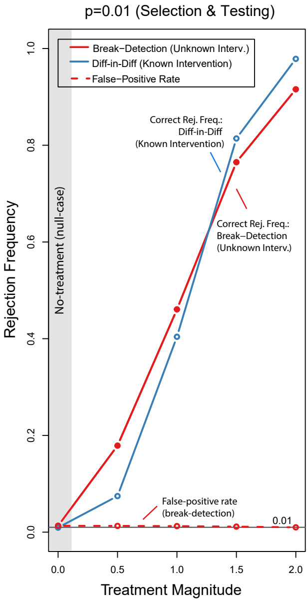
Simulation Performance: 1 Treated, 9 Control



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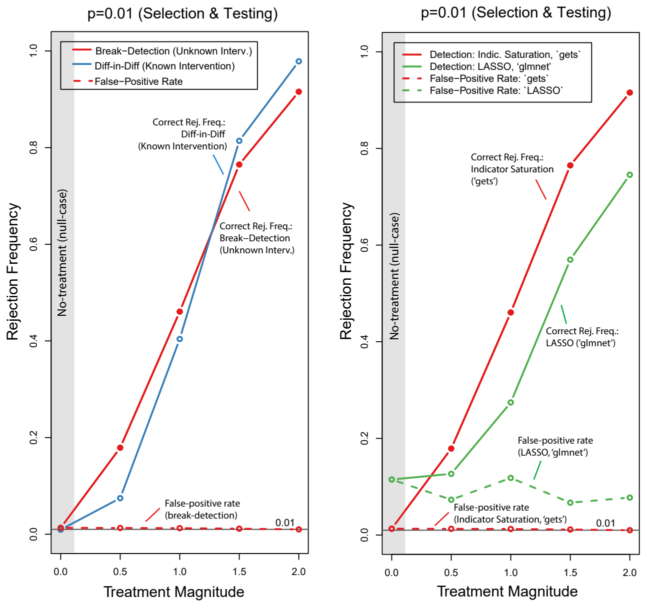

Application: EU Transport Emissions

Starting Model (treatment at any point in time for each unit):

$$log(CO_2)_{i,t} = \alpha_i + \phi_t + \sum_{j=1}^{N} \sum_{s=1996}^{2018} \tau_{j,s} 1_{\{i=j,t \geq s\}} + x'_{i,t}\beta + \varepsilon_{i,t}$$

Selection (targeting $\gamma_c = 0.05$, =0.01 & =0.001) – yielding **Sparse Model**:

$$\widehat{log(CO_2)}_{i,t} = \hat{\alpha}_i + \hat{\phi}_t + \sum_{j \in \widehat{Tr}} \sum_{s \in \hat{T}_j} \hat{\tau}_{j,s} 1_{\{i=j,t \geq s\}} + x'_{i,t}\hat{\beta}$$

gets: Expected False Positive – Example: $\gamma_c = 0.001, T = 24$

- Expected number of false positive periods for a single country = $0.001 \times (T-1) = 0.023 < 1$
- Probability of at least one false-positive treated period (per ctry): $1 - (1 - 0.001)^{(T-1)} = 0.02$
- Expected number of false-positive treated countries:
  - EU-15: $0.02 \times 15 = 0.36 < 1$
  - EU-31: $0.02 \times 31 = 0.73 < 1$