

Have climate policies been effective in Austria? A reverse causal analysis

Tebecis, Talis

DOI:

[10.57938/92adb3ea-18cd-4d05-8d09-223bea611536](https://doi.org/10.57938/92adb3ea-18cd-4d05-8d09-223bea611536)

Published: 01/08/2023

Document Version

Publisher's PDF, also known as Version of record

[Link to publication](#)

Citation for published version (APA):

Tebecis, T. (2023). *Have climate policies been effective in Austria? A reverse causal analysis*. WU Vienna University of Economics and Business. Department of Economics Working Paper Series No. 346
<https://doi.org/10.57938/92adb3ea-18cd-4d05-8d09-223bea611536>

Department of Economics
Working Paper No. 346

Have climate policies been effective in Austria? A reverse causal analysis

Talis Tebecis

August 2023



Have climate policies been effective in Austria? A reverse causal analysis

Talis Tebecis

August 2023

Vienna University of Economics and Business (WU)
talis.tebecis@wu.ac.at

Abstract

Around the world, countries are becoming more ambitious in their emission reduction pledges. Developing policies to actually meet these targets requires carefully evaluating which policies have been most effective at reducing emissions to date. We use reverse causal policy evaluation to answer this question, asking, “Which climate policies have reduced CO_2 emissions the most in Austria since 1995?” This novel approach allows us to identify negative structural breaks, i.e. large reductions in emissions that are not accounted for by the main determinants of CO_2 emissions (population and economic growth), and attribute these breaks to relevant policies. We find statistically significant breaks in only four out of 21 sectors, altogether representing a reduction of less than 2.5% of Austria’s total CO_2 emissions beyond what would have been expected, given its socio-economic development, which is significantly shy of the country’s 48% emission reduction target.

Keywords: CO_2 emissions, climate policy, reverse causal analysis, Austria, structural breaks

Acknowledgements: We thank Christian Keuschnigg for his initial consultation on the methodological approach. We thank Felix Pretis, Jesus Crespo Cuaresma and Moritz Schwarz for their consultation on the approach and review of the initial results. We acknowledge the support from the eXplore! initiative, funded by the B&C Privatstiftung and Michael Tojner, under the grant “Ein Klimaplan für Österreich.”

1 Introduction

The European Union’s (EU’s) target of becoming climate neutral by 2050 requires significant reductions in greenhouse gas emissions, but the most effective path to reducing these emissions is debated. Austria is required by EU law to reduce emissions by 48% by 2030, compared to 2005 levels, under the EU Effort Sharing Regulation (ESR). In support of this, the country has implemented a range of targets surrounding carbon neutrality, renewable energy use and investment in climate research and innovation (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie 2023). While somewhat ambitious, Austria’s climate policies have been largely criticised for their ineffectiveness (Niedertscheider, Haas, and Görg 2018; Winkler and Winiwarter 2016; Schaffrin, Sewerin, and Seubert 2014; Kettner and Kletzan-Slamanig 2018; Steurer and Clar 2015; Steurer, Clar, and Casado-Asensio 2020), and it is expected that the country will not reach its targets, given its current trajectory (The European Commission 2020; Winkler and Winiwarter 2016). Further, the National Energy and Climate Plan (NECP) for Austria outlines that the current and planned policies (denoted as “with existing measures” and “with additional measures”) will not be sufficient to meet this emission reduction target (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie 2023).

These criticisms have been largely derived using traditional approaches to policy evaluation: identifying a policy and determining its effect on emissions, having controlled for relevant factors. Such approaches are often based on economic theory alone, rather than being grounded in empirical evidence. While these traditional approaches are powerful, they require the exogenous selection of specific policies, which risks overlooking policies or policy mixes that may have been effective, but have not received due attention in the literature.

In this study, we complement the existing literature around Austria’s climate policies by using the more holistic, reverse causal approach to policy evaluation. Rather than selecting a policy and determining its effect, the reverse causal approach first identifies significant effects, then attributes these effects to relevant causes. In the context of Austrian climate policy, this means looking for large significant reductions in emissions, then attributing these to relevant policies. Intuitively, this is like asking the question, “What reduced emissions the most?” rather than asking, “How much did a given policy reduce emissions?” We examine CO_2 emissions in all Austrian sectors, from 1995-2021.

We apply a reverse causal statistical method based on machine learning (Koch et al. 2022; Pretis 2022) to identify significant reductions in Austrian CO_2 emissions, which are not explained by changes in population size and GDP, and relative to a control group of EU countries with comparable regulatory environments. Such significant reductions are identified as structural breaks, which are more generally defined as breaks in the relationship between variables (Castle, Clements, and David F Hendry 2016). Population and GDP are used as control variables as they are the two key determinants of CO_2 emissions (Hamilton and Turton 2002), replicating the approach of Koch et al. (2022). We then attribute these structural breaks to relevant policies occurring in the 95% confidence interval around the year of the break. The reverse causal approach is agnostic compared to traditional policy evaluation, as it does not require the prior selection of specific policies to evaluate.

Our analysis confirms the findings from previous literature that climate policies in Austria have been largely ineffective since 1995. Across 21 sectors, we identify five structural breaks in CO_2 emissions across four sectors - petroleum refining, waste incineration, lime production, and water-borne navigation. These four sectors

together make up less than 9% of total annual emissions in Austria, and the identified breaks together represent a reduction in emissions of less than 2.5% of Austria’s total emissions, based on 2005 levels. Further, in the remaining 17 sectors, which account for over 90% of Austria’s total emissions, no structural breaks are identified. In other words, our results provide no evidence of significant reductions in emissions in the majority of sectors, beyond what would have been expected, given the socio-economic development.

Next, we link significant structural breaks to relevant policies, which include subsidy schemes, a climate strategy and an emissions trading system, but the causal attribution of these policies to the reductions are tenuous, due to the idiosyncrasies of these sectors. Namely, four of the identified breaks are in categories with very low baseline emissions (waste incineration, lime production, and water-borne navigation), so structural breaks represent materially-minor emissions reductions. The remaining break is identified in a sector (petroleum refining) for which emissions are entirely determined by the operations of one petroleum refining facility in Austria, for which production was highly influenced by European market conditions at the time of the negative break, rather than by policy changes (OMV 2015). Overall, our research shows that climate policy in Austria since 1995 has resulted in materially small reductions in national CO_2 emissions.

The rest of the paper is structured as follows. Section 2 outlines the institutional and historical context of climate policies in Austria and the nature of CO_2 emissions in Austria. Section 3 outlines the methodology of the reverse causal approach, identifying structural breaks and policy attribution. The results are detailed in section 4. We conclude in Section 5 by highlighting policy implications, potential limitations of our approach and future areas for research.

2 Emissions and climate policy in Austria

2.1 Austrian climate policy

EU member nations are required to submit National Energy and Climate Plans (NECPs), outlining their 10-year strategic plan to contribute to the EU’s climate target, which includes emission reduction policies. Austria initially submitted their NECP in December 2019, and the following year, the European Commission’s assessment of the plan highlighted that Austria was unlikely to meet its emission reduction obligations, according to the EU Effort Sharing Regulation (ESR) (The European Commission 2020). The measures outlined in the NECP were expected to result in a 27% reduction in emissions by 2030, compared to 2005 levels, which was nine percentage points short of the 36% target outlined in the plan at the time. The emission reduction target has since been revised to 48%, and the projections in the updated NECP based on updated policies still fall short of the ambitious target (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie 2023). Despite this target and Austria’s non-binding ambition of becoming climate neutral by 2040, Austria’s emissions reductions have been slower than the EU average (European Parliament 2021). Current projections predict that emissions will remain relatively constant in Austria (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie 2023), highlighting the need for policy intervention if the country is to meet its climate goals. Designing effective climate policy into the future requires evaluating the effectiveness of policies that have been implemented to date.

Much research has explored the effectiveness of climate policy in Austria, overwhelmingly concluding that policies have been ineffectual compared to the reduc-

tions needed to meet Austria’s climate goals (Niedertscheider, Haas, and Görg 2018; Winkler and Winiwarter 2016; Schaffrin, Sewerin, and Seubert 2014; Kettner and Kletzan-Slamanig 2018; Steurer and Clar 2015; Steurer, Clar, and Casado-Asensio 2020). Austria’s approach to climate policy has primarily relied on regulatory and financial instruments (Schaffrin, Sewerin, and Seubert 2014), and since 1990, the country has implemented a climate protection act in 2013 (with binding targets towards 2020), two climate strategies, an adaptation strategy, and many new institutions, programs and climate change mitigation measures at the local and regional levels (Niedertscheider, Haas, and Görg 2018). Emissions themselves peaked in 2005 and have generally fallen since, but evidence suggests that this is primarily due to short-term drivers of emissions and structural changes in the economy rather than effective policy (Niedertscheider, Haas, and Görg 2018; Winkler and Winiwarter 2016; Schaffrin, Sewerin, and Seubert 2014; Kettner and Kletzan-Slamanig 2018; Steurer and Clar 2015; Steurer, Clar, and Casado-Asensio 2020). The reasons for the failure of Austrian climate policy include inconsistency across policies and low commitment levels (Niedertscheider, Haas, and Görg 2018), weakened climate policy in favour of other objectives, such as competitiveness or employment (Kettner and Kletzan-Slamanig 2018), and Austria’s federalist political system (Steurer and Clar 2015; Steurer, Clar, and Casado-Asensio 2020). The latter explains why, even in the presence of ambitious federal and EU-level targets, policy has been watered-down at the provincial level in order to find lowest-common-denominator solutions. Criticisms of Austria’s policy range from the balanced view that, “[Austria is] neither an environmental policy leader nor a laggard, but an opportunist,” (Steurer and Clar 2015), to more critical remarks, such as, “Austria tends towards symbolic policy innovations without ‘real teeth’” (Schaffrin, Sewerin, and Seubert 2014).

While the literature has been critical of Austria’s climate policy, it confirms that policy itself is a key factor in reducing emissions across Austrian sectors. Emission forecasts under different scenarios indicate that significant reductions are possible, and that they require significant government intervention to meet climate targets (Winkler and Winiwarter 2016). Policies targeting sector-level emissions are necessary, as has been explored with regard to the Austrian building and construction (Steurer, Clar, and Casado-Asensio 2020), land and water use (Schönhart et al. 2018), tourism (Gössling and Lund-Durlacher 2021) and energy sectors (Schmidt et al. 2011).

2.2 Carbon dioxide (CO_2) emissions in Austria

In determining which emissions reduction policies are most effective, it is useful to first understand the nature of emissions in Austria. In this paper, we focus on CO_2 emissions from fossil fuels, as they make up the largest share of greenhouse gas emissions, and they have contributed most to global greenhouse gas emissions growth (IPCC 2022). The Intergovernmental Panel on Climate Change (IPCC) outlines stringent guidelines on the reporting of CO_2 emissions, and they provide a framework for disaggregating emissions into categories based on sectors (Eggleston et al. 2006). Table 1 outlines the 21 relevant IPCC sectors for Austria, aggregated at three different levels. Level 1 is the highest level of aggregation, whereby CO_2 emissions are split into only four categories, while level 3 includes all 21 categories.

To achieve climate neutrality, it is necessary to target sectors for which emissions are highest. In 2021, total emissions for Austria were driven primarily by road transportation (33% of CO_2 emissions), electricity and heat production (19%), manufacturing and construction (16%), and residential uses (12%) (IEA-EDGAR CO2 2022). Figure 1 provides a breakdown of total annual emissions for all 21 categories in 2021. The four aforementioned IPCC categories collectively make up more than 80% of annual emissions. Aggregated to level 1, energy makes up over 90% of emissions,

Table 1: IPCC sectors aggregated at three levels

Level 1	Level 2	Level 3
Agriculture, Forestry, and Other Land Use	Aggregate sources and non-CO2 emissions sources on land	Liming
Agriculture, Forestry, and Other Land Use	Aggregate sources and non-CO2 emissions sources on land	Urea application
Industrial Processes and Product Use	Mineral Industry	Glass Production
Industrial Processes and Product Use	Mineral Industry	Other Process Uses of Carbonates
Industrial Processes and Product Use	Mineral Industry	Lime production
Industrial Processes and Product Use	Mineral Industry	Cement production
Industrial Processes and Product Use	Non-Energy Products from Fuels and Solvent Use	Non-Energy Products from Fuels and Solvent Use
Industrial Processes and Product Use	Chemical Industry	Chemical Industry
Industrial Processes and Product Use	Metal Industry	Metal Industry
Energy	Fuel Combustion Activities	Main Activity Electricity and Heat Production
Energy	Fuel Combustion Activities	Manufacturing Industries and Construction
Energy	Fuel Combustion Activities	Residential and other sectors
Energy	Fugitive emissions from fuels	Solid Fuels
Energy	Fuel Combustion Activities	Civil Aviation
Energy	Fuel Combustion Activities	Road Transportation no re-suspension
Energy	Fuel Combustion Activities	Water-borne Navigation
Energy	Fuel Combustion Activities	Other Transportation
Energy	Fugitive emissions from fuels	Oil and Natural Gas
Energy	Fuel Combustion Activities	Petroleum Refining - Manufacture of Solid Fuels and Other Energy Industries
Energy	Fuel Combustion Activities	Railways
Waste	Incineration and Open Burning of Waste	Incineration and Open Burning of Waste

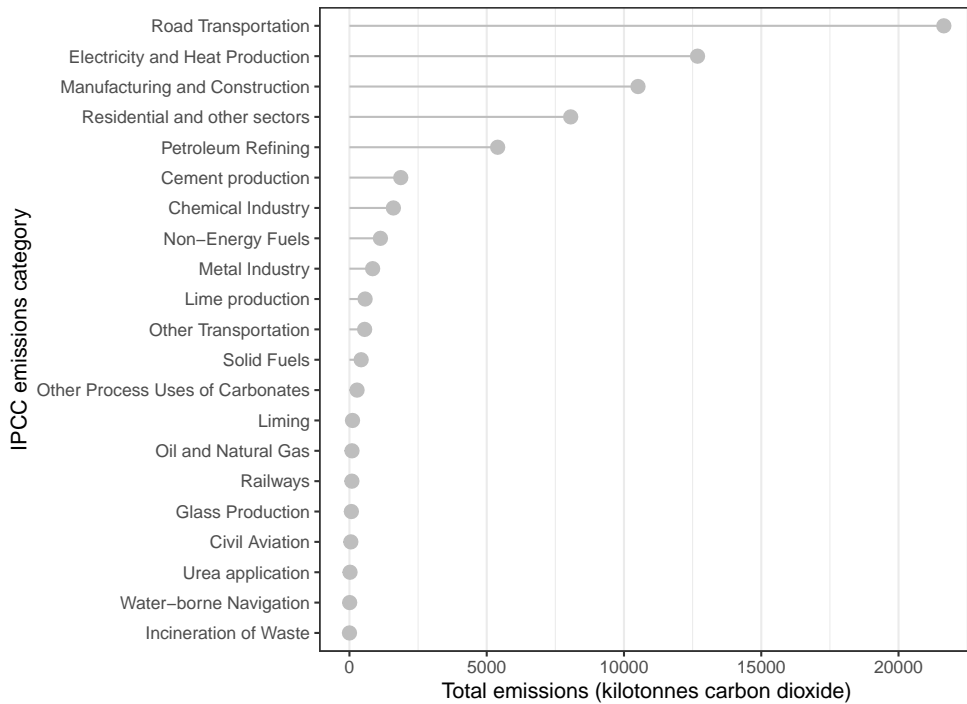


Figure 1: Breakdown of total CO_2 emissions by IPCC emissions category in Austria, 2021. Emissions are in kilotonnes of carbon dioxide.

and 9.6% comes from emissions of industrial processes and product use (IPPU). This means that waste, agriculture, forestry and other land use emissions account for less than one percent of the total CO_2 emissions in Austria.

On top of aggregate levels of emissions, it is important for policy makers to consider differences in the dynamics of CO_2 emissions over time. Figures 2, 3 and 4 display the time series of CO_2 emissions for Austria from 1995-2021, aggregated at levels 1, 2 and 3, respectively. Considering level 1 categories, we observe markedly different dynamics between sectors, with agricultural emissions trending upwards, energy emissions peaking sharply in 2005 and declining afterwards, industrial emissions appearing to have dropped to a new steady-state around 1990, and emissions from waste showing two significant drops around 1990 and 2008. It is important to note the difference in scale between categories in the figure, being mindful of the large differences in absolute emissions, as outlined above. The differences in temporal dynamics of sectors highlights the need to evaluate climate policies on the sector level, as we implement in our approach.

3 Methods

3.1 Which policies have reduced emissions the most?

Systematically evaluating all of Austria’s climate policies presents significant challenges and requires thinking about policy evaluation in a new way, compared to traditional approaches. Traditional policy evaluation involves selecting a specific policy and determining if it had a significant effect, having controlled for relevant factors. Various methods have been developed using this approach to assess climate policy, largely based on difference-in-difference estimation and matching methods (Lin and Li 2011; Klemetsen, Rosendahl, and Jakobsen 2020; Colmer et al. 2022). With such

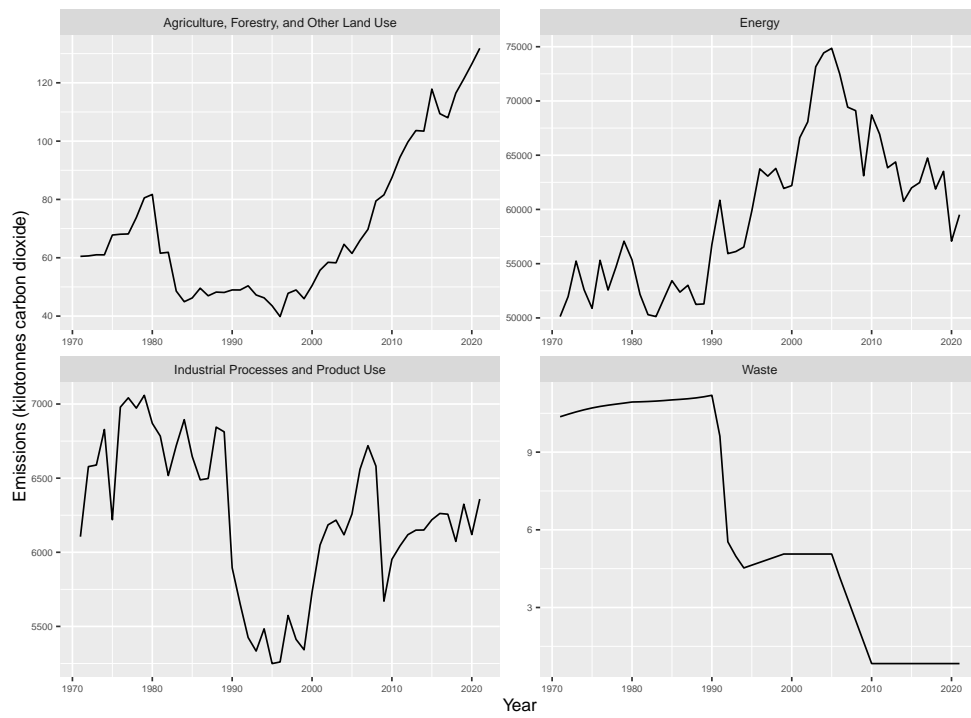


Figure 2: Emissions for IPCC emissions (level 1). CO_2 emissions in kilograms are shown for the period 1995 to 2021.

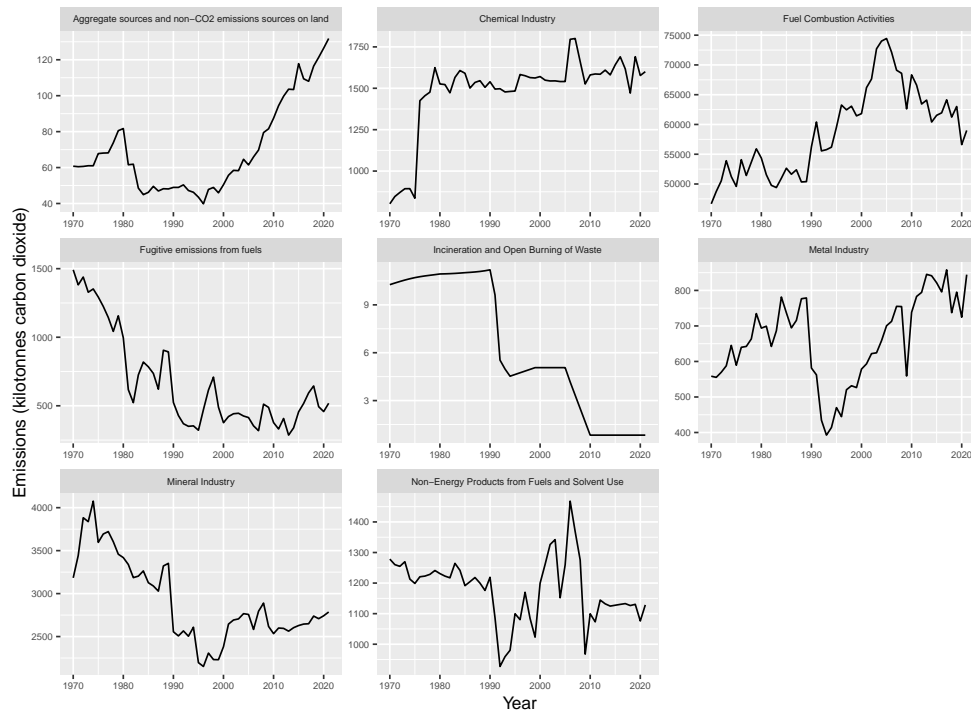


Figure 3: Emissions for IPCC emissions (level 2). CO_2 emissions in kilograms are shown for the period 1995 to 2021.

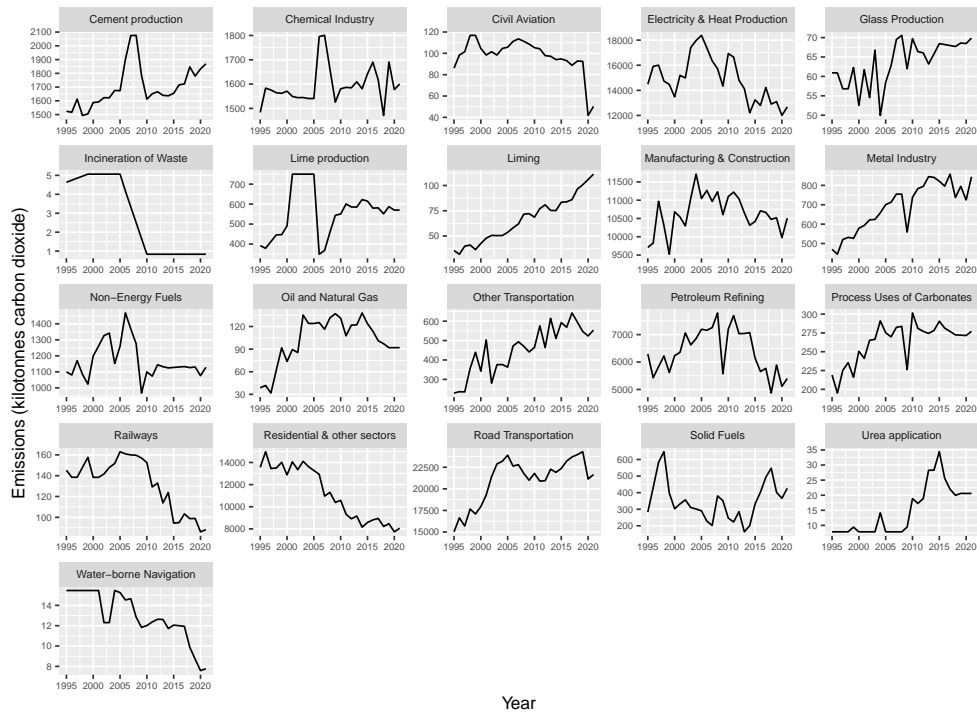


Figure 4: Emissions for IPCC emissions (level 3). CO_2 emissions in kilotonnes are shown for the period 1995 to 2021.

methods, answering the question, “Which policies have reduced emissions the most?” would require the researcher to have knowledge of all policies in all sectors, and they would need to test the effect of each of these policies, individually. Not only would this be highly intensive, but it risks overlooking policies and fails to account for the effect of policy mixes if one only evaluates policies on an individual basis (Koch et al. 2022). Thus, to answer this question, it would be useful to take an approach that does not require individually evaluating all known policies.

In this paper, we use an alternative approach based on reverse causal reasoning, which searches for “causes of effects,” rather than for “effects of causes” (Gelman and Imbens 2013). Simply, we ask the question, “What reduced emissions the most?” rather than, “How much did policy X reduce emissions by?” Reverse causal analysis involves identifying significant reductions in emissions, having controlled for relevant factors, then reverse-attributing these reductions to a policy or policy mix. Koch et al. (2022) pioneer this approach in evaluating emission reduction policies, specifically for road transport CO_2 emissions in the EU. They then attribute these significant emission reduction events to relevant policies.

We employ the approach of Koch et al. (2022) to find which CO_2 emission reduction policies have been most effective in Austria between 1995 and 2021. We implement a general-to-specific (GETS) variable selection method (Krolzig and David F. Hendry 2001) to identify statistically significant structural breaks in emissions, using other EU countries as a control group. EU member nations are suitable controls as the bloc has EU-wide technological standards and harmonised regulatory frameworks, while still allowing for individual countries to implement their own climate policies. Alternative approaches to variable selection could be employed, such as LASSO based shrinkage methods (Tibshirani 1996), or Bayesian approaches to variable selection (O’Hara and Sillanpää 2009).

3.2 Data

The data for CO_2 emissions come from the IEA-EDGAR CO2 database, a component of the EDGAR (Emissions Database for Global Atmospheric Research) Community GHG database, version 7.0 (IEA-EDGAR CO2 2022). We use only CO_2 emissions from fossil fuel sources. The data for GDP and population are taken from the World Bank database (The World Bank 2022a; The World Bank 2022b). The dependent variable in our empirical model specification is the natural logarithm of CO_2 emissions. The natural logarithm of GDP, its square, and the natural logarithm of the population level are used as control variables.

We use two separate samples of EU countries to test the robustness of identified structural breaks. The first is the EU15 countries (Austria, Belgium, Germany, Denmark, Spain, Finland, France, United Kingdom, Ireland, Italy, Luxembourg, Netherlands, Greece, Portugal and Sweden). These countries are subject to similar regulations, specifically because they were part of the European Single Market during most of the sample period of 1995-2021. The second sample includes a broader sample of countries, including the EU27 countries (EU15, Croatia, Bulgaria, Cyprus, Czechia, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia, Slovenia), and the European Free Trade Association (EFTA) states (Iceland, Liechtenstein, Norway and Switzerland). This sample is referred to as EU31.

3.3 Empirical approach

We estimate a panel model using two-way fixed effects (TWFE), and using a general-to-specific (GETS) variable selection approach to identify significant structural breaks in Austrian CO_2 emissions, across all 21 IPCC sectors from 1995-2021. We repeat the modelling at aggregation levels 1, 2 and 3 of the sectors, as detailed in Table 1. Generally, the GETS model places no restriction on the number of variables one can include in a general model, and uses a block search machine learning algorithm to keep only the statistically significant variables, given a target level of significance. This allows us to include every possible treatment effect (every country-year pair), for a given emissions category. The algorithm then removes insignificant variables, or country-year pairs that do not represent a significant structural break in emissions, resulting in a specific model that includes only the statistically significant breaks. A detailed explanation of this approach is outlined in Pretis and Schwarz (2022).

This approach becomes clearer when considering our specific model. We model the natural logarithm of CO_2 emissions for a given sector as a function of control variables $\log(GDP)$, $\log(GDP)^2$ and $\log(Population)$, we include country and year fixed effects, and a saturated set of possible treatment effects. We re-estimate this model individually for all sectors, aggregated at levels 1, 2 and 3, and for both samples: EU15 and EU31. Treatment effects for a given emissions category enter the model as indicators: interaction terms of country and year fixed effects. This allows for any country-year combination to be considered as a potential structural break. For example, in modelling road transportation CO_2 emissions, an indicator which interacts Austria and 2010 will display as a 1 for all observations for Austria from 2010 onward, and 0 otherwise. The coefficient on this indicator can be interpreted as a heterogeneous treatment effect, revealing a step-change in road transportation CO_2 emissions from 2010 onward, as compared to other countries in the sample. The interpretation of the coefficient is similar to that of a difference-in-difference estimator.

In a standard difference-in-difference estimation, the researcher would include an indicator for a specific, known treatment, such as a policy implemented in a given year. Here, rather than using a known treatment effect, we include all potential treatment effects as indicator variables, and significant ones can be interpreted

as a treatment for a particular country in a given sector. Insignificant indicators are omitted from the final specific model. While this may be intuitive, implementing such a method is problematic as the saturated model contains more variables than observations. With the EU15 sample and 26 time periods, we would have 390 indicators (or potential treatment effects). The country-year indicator variables that are insignificant are removed from the model, allowing us to move from the general to the specific model containing only significant indicator variables. A significant indicator, or structural break, represents a large, statistically significant step change in country-specific CO_2 emissions for that emissions category, relative to the control group and conditional on GDP and population.

Using a balanced panel with N countries and T time periods, the resulting general model for a given emissions category includes $N(T - 1)$ potential breaks, with corresponding coefficients $\tau_{j,s}$ on the indicator variables as shown below,

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

where α_i and ϕ_t denote the country and time fixed effects, $x'_{i,t}$ is a vector of control variables, including $\log(GDP)$, $\log(GDP)^2$ and $\log(Population)$, with the corresponding vector of coefficients, β , and an error term, $\epsilon_{i,t}$. The coefficients, $\tau_{j,s}$, on the indicator variables, $1_{\{i=j, t \geq s\}}$, are 0 for all but the treated country, and for all time periods before that of the relevant break. $\tau_{j,s}$ represents the coefficients on the full set of step functions, which is reduced to only the significant structural breaks in the specific model,

$$\log(\widehat{CO_2})_{i,t} = \hat{\alpha}_i + \hat{\phi}_t + \sum_{j \in \widehat{Tr}} \sum_{s \in \widehat{T}_j} \hat{\tau}_{j,s} 1_{\{i=j, t \geq s\}} + x'_{i,t} \hat{\beta} \quad (2)$$

where \widehat{Tr} represents treated countries and \widehat{T}_j represents treatment times for each treated country, $j \in \widehat{Tr}$. $\hat{\tau}_{j,s}$ corresponds to the coefficients on the set of significant, heterogeneous treatments effects, or identified structural breaks. This determines our estimated set of statistically significant CO_2 emission reduction events. Following the previous example, the coefficient on a significant reduction in road transportation emissions in Austria in 2010 would be denoted $\hat{\tau}_{Austria, 2010}$, representing a significant step change in road CO_2 emissions from 2010 onward.

Moving from the general model (1) to the specific model (2) relies on machine learning, using the “getspanel” package in the statistical software, R (Pretis and Schwarz 2021), based on the block search algorithm in the “gets” R package (Pretis, Reade, and Sucarrat 2018). This method is part of the general-to-specific family of model selection methods. Calibrating this model primarily involves choosing the level of target significance, to control for the expected false-positive rate of the selected indicators, or structural breaks in the specific model. We estimate coefficients with three different levels of target significance, 5%, 1% and 0.1%. It has been shown that in this setting, the expected false-positive rate asymptotically tends towards the target significance level (Nielsen and Qian 2018). In the context of identifying structural breaks, a target significance of 0.1% would be expected to falsely identify $0.1\% \times N(T - 1)$ spurious breaks, which would be less than 1 using either the EU15 or EU31 sample. Using different target significance levels provides a test of the robustness of the identified breaks. We use low target significance levels to target low false positive rates, which means identified breaks are likely to constitute large reductions in emissions. The target significance effectively implies a minimum effect size, and smaller CO_2 emission reduction events may not be identified with very low target significance levels. We believe that this focus on large reductions in emissions is justified by the urgency

of the need to address the climate crisis and the ambition of Austria’s emissions reduction target.

Once the specific model has been identified for each emissions category, we extract only the treatments relating to negative structural breaks in Austria, and attribute these to relevant policies. As the process reveals an emissions break with an approximate margin of error, denoted by a 95% confidence interval around the break year, we seek to attribute policies to each identified break within the interval, using the International Energy Agency’s (IEA’s) Policies and Measures Database. This includes past, current and planned climate and energy policies from governments, international organisations and the IEA, periodically reviewed by national governments. Breaks of other countries and positive structural breaks are excluded from this analysis.

4 Results

In response to the question, “Which policies have reduced emissions the most in Austria?” the reverse causal approach identifies five significant, negative structural breaks in emissions, in the period 1995-2021. Out of a potential 525 treatment effects for Austria alone, based on 25 treatment periods and 21 sectors, only these five breaks were identified as being statistically significant. The first key result is that there were very few significant reductions in CO_2 emissions which were not explained by variations in population size and GDP. The identified breaks collectively represent a total reduction in CO_2 emissions of less than 2.5% of Austria’s total annual emissions, based on 2005 levels. This is considerably lower than the 48% target for 2030 as outlined in Austria’s NECP.

Table 2 summarises the five identified breaks. The table is split into three sections, delineating between the aggregation level of sectors. The IPCC Category column shows which emissions category the break was identified for, with the corresponding year in the second column. The coefficient can be interpreted as the proportion by which emissions were reduced, compared to a counterfactual, i.e. if there had been no structural break. The coefficient displayed here is that for the model with the lowest target significance level (the highest confidence level). The dots (denoted as •) in the Significance Level and Sample columns correspond to models in which the given break was identified. For example, while the 2009 break in incineration of waste was found in both samples and at all target significance levels, the 2015 break in petroleum refining was only identified at a 5% significance level, using the EU15 sample. Further, the lower the target significance level, the lower the expected false positive rate, and thus the more confident one can be about the identified break.

Looking at the individual breaks, the break sizes differ in magnitude between a -0.19 in 2015 emissions from petroleum refining, to -1.54 in 2009 emissions for the incineration of waste. The -0.19 coefficient can be interpreted as CO_2 emissions being 19% lower than they would have been, in the absence of a structural break. For lime production emissions, we identify a break of -0.82 in 2006. For water-borne navigation, we identify two breaks, one in 2006 with a coefficient of -0.25 and one in 2007 with a coefficient of -0.22. Given that the two breaks for water-borne navigation are of similar magnitude and are identified in separate samples with overlapping confidence intervals, it is likely that they represent the same underlying structural break. Tables 3, 4 and 5 outline the individuals breaks in detail, aggregated at the level 1, 2 and 3 sectors, respectively. These tables can be used to compare coefficient estimates between models to determine the stability of the magnitude of the structural breaks between models. While there is some variation in coefficient estimates, they are generally stable.

Table 2: Negative structural breaks identified across all IPCC sectors for Austria between 1996 and 2021

IPCC Category (Level 1)	Year	Coefficient	Significance level			Sample	
			5%	1%	0.1%	EU15	EU31
Waste	2009	-1.54	•	•	•	•	•
IPCC Category (Level 2)							
Incineration of Waste	2009	-1.54	•	•	•	•	•
IPCC Category (Level 3)							
Incineration of Waste	2009	-1.54	•	•	•	•	•
Lime production	2006	-0.82	•	•	•	•	
Petroleum Refining	2015	-0.19	•			•	
Water-borne Navigation	2006	-0.25	•	•			•
Water-borne Navigation	2007	-0.22	•	•		•	

Note: coefficients displayed here are those for the model with the lowest target significance.

Table 3: Negative structural breaks in Austrian emissions (Level 1)

	Category	Sample	Significance	Year	Coefficient
1	Waste	EU15	5%	2009	-1.43
2	Waste	EU15	1%	2009	-1.55
3	Waste	EU15	0.1%	2009	-1.65
4	Waste	EU31	5%	2009	-1.39
5	Waste	EU31	1%	2009	-1.49
6	Waste	EU31	0.1%	2009	-1.54

Table 4: Negative structural breaks in Austrian emissions (Level 2)

	Category	Sample	Significance	Year	Coefficient
1	Incineration and Open Burning of Waste	EU15	5%	2009	-1.43
2	Incineration and Open Burning of Waste	EU15	1%	2009	-1.55
3	Incineration and Open Burning of Waste	EU15	0.1%	2009	-1.65
4	Incineration and Open Burning of Waste	EU31	5%	2009	-1.39
5	Incineration and Open Burning of Waste	EU31	1%	2009	-1.49
6	Incineration and Open Burning of Waste	EU31	0.1%	2009	-1.54

Table 5: Negative structural breaks in Austrian emissions (Level 3)

	Category	Sample	Significance	Year	Coefficient
1	Incineration and Open Burning of Waste	EU15	5%	2009	-1.43
2	Incineration and Open Burning of Waste	EU15	1%	2009	-1.55
3	Incineration and Open Burning of Waste	EU15	0.1%	2009	-1.65
4	Incineration and Open Burning of Waste	EU31	5%	2009	-1.39
5	Incineration and Open Burning of Waste	EU31	1%	2009	-1.49
6	Incineration and Open Burning of Waste	EU31	0.1%	2009	-1.54
7	Lime production	EU15	5%	2006	-0.63
8	Lime production	EU15	1%	2006	-0.82
9	Lime production	EU15	0.1%	2006	-0.82
10	Petroleum Refining	EU15	5%	2015	-0.19
11	Water-borne Navigation	EU15	5%	2007	-0.21
12	Water-borne Navigation	EU15	1%	2007	-0.22
13	Water-borne Navigation	EU31	5%	2006	-0.26
14	Water-borne Navigation	EU31	1%	2006	-0.25

We generate counterfactual plots of the time series, showing what the time series would look like in the absence of the break, and also plot the fitted models, based on the obtained coefficients. Figure 5 displays the counterfactual plots for three years following the break date plotted in red, displayed as $\log(CO_2)$ in the absence of the estimated breaks. The black line shows the actual time series of $\log(CO_2)$, the blue line displays the fitted model and the vertical red lines denote the date of the structural break, with grey bands displaying the 95% confidence intervals around the break date.

After identifying significant structural breaks, we attribute them to relevant policies occurring around the break date, as displayed in Table 6. The policies range in their nature, from subsidy schemes, to climate strategies and cap-and-trade systems. It should be noted that none of the policies identified were developed to directly target the corresponding emissions category, but they can be indirectly attributed to reducing emissions in that category. For example, the *Ökostromverordnung* policy (Bundeskanzleramt Österreich 2009) attributed to waste incineration emissions in 2009 is a schedule of subsidies provided for green electricity production, including for electricity from landfill gas and biomass. This may have indirectly reduced the amount of waste being incinerated, using the waste material to make fuels instead. Alternatively, this reduction in emissions from waste incineration in 2009 could have been caused by the phasing out of the low-standard-landfill tax in 2009, while the tax on waste incineration remained in place, potentially incentivising substitution away from from incineration to landfill (European Environment Agency 2013). These taxes are not displayed in Table 6 as this explanation constitutes an unintended impact of the removal of a policy, rather than the direct attribution of a policy's impact.

Regarding the reduction in lime production emissions, the emissions trading system implemented in 2005 included the iron, steel and mineral industries. While the policy may not have targeted lime production directly, it may have reduced the demand for lime, an input in the production of iron and steel. The 2015 break in petroleum refining is linked to subsidies implemented in 2014 for residential buildings

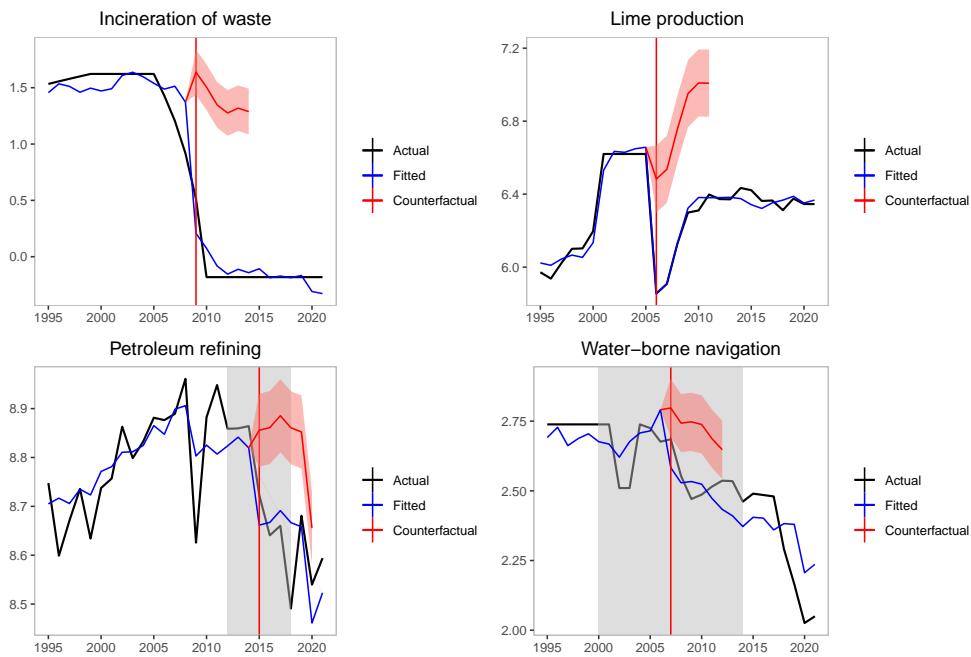


Figure 5: Actuals, fitted model and counterfactuals for $\log(CO_2)$ emissions. The figure contrasts actual emissions (black) with the fitted model based on estimated coefficients (blue) and counterfactuals for three years after the identified break (red). Light red shading depicts 95% confidence intervals around the counterfactuals. Vertical red lines show the date of structural breaks, with grey shading representing the symmetrical 95% confidence intervals around break dates. Models were run with a 5% target significance level.

Table 6: Policy attribution to negative structural breaks

Sector	Year of break	Policy title	Policy year	Policy type	Description
Incineration of waste	2009	Ökostrom-verordnung	2009	Subsidy	Feed-in tariffs for green electricity, including landfill gas, biomass and biogas, diverting waste from landfill.
Lime production	2006	Emission Trading System	2005	Cap & trade	Emission Trading System implemented in 2005, which affected the iron, steel and other mineral industries.
Petroleum refining	2015	Residential building, energy and environmental subsidies	2014	Subsidy	Subsidies aimed at reducing natural gas consumption by residential actors.
Water-borne navigation	2006-2007	Klima:aktiv programme Renewable Energy	2005	Strategy	Climate strategy including provisions for biogas and biomethane for transport use.

to improve heating standards, thereby potentially reducing demand for natural gas, and subsequently for petroleum refining. Finally, the reduction in water-borne navigation emissions are linked to the climate strategy developed in 2005, which included provisions for bio-gas and bio-methane for transport use.

The attribution of policies to structural breaks should be interpreted with caution due to the nature of emissions in the categories in which breaks were identified. Firstly, three of the sectors - the incineration of waste, lime production and water-borne navigation - together make up less than 1% of Austria's total CO_2 emissions. As the absolute level of emissions in these categories is very low, even a small reduction in emissions would represent a large relative decrease, and thus be identified as a statistically significant reduction. This implies that CO_2 reductions in these sectors would not significantly contribute to Austria's climate targets. The fourth sector in which we identify a structural break is petroleum refining, which contributes to 8% of Austria's total emissions. These emissions, however, come from just a single refinery in Austria, meaning emissions in this category are entirely subject to idiosyncrasies in the emissions of this particular facility. A myriad of external factors could have affected the operations and performance of this facility in 2015, making the causal link of the break to a single policy tenuous. For example, the refinery's company, OMV, highlighted in their 2015 Annual Report that the Europe region has too much refining capacity for its demand, causing them to reduce production (OMV 2015).

Finally, we consider the performance of the model by comparing the fitted model to the actual time series of emissions in four sectors with the most emissions: road transportation, electricity and heat production, residential and other sectors, and manufacturing and construction (Figure 6). The fitted models show expected emissions, based on GDP and population data, using the coefficients obtained in the estimated model. No structural break was found in the four sectors displayed, so we use these plots to infer how well the model performs in predicting emissions. As can be seen from the close fit between actual and predicted emissions, one can be confident in the setup of the model, both in using GDP and population as control variables, and in using EU countries as a control group.

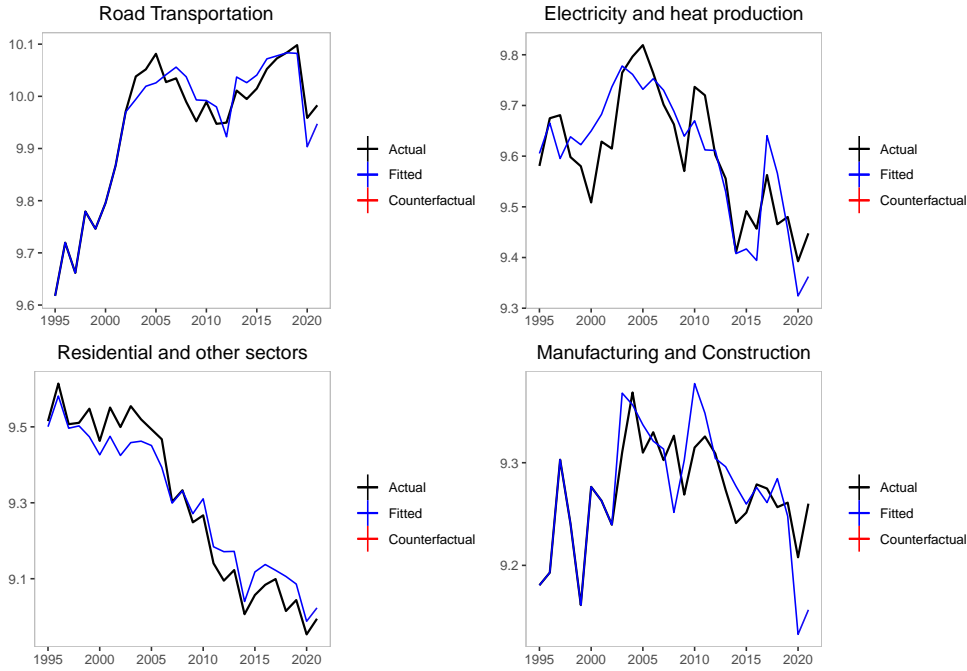


Figure 6: Actuals and fitted model for $\log(CO_2)$ emissions. The figure depicts the actual emissions (black) and the fitted model based on estimated coefficients (blue) for the four largest sectors. Models were run with a 5% target significance level.

5 Conclusion

In this study, we apply a reverse causal approach to policy evaluation to answer the question, “Which policies have reduced emissions the most in Austria?” This analysis complements existing literature about climate policy evaluation, which is based largely on forward-causal reasoning. The reverse causal approach is holistic and policy-agnostic as it does not require the exogenous, prior selection of policies for analysis, and rather, it identifies significant reductions in emissions, then seeks to attribute these to relevant policies. With Austria’s goal of reducing emissions by 48% by 2030 compared with 2005 levels, towards the EU’s overall 2050 climate neutrality goal, it is critical to determine which policy or set of policies have been most effective to date, to thus inform future policy design.

Our analysis confirms the findings of the existing literature that Austria’s climate policies have been largely ineffectual from 1995-2021. We identify five structural breaks in CO_2 emissions, that is, significant reductions in emissions that are not accounted for by variations in GDP or population, relative to a control group of similar EU countries. These are in the following sectors: petroleum refining, waste incineration, lime production, and water-borne navigation. Overall, emissions from these sectors make up less than 9% of Austria’s emissions, and the combined reduction in total emissions estimated by the structural breaks accounts for less than 2.5% of Austria’s emissions. This is markedly lower than Austria’s emissions reduction target. We attribute these emissions reductions to a range of policies, including subsidies for green electricity, the emissions trading scheme and Austria’s climate strategy, but the causal links are tenuous due to the idiosyncratic nature of the four sectors. The overall policy implication of our findings is that significant work needs to be done to implement more effective policies, if Austria is to meet its climate targets.

The reverse causal approach derives its greatest benefit from its holistic and agnostic nature, but it is not without its limitations. As the structural break identification approach relies on a control group (other EU member nations), the method will not identify breaks that are apparent across the entire sample. This means, EU-wide policies that were implemented in all countries at the same time, providing that they have similar impacts on emissions, would not be detected. This can be overcome in future research by using a broader sample, such as the use of all OECD countries as the sample group. Further, the calibration of the model with low target significance levels (and thus low false positive rates), means that real, but small, structural breaks may not be detected. Simply, this approach is likely to only identify larger effects. The inability to detect smaller breaks would mean the magnitude of identified breaks can be considered a lower bound estimate. Given the need for timely and large-scale emissions reductions, this focus on larger breaks may be justified.

Further research into climate policy effectiveness could benefit from using the reverse causal approach, extending the analysis beyond the identification of negative structural breaks in Austria's emissions. Repeating such an exercise for other countries will improve the external validity of the findings, specifically the attribution of policies and identifying which policies are most useful across a range of contexts and countries. This may provide for more general policy guidance on which policies across Europe, for example, have been most effective in reducing emissions, highlighting "role models" for future policy development. Additionally, investigation of positive structural breaks may provide insight into causes of increased emissions, which may allow researchers to identify unintended consequences of policies. Overall, given the significant challenges across the world to achieve climate goals, further research into effective policy evaluation is critical to ensuring policy makers implement interventions that will achieve emissions reductions in the most effective way possible.

References

- Bundeskanzleramt Österreich (2009). *53. Verordnung: Ökostromverordnung 2009*. URL: https://rdb.manz.at/document/ris.c.BGB1__II_Nr__53_2009.
- Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie (2023). *Integrierter nationaler Energie- und Klimaplan für Österreich. Periode 2021-2030*. URL: https://www.bmk.gv.at/themen/klima_umwelt/klimaschutz/nat_klimapolitik/energie_klimaplan.html.
- Castle, Jennifer L, Michael P Clements, and David F Hendry (2016). “An overview of forecasting facing breaks”. In: *Journal of Business Cycle Research* 12.1, pp. 3–23.
- Colmer, Jonathan et al. (2022). “Does pricing carbon mitigate climate change? Firm-level evidence from the European Union emissions trading scheme”. In: *CEPR Discussion Paper No. DP16982*. URL: <https://ssrn.com/abstract=4026889>.
- Eggleston, HS et al. (2006). *2006 IPCC guidelines for national greenhouse gas inventories*. URL: https://www.ipcc-nggip.iges.or.jp/meeting/pdffiles/Washington_Report.pdf.
- European Environment Agency (2013). *Municipal waste management in Austria*. URL: <https://www.eea.europa.eu/publications/managing-municipal-solid-waste/austria-country-paper-on-municipal>.
- European Parliament (2021). *Climate action in Austria - Latest state of play. EU progress on climate action – How are the Member States doing?* European Parliamentary Research Service. URL: [https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/696186/EPRS_BRI\(2021\)696186_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/696186/EPRS_BRI(2021)696186_EN.pdf).
- Gelman, Andrew and Guido Imbens (Nov. 2013). “Why ask Why? Forward Causal Inference and Reverse Causal Questions”. In: Working Paper Series 19614. DOI: 10.3386/w19614. URL: <http://www.nber.org/papers/w19614>.
- Gössling, Stefan and Dagmar Lund-Durlacher (2021). “Tourist accommodation, climate change and mitigation: An assessment for Austria”. In: *Journal of Outdoor Recreation and Tourism* 34, p. 100367.
- Hamilton, Clive and Hal Turton (2002). “Determinants of emissions growth in OECD countries”. In: *Energy Policy* 30.1, pp. 63–71.
- IEA-EDGAR CO2 (2022). *IEA-EDGAR CO2, a component of the EDGAR (Emissions Database for Global Atmospheric Research) Community GHG database version 7.0 (2022) including or based on data from IEA (2021) Greenhouse Gas Emissions from Energy*. Online; accessed 22 December 2022. URL: https://edgar.jrc.ec.europa.eu/dataset_ghg70.
- IPCC (2022). “Summary for Policymakers”. In: *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by P.R. Shukla et al. Cambridge, UK and New York, NY, USA: Cambridge University Press. DOI: 10.1017/9781009157926.001. URL: https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_SummaryForPolicymakers.pdf.
- Kettner, Claudia and Daniela Kletzan-Slamanig (2018). “Climate policy integration on the national and Regional level: A case study for Austria and styria”. In: *International Journal of Energy Economics and Policy* 8.4, p. 259.
- Klemetsen, Marit, Knut Einar Rosendahl, and Anja Lund Jakobsen (2020). “The impacts of the EU ETS on Norwegian plants’ environmental and economic performance”. In: *Climate Change Economics* 11.01, p. 2050006.
- Koch, Nicolas et al. (2022). “Attributing agnostically detected large reductions in road CO2 emissions to policy mixes”. In: *Nature Energy* 7.9, pp. 844–853.
- Krolzig, Hans-Martin and David F. Hendry (2001). “Computer automation of general-to-specific model selection procedures”. In: *Journal of Economic Dynamics*

- and Control* 25.6. Computing, economic dynamics, and finance, pp. 831–866. ISSN: 0165-1889. DOI: [https://doi.org/10.1016/S0165-1889\(00\)00058-0](https://doi.org/10.1016/S0165-1889(00)00058-0). URL: <https://www.sciencedirect.com/science/article/pii/S0165188900000580>.
- Lin, Boqiang and Xuehui Li (2011). “The effect of carbon tax on per capita CO₂ emissions”. In: *Energy policy* 39.9, pp. 5137–5146.
- Niedertscheider, Maria, Willi Haas, and Christoph Görg (2018). “Austrian climate policies and GHG-emissions since 1990: What is the role of climate policy integration?” In: *Environmental science & policy* 81, pp. 10–17.
- Nielsen, B and M Qian (2018). “Asymptotic properties of the gauge of step-indicator saturation”. Working paper. URL: <https://ora.ox.ac.uk/objects/uuid:2d273e00-b88d-4741-afef-2af764622265>.
- O’Hara, R. B. and M. J. Sillanpää (2009). “A review of Bayesian variable selection methods: what, how and which”. In: *Bayesian Analysis* 4.1, pp. 85–117. DOI: 10.1214/09-BA403. URL: <https://doi.org/10.1214/09-BA403>.
- OMV (2015). *Annual Report 2015*. URL: <https://www.omv.com/en/investor-relations/publications?year=2015#interim-reports>.
- Pretis, Felix (2022). “Does a carbon tax reduce CO₂ emissions? Evidence from British Columbia”. In: *Environmental and Resource Economics* 83.1, pp. 115–144.
- Pretis, Felix, James Reade, and Genaro Sucarrat (2018). “Automated general-to-specific (GETS) regression modeling and indicator saturation for outliers and structural breaks”. In: *Journal of Statistical Software* 86, pp. 1–44.
- Pretis, Felix and Moritz Schwarz (2021). *getspanel*. GitHub repository.
- (2022). “Discovering what mattered: answering reverse causal questions by detecting unknown treatment assignment and timing as breaks in panel models”. In: *SSRN 4022745*. URL: <https://ssrn.com/abstract=4022745>.
- Schaffrin, André, Sebastian Sewerin, and Sibylle Seubert (2014). “The innovativeness of national policy portfolios—climate policy change in Austria, Germany, and the UK”. In: *Environmental Politics* 23.5, pp. 860–883.
- Schmidt, Johannes et al. (2011). “Cost-effective policy instruments for greenhouse gas emission reduction and fossil fuel substitution through bioenergy production in Austria”. In: *Energy Policy* 39.6, pp. 3261–3280.
- Schönhart, Martin et al. (2018). “Modelled impacts of policies and climate change on land use and water quality in Austria”. In: *Land Use Policy* 76, pp. 500–514.
- Steurer, Reinhard and Christoph Clar (2015). “Is decentralisation always good for climate change mitigation? How federalism has complicated the greening of building policies in Austria”. In: *Policy Sciences* 48, pp. 85–107.
- Steurer, Reinhard, Christoph Clar, and Juan Casado-Asensio (2020). “Climate change mitigation in Austria and Switzerland: The pitfalls of federalism in greening decentralized building policies”. In: *Natural Resources Forum*. Vol. 44. 1. Wiley Online Library, pp. 89–108.
- The European Commission (2020). *Assessment of the final national energy and climate plan of Austria. Commission staff working document*. URL: https://energy.ec.europa.eu/system/files/2021-01/staff_working_document_assessment_necp_austria_en_0.pdf.
- The World Bank (2022a). *GDP (constant 2010 US\$). World Bank Open Data. 2022*. Online; accessed 22 December 2022.
- (2022b). *Population, total. World Bank Open Data. 2022*. Online; accessed 22 December 2022.
- Tibshirani, Robert (1996). “Regression shrinkage and selection via the lasso”. In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 58.1, pp. 267–288.
- Winkler, Thomas and Wilfried Winiwarter (2016). “Greenhouse gas scenarios for Austria: a comparison of different approaches to emission trends”. In: *Mitigation and Adaptation Strategies for Global Change* 21, pp. 1181–1196.