Shifting Gears? The Impact of Austria's Transport Policy Mix on CO2 Emissions from Passenger Cars

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Abstract

Passenger transport plays a crucial role in achieving carbon-neutrality. While a switch to zero-emission vehicles is a crucial part in this process, policy makers likely have to resort to a differentiated mix of complementary policy measures to achieve global targets on carbon-neutrality. To help policy makers design effective measures, we analyse the effect of environmental policies on CO2 emissions from passenger cars in Austria from 1965-2019. In a first step, we propose a novel environmental policy stringency index tailored to the Austrian transport sector for the period 1950-2019. In a second step, we analyse the effect of different policies on transport-related CO2 emissions in a structural vector autoregressive model. This allows us to control for possible interdependencies between the policies and remaining variables. We find that policies targeting the investment decision to buy new cars reduced emissions in Austria more significantly than policies targeting the usage of cars. The engine-related insurance tax quantitatively shows the strongest impact on emissions, while the standard fuel consumption tax shows the strongest statistical significance.

Keywords: Climate change, CO2 emissions, Passenger transport, Mitigation, Policy stringency, Vector autoregression

JEL classification: C32, C54, Q54, Q58, R48

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1 Introduction

The international community agreed on the climate target to stay well below 2°C of global warming (IPCC, 2018; UNFCCC, 2015). The European Union (EU) to this end set itself the ambitious target to become climate-neutral by 2050 (EC, 2021) and is currently implementing more stringent emission targets with its "Fit-for-55" package to achieve this goal. The transport sector will play a crucial role in the transition towards a carbon neutral society. While overall greenhouse gas (GHG) emissions in the EU decreased by 28% during 1990-2019, emissions from transport increased by 20% and in 2019 accounted for about a quarter of the EU's total GHG emissions. The largest share of transport emissions (mostly CO2) stems from road transport (EEA, 2021). One major pillar of the "Fit-for-55" package to reduce transport emissions is the Effort Sharing Regulation (ESR), under which each member state has to fulfill binding emission targets through implementation of national policies.

The Transport and Environment Report 2021 from the EEA (2022) emphasizes the challenges in reducing road transport emissions. While current policies are projected to reverse the trend of increasing transport emissions and lead to a reduction of 35% by 2050 relative to 1990 levels, they are not sufficient to achieve the EU's 2050 target to become climate neutral. The increasing demand for transport is identified as a key driver of emissions. Despite improvements in vehicle energy efficiency and the use of biofuels, the growth in motorized transport volumes continues to drive emissions upward. Martin et al. (2020) explore policy mixes to decarbonize the EU's transport sector by 2040, which aligns with the national target timeline of the country we analyze, Austria. They highlight that supply-side measures, such as employment of zero-carbon vehicles, need to be complemented by demand-side policies that reduce overall demand and increase a modal shift away from individual private transport.

To devise effective policy measures, decision makers need information on the expected effectiveness of various policies and combinations thereof. One avenue to evaluate the emission reduction potential of policies is to take a retrospective look. Knowing the effect of past policies on transport related emissions provides policy makers with a guide on which measures to include in a policy package to achieve the global target. In this paper, we provide an analysis of transport related policies in one of the EU member states, Austria, from 1950-2019 in a dynamic econometric framework. We thereby recognize that the transport sector is characterized by systemic delays. These are, in part, governed by the fact that vehicles have a relatively long lifetime. The effect of policies aimed at influencing the existing vehicle stock thus comes with a delay, which should be kept in mind when trying to devise effective policy measures to reduce transport related emissions.

We focus our investigation on Austria, which poses a particularly interesting case for analysis. It was one of the first countries to ratify the Paris Agreement, and it recently even set itself the ambitious goal to become carbon-neutral by 2040 (BKA, 2020). Here again, the transport sector will play a critical role in achieving this goal. In Austria, GHG emissions from the transport sector have risen for decades. Between 1990 and 2019, GHG emissions from transport increased by 74.4%. In 2019, the transport sector accounted for 30% of total GHG emissions. 19% of total emissions were emitted by road passenger transport alone (Anderl, Bartel, et al., 2021). Policy instrument packages to meet Austria's environmental target are yet to be implemented and existing policy measures in Austria are not expected to achieve a significant reduction in motorized individual transport emissions. Anderl, Gössl, et al. (2021) show that the existing policy measures for the Austrian transport sector will not suffice to reach Austria's ambitious climate goals. They argue that with existing policy measures, the Austrian road transport sector will only realize a reduction in emissions of about 21% by 2040 compared to 1990 levels.

To evaluate transport related policies in Austria, we employ a two-step procedure. In a first step, we construct a new policy stringency index for the Austrian transport sector covering the period 1950-2019. The policies under consideration have been carefully chosen in cooperation with experts from the Austrian Environmental Agency. In a second step, the index is incorporated into a dynamic econometric model that estimates the drivers of transport related emissions and recognizes that determinants of emissions may be interdependent. This is especially relevant in an analysis of policies aimed at influencing these emissions, as these are likely to be endogenous to a certain degree.

The importance of policy mixes in addressing transport emissions is notably emphasized by Dugan et al. (2022), who analyse a range of policy packages that comprise different policies for Austria with a computable general equilibrium model. They show that a balanced policy package can mitigate negative effects associated with single policies (e.g. regressive impacts, rural-urban conflicts, negative budget implications). Winkler et al. (2023) also recognize the importance of policy mixes and the interdpendency between single policies. They focus on London as a case study and argue that to meet carbon-budgets compatible with meeting the Paris agreement, not only are emission-reducing changes in vehicle design necessary, but also a rapid and large-scale reduction in car use is essential. Koch et al. (2022) uses a break detection method for time series on transport emissions and attributes breaks to policy changes, finding no effective transport-related policies for Austria. Gerlagh et al. (2018) examines the effect of fiscal policies on vehicle efficiency, including in Austria, finding that increased CO2 sensitivity of registration taxes reduced new vehicle emissions.

Studies on individual transport policies are more prevalent than those examining policy mixes and interdependencies between policies. For example, Ostermeijer et al. (2019) investigate the impact of residential parking costs on car ownership in the Netherlands, indicating significant variances in parking costs and their effect on car ownership rates. Adler and van Ommeren (2016) explore the congestion relief benefits of public transit during transit strikes in Rotterdam, finding substantial reductions in car congestion. Hintermann et al. (2022) provide insights into Pigovian road pricing through a large-scale field experiment in Switzerland. They find that the group that received a pricing treatment significantly reduced external transport costs. Andersson (2019) explores the impact of a carbon tax in Sweden and finds a modest reduction in transport emissions, while Pretis (2022) studies a carbon tax in British Columbia and finds that it led to a decrease in transport emissions but not a significant reduction in overall emissions. Berger et al. (2022) estimate that the impact of speed limit policies can significantly reduce greenhouse gas emissions and improve road safety in Austria. Kuss and Nicholas (2022) conduct a meta-analysis of interventions to reduce car use in European cities, identifying a dozen effective strategies, including congestion charges, parking and traffic control, and limited traffic zones.

Several characteristics of our study make it a unique contribution to the literature. First, a transport-specific policy stringency index does not exist to the best of our knowledge for any country. Second, we cover a long time period from 1950-2019, which allows us to exploit stronger variations in policy stringencies than most other studies. Third, we incorporate the index in a dynamic econometric framework that can deal with possible endogeneity and interdependencies. The model thus allows us to study the dynamic diffusion of the effect of policy bundles as well as single policies over time while acknowledging interdependencies. Overall, such a comprehensive analysis seems to be novel in the literature.

We find that the observed increase in the stringency of policies that target the investment decision to buy cars has proven more effective than those observed targeting the usage of cars. The engine-related insurance tax is found to have had the strongest long-run impact on emissions in our study. But the standard fuel consumption tax - an emission sensitive tax on new vehicles - shows the strongest statistical significance in reducing emissions. The effect of both policies comes with a time delay as it takes time for more efficient cars to significantly impact fleet emissions. That being said, the magnitude of the effect of any policy that we consider is very limited. Austria will need to drastically increase these policies in stringency and implement additional measures to meet its policy targets.

The remainder of the paper is organised as follows. Section 2 is dedicated to the computation of the policy stringency index. It starts with a short literature overview, discusses transport-related policies in Austria, and then explains the construction of the index. Section 3 establishes the econometric model used to analyse the determinants of transport related CO2 emissions and provides empirical results. Section 4 provides a policy discussion, and Section 5 concludes.

2 Policy Stringency Index

In this section, we develop the policy stringency index for the Austrian transport sector. We first provide a brief literature overview on the construction of indexes and the incorporation of policy stringency measures, such as indexes, in econometric analyses. Then, we go on to discuss transport-related policies that Austria introduced over the period 1950-2019. We group these policies into two categories, one related to the purchase behavior of new vehicles and one related to the usage of vehicles. The policies and categories have been established with the help of policy experts from the Austrian Environmental Agency. Finally, we describe how we assign stringency scores to the different policies for every year and discuss the resulting stringency index.

2.1 Literature

Indexes that aim to quantify the stringency of policies face the problem of multidimensionality (e.g. Brunel and Levinson, 2016; Galeotti et al., 2020). Countries can draw on a diverse toolkit comprising different measures to achieve policy goals. These may include taxation, subsidies, and regulation. Policies in each of these categories can be characterized by disparate levels of effectiveness and metrics. An index has be constructed such that these different policies are comparable on a common scale. Several approaches to devise such indexes have been proposed in the literature. Among them, composite indexes have more recently gained popularity. These indexes aim to aggregate individual indicators by simply counting the number of regulations or the use statistical and data-driven techniques to create the index.

A very popular index of this type is the OECD environmental policy stringency index developed by Botta and Koźluk (2014). The index is composed of several market-based and non-marked-based policies. Numerous studies have used this index since its introduction in 2014. For instance, Georgatzi et al. (2020) studied (among other variables) the effect of environmental policy stringency on CO2 emissions in 12 EU countries from 1994-2014 using panel cointegration techniques. Yirong (2022) used the index within a nonlinear autoregressive-distributed-lag (ARDL) model to analyze policy effects on CO2 emissions in high-polluting economies from 1990-2019. Wang et al. (2020) analysed the effect of stricter environmental policies on air quality for a panel of OECD countries for the period 1990-2015 using system generalized-method-of-moments (GMM) to account for endogeneity. Corrocher and Mancusi (2021) studied OECD and BRICS countries for the period 1995-2014 and found that higher discrepancies in the stringency of the index hinders international collaboration on energy-related technologies.

A different measure of environmental policy stringency can be found in Probst and Sauter (2015), who use a count-based indicator to study the effect of policy stringency on CO2 emissions for 46 countries over the period 1990-2010. To account for endogeneity issues, they apply a vector autoregressive model, which is similar in spirit to our econometric analysis. Neves et al. (2020) proxy policy stringency by counting market-based instruments in EU countries. To control for endogeneity, they use an ARDL type model and find that environmental regulations reduced CO2 emissions EU countries during 1995-2017 in the long run. Hille and Möbius (2019) use shadow prices to compute environmental policy stringency and estimate their effect on air emission in OECD countries over 1996-2009. They use a system GMM approach to account for endogeneity and find that carbon-related policies significantly reduced air emissions. Hashmi and Alam (2019) proxy policy stringency by environmental tax revenue. They found that larger environmental taxes reduced CO2 emissions in OECD countries during 1999-2014.

2.2 Transport-Related Policies in Austria

The policies under consideration for our index as well as their categorizations have been established in accordance with experts from the Austrian Environmental Agency. We identified two broad categories: 1) Taxes mainly affecting the investment decision to buy a new car and 2) measures affecting the usage of cars. Table 1 outlines this structure and lists the individual indicators (policies) for each category, which are explained in more detail below. We focus our analysis on policies that directly impact combustion engine vehicles. We exclude subsidies on electric vehicles, because our sample-period ends in 2019 and until very recently electric vehicles in Austria were almost nonexistent relative to combustion-engine cars, making an analyses of the effect of policies directly promoting the switch to electric vehicles in our framework infeasible. We focus our analysis on national policies and did not include EU regulations, such as the fleet regulation and the biofuels directive. The EU fleet regulation sets emissions limits on newly registered cars, while the biofuels directive set minimum shares for the use of biofuels and other renewable fuel in the transport sector. Both policies directly impact the efficiency of vehicles and as a result CO2 emissions. We capture this mechanism in our model described in Section 3 by directly including an indicator for energy-efficiency in our analysis.

Table 1: Categorized Policy Instruments

Invest	Usage
Standard Fuel Consumption Tax	Excise Duty on Mineral Oils (Fuel Tax)
Engine-Related Insurance Tax	Temporary Speed Limits
	Car-Free Days
	IG-L

Note: The composite index can be disaggregated into the two main categories Invest and Usage. These can further be disaggregated into their sub-components.

The Standard Fuel Consumption Tax (commonly referred to as NoVA - Normverbrauchsabgabe) is a tax on new cars; it was introduced in 1992 (Normverbrauchsabgabegesetz, 1991). It is a direct successor to the Luxury Tax introduced in 1978, which put a tax on the purchase of luxury goods, including cars (2. Abgabenänderungsgesetz, 1977). The NoVA was calculated based on fuel consumption from 1992 to 2013, and based on CO2 emissions from 2014 onwards. The Engine-Related Insurance Tax is a yearly tax covering all registered vehicles. It was calculated based on engine size from 1952 to 1992 (Kraftfahrzeugsteuergesetz, 1952), and from 1993 onwards based on engine power (Kraftfahrzeugsteuergesetz, 1992). Both the NoVA and the Insurance Tax can be quite high for large cars such a SUVs and drive up the costs for purchase and maintenance significantly.

The Excise Duty on Mineral Oils is in essence a tax on petrol and diesel fuels. It is the only policy in the index that was already in place in 1950 (Mineralölsteuergesetz, 1949). In its current version, the law on the mineral oil tax was implemented in 1995 (Mineralölsteuergesetz, 1994). The Air Pollution Control Act (IG-L) allows provincial governors to enact speed limits in areas with strong air pollution since 1997 (Immissionsschutzgesetz – Luft, 1997). As a response to the oil crisis and higher fuel prices, Austria enacted a temporary speed limit of 100 km/h from November 1973 to March 1974 (Geschwindigkeitsbeschränkungs-Verordnung, 1973). In 1974, Austria additionally implemented car-free days (Änderung des Bundesgesetzes über Verkehrsbeschränkungen zur Sicherung der Treibstoffversorgung, 1974).

2.3 Computing the Stringency Index

We base our index on the widely adopted OECD environmental policy stringency index Botta and Koźluk (2014). This provides us with a solid methodologically foundation to compute our index. Both policy categories ($Invest$ and $Usage$) will contribute equally to the composite index. The individual policies within each category are also weighted equally. This ensures that the effect of a given measure is not a priori influenced by different pre-determined weights.[1] Following the OECD Stringency Index, we adopt a 7-step scale for the index. It spans from from 0 (indicating absence) to 6 (indicating highest stringency).

To assign a stringency score to each policy in each year, we first calculate the associated impact (cost) of a policy. The cost of the Fuel Tax is given in Eurocents and thus straightforwardly available. The remaining policies in the $Usage$-category (Temporary Speed Limits, Car-Free Days, IG-L) are of a qualitative nature. Such policies do not change in stringency over time, as they are either in force or not. Whenever such instruments are implemented, they are indicated by a dummy. The dummy is set equal to one if the policy was in effect over the entire year, otherwise it is weighted according to the time it was in force in a given year.

The cost of policies in the $Invest$-category (Standard Fuel Consumption Tax and the Engine-Related Insurance Tax) depend on the characteristics of vehicles (see Section 2.2 for details). To calculate coherent effective policy costs for this category, we could use average attributes of a car in a given year, but this approach would lead to changes in the index even if policy measures did not change. This is because the attributes of cars change over time and it could even lead to decreases in stringency despite policy measure being unchanged. Therefore, we resort to constant attributes of cars. Data on characteristics of vehicles has been gathered from the National Inventory Reports from the Austrian Environmental Agency as well as

[1] Obviously, this assumes that each policy is of equal significance. Below we also consider a decomposition of the indices to analyse the effect of individual policy types to address the concern.

from “Verkehr in Zahlen” from the German BMDV (2019).[2]

To compute the effective cost of the Standard Fuel Consumption Tax, we construct the average newly registered vehicle over the period 1970-2019, as this tax only applies to new cars.[3] Let x_t be the realization of a specific characteristic of a newly registered car (e.g. power, fuel consumption, emissions, price) in year t. Let P_t^{new} and D_t^{new} stand for the number of newly registered diesel and petrol vehicles in a given year, respectively. The characteristics of the average newly registered car are given by[4]:

$$\overline{x}^{new} = \frac{\sum_t \left(D_t^{new} \cdot \overline{x}_{d,t}^{new} + P_t^{new} \cdot \overline{x}_{p,t}^{new}\right)}{\sum_t \left(D_t^{new} + P_t^{new}\right)},$$

where $\overline{x}_{d,t}^{new}$ and $\overline{x}_{p,t}^{new}$ are the average characteristics of newly registered diesel and petrol cars in a given year t, respectively, with:

$$\overline{x}_{d,t}^{new} = \frac{1}{D_t^{new}} \sum_d x_{d,t},$$

and

$$\overline{x}_{p,t}^{new} = \frac{1}{P_t^{new}} \sum_p x_{p,t},$$

where $d = 1, \ldots, D_t^{new}$ and $p = 1, \ldots, P_t^{new}$, i.e., we sum over all cars of type diesel or petrol, respectively.

We calculate the associated cost of the Engine-Related Insurance Tax for the average car over the period 1970-2019 considering the entire fleet (contrasted to considering only newly registered vehicles). We compute this average car similarly as above[5]:

$$\overline{x}^{fleet} = \frac{\sum_t \left(D_t^{fleet} \cdot \overline{x}_{d,t}^{fleet} + P_t^{fleet} \cdot \overline{x}_{p,t}^{fleet}\right)}{\sum_t \left(D_t^{fleet} + P_t^{fleet}\right)},$$

where P_t^{fleet} and D_t^{fleet} stand for the number of registered diesel and petrol vehicles in a given year, respectively. $\overline{x}_{d,t}^{fleet}$ and $\overline{x}_{p,t}^{fleet}$ give the average registered diesel and petrol car in

[2]We do not take a stance on whether characteristics from cars driven in Germany proxy attributes of cars driven Austria well. For the construction of the index it is important to compute policy costs based on constant average vehicle characteristics.

[3]This period has been chosen according to data availability on vehicle characteristics.

[4]The relevant characteristics of the average newly registered car are: 7.1 l/100km, 173 gCO2/100km, 18,650 EUR net price.

[5]The relevant characteristics of the average car over the entire fleet are: 1660 ccm, 69 kW

a given year t, respectively, with:

$$\overline{x}_{d,t}^{fleet} = \frac{1}{D_t^{fleet}} \sum_d x_{d,t},$$

and

$$\overline{x}_{p,t}^{fleet} = \frac{1}{P_t^{fleet}} \sum_p x_{p,t},$$

where $d = 1, \ldots, D_t^{fleet}$ and $p = 1, \ldots, P_t^{fleet}$.

Once the associated costs of all policies have been calculated, we can assign stringency scores to the policies. We employ a data-driven approach and first compute the inter-percentile range between the 90th and 10th percentile of the distribution of a policy cost over the years and then segment it into five equally sized bins with width:

$$w = \frac{(p_{90} - p_{10})}{5}.$$

The cost of a non-qualitative policy in a given year is then matched with these bins and assigned the corresponding score.

Table 2 shows the score assignment and the associated thresholds for policies for which a direct cost can be calculated (Fuel Tax, SFC Tax, Insurance Tax). The first three columns show the intervals that are matched with policy costs c_t for a given year and the last column shows the associated scores with these intervals. A policy that is not in effect is assigned a score of 0 and a policy that has cost higher or equal than the 90th percentile of the distribution of the costs of a policy over the years is assigned a score of 6. The remaining scores are assigned according to the bins with width w. The policy with cost c_t in a given year is then assigned the score according to the associated bin.

Costs for the Fuel Tax and Insurance Tax are given in EUR, while the SFC Tax is given in percentages.[6] For the Insurance Tax, for example, c_t ranges from 34.88 EUR in 1952 to 310.06 EUR in 2019. The 10th percentile is at 34.88 EUR and the 90th percentile at 272.58 EUR. We then have $w = (272.58 - 34.88)/5 = 47.54$, which gives the bin width, i.e., the threshold from one bin to the next. The score for each year is then assigned by matching c_t

[6] Monetary values are taken in nominal terms so that the index is not affected by changes in prices unrelated to changes in policy stringency. For the SFC Tax, we are computing costs based on an average newly registered vehicle. Specifying percentages or transforming those to EUR based on the constant price of the average newly registered vehicle is thus equivalent.

in a given year with the associated bin. Table A.1 in Appendix A provides a full list of costs assigned to a policy alongside the associated scores for each year.

Table 2: Score Assignment to Policies

Fuel Tax	SFC Tax	Insurance Tax	Score
0	0	0	0
$0 < c_t < 0.0996$	$0 < c_t < 0.1$	$0 < c_t < 82.42$	1
$0.0996 \leq c_t < 0.1878$	$0.1 \leq c_t < 0.11$	$82.42 \leq c_t < 129.96$	2
$0.1878 \leq c_t < 0.2759$	$0.11 \leq c_t < 0.12$	$129.96 \leq c_t < 177.50$	3
$0.2759 \leq c_t < 0.3642$	$0.12 \leq c_t < 0.13$	$177.50 \leq c_t < 225.04$	4
$0.3642 \leq c_t < 0.4524$	$0.13 \leq c_t < 0.14$	$225.04 \leq c_t < 272.58$	5
$c_t \geq 0.4524$	$c_t \geq 0.14$	$c_t \geq 272.58$	6

Note: Score assignments are shown for policies which can be attributed a cost in monetary terms. Scores range from 0 (not in effect) to 6 (most stringent implementation in the observed period).

When each policy has been assigned a score in each year, we simply aggregate the score for every policy into the two main categories ($Invest$ and $Usage$) for each year, where every policy receives equal weight. The composite index can reach a maximum value of 6, implying that each of the two main categories can contribute a maximum of 3 to the composite index. We compute:

$$Invest_t = \frac{1}{2}\left(\frac{1}{2}SFC\ Tax_t + \frac{1}{2}Ins\ Tax_t\right),$$

where the weights inside the brackets attach equal weights to the two policies $SFC\ Tax$ and $Ins\ Tax$. The weight outside the brackets attaches equal weight to the $Invest$ and the $Usage$ categories. $SFC\ Tax_t$ and $Ins\ Tax_t$ can thus contribute a maximum of 1.5 to the composite index each and $Invest_t$ can contribute a maximum of 3. Similarly, we can compute:

$$Usage_t = \frac{1}{2}\left(\frac{1}{4}Fuel\ Tax_t + \frac{1}{4}Speed\ Limit_t + \frac{1}{4}Car\text{-}Free\ Days_t + \frac{1}{4}IG\text{-}L_t\right)),$$

where the weights inside the brackets again attach equal weights to the four policies in the $Usage$ category and the weight outside the brackets signals equal weights for the two main policy categories ($Invest$ and $Usage$). Each of the four policies can thus contribute a maximum of 0.75 to the composite index and $Usage_t$ can overall contribute a maximum of 3. We can then further aggregate the two categories into the overall composite index with equal weights for each of the two policy categories:

$$Comp_t = Invest_t + Usage_t,$$

where $Comp_t$ can take a maximum value of 6.

The final index is shown in Figure 1. The composite index is given by the solid line. The sub-index based on policies affecting investment decisions is given by the dashed line and measures affecting the usage of cars by the dotted line. The actual maximum value of the composite index is 4.5 and thus lower than the theoretical maximum of 6. This is because the scale of the composite index in a given year is relative to the most stringent value of all policy measures over the entire sample period. While some measures are at their most stringent level in 2019, this is not true for all instruments. The sub-index for the policy category $Invest$ reaches its maximum value of 3 in 2014. While the sub-index for $Usage$ only reaches a maximum of 1.5 with a theoretical maximum of 3. This is because the temporary speed limits and car-free days were temporary measures in the 1970s (each of them can take a theoretical maximum value of 0.75).

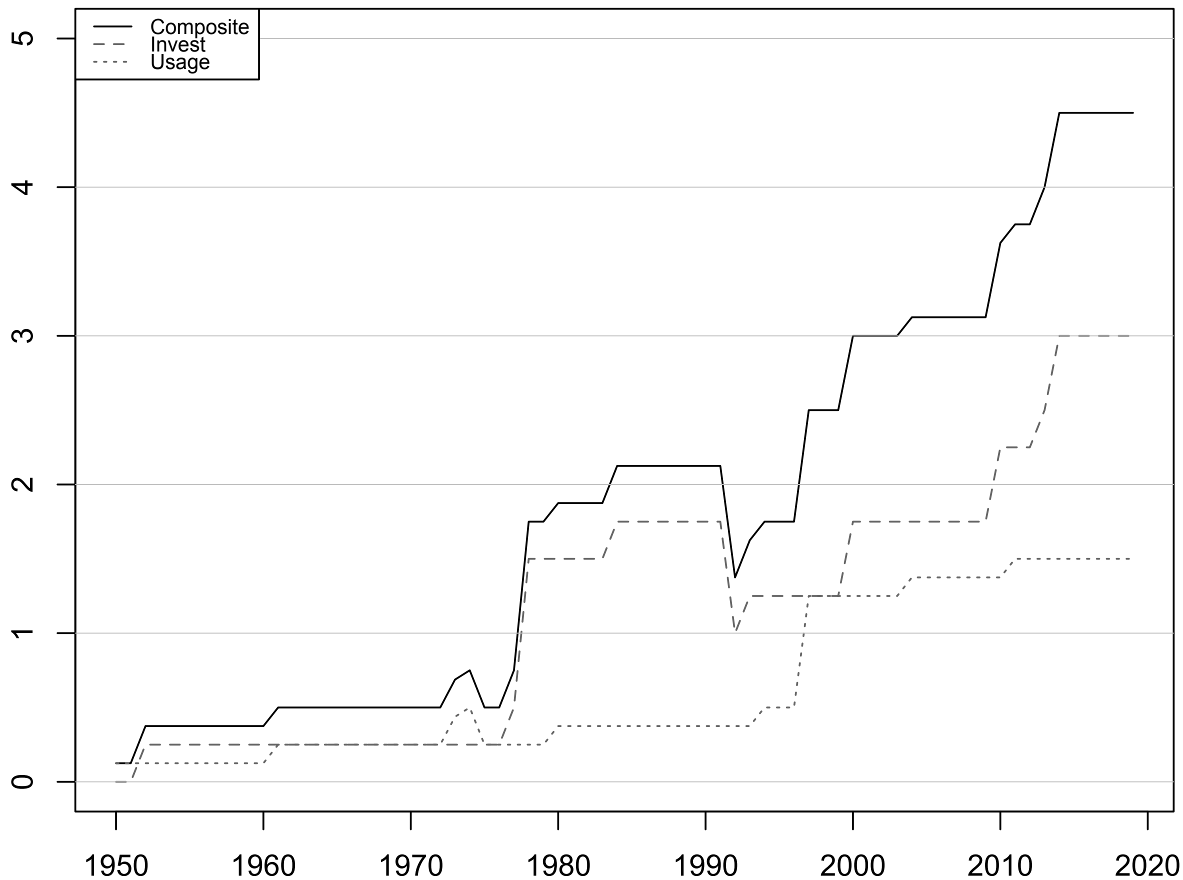
Measures on the usage of cars spiked in 1973-1974 due to the introduction of the car-free day and temporary speed limits. The policies do not achieve their theoretical maximum value of 3 because they were not in effect over an entire given year. A particularly steep increase can be noticed in 1997, which can be attributed to the implementation of the the Air Pollution Control Act. Other small increases are due to increases in the fuel tax. Measures affecting the investment category sharply increased in 1978, when the luxury tax on new cars (which later transformed into the NoVA) was introduced. The tax was restructured and based on fuel usage from 1992 on. The effective tax rate on the average car dropped markedly.[7] In 2000, the insurance tax increased sharply. Increases in 2010 and 2014 can be attributed to an increased stringency in the NoVA.

3 A Dynamic Econometric Analysis

In this section we go on to study the effect of the instruments embodied in the transport related environmental policy stringency index on CO2 emissions from passenger transport. As policies aimed at influencing emissions from the transport sector are characterized by interdependencies, direct or indirect ones, endogeneity issues have to be considered. To address this, we employ a vector autoregressive (VAR) model that, by construction, treats all variables as endogenous. Aside from the index variables and CO2 emissions, the VAR model should include other determinants of transport emissions. A widely used approach for

[7] The tax rate would have dropped equally for the average car in 1992.

Figure 1: Passenger Transport Policy Stringency Index for Austria, 1950-2019



analysing driving factors of greenhouse gas emission from the transport sector is to employ accounting identities. This analysis makes use of the IPAT identity, proposed by Ehrlich and Holdren (1971). In an ecological context (York et al., 2003) it states that the environmental impact (I) is the product of population (P), affluence (A) and technology (T). To facilitate the econometric analysis and hypothesis testing on the IPAT identity, Dietz and Rosa (1997) transformed the identity into an econometric model called Stochastic Impact by Regression on Population, Affluence, and Technology (the STIRPAT model), which forms the basis of our model specification and is reviewed in Section 3.2.

3.1 Data and Descriptive Statistics

Data on CO2 emissions, energy intensity, and the fleet composition has been provided by the Austrian Environmental Agency. The data have been extracted from their Network and Emissions Model (NEMO), developed by Dippold et al. (2012). CO2 emissions are measured

Table 3: Description of Variables

Variable	Description
CO2/CAP	CO2 emissions from combustion engine passenger cars (diesel, petrol, hybrids, and plug-in hybrids) in 1000t divided by the average population in a given year in 1000 persons.
EI	Energy intensity measured by grams CO2 emitted per 100km
Fleet/CAP	Total number of passenger cars with combustion engines (including hybrids and plug-in hybrids) divided by the average population in a given year in 1000 persons.
GDP/CAP	Real gross domestic product in 2015 prices divided by the average population in a given year.
Oil	Real international oil prices in 2015 prices (WTI up to 1986, BRENT thereafter).

in 1000t, data on the vehicle fleet contain the total fleet of petrol and diesel powered cars (including hybrid and plug-in hybrid vehicles) in a given year, and data on the energy intensity of vehicles are given by gCO2/100km. Population statistics have been extracted from Statistik Austria (2021). For the econometric analyses, we use CO2, vehicle fleet, and energy intensity in per capita terms. Data on GDP is measured in real GDP and has been taken from the Austrian Economic Chamber (WKO, 2021). Oil prices are composed of WTI prices up to 1986 and Brent (Europe) from 1987 onwards. Both time series were extracted from the FRED Economic Data base (U.S. Energy Information Administration, 2022a, 2022b). To calculate GDP/CAP and oil prices in real terms, we used the Austrian consumer price index, which we extracted from OENB (2022).

Clean data for all mentioned variables are available for the period 1965-2019. Table 3 summarizes and describes the variables.
Table 4 presents the summary statistics of these variables, time series plots are shown in Figure 2. CO2/CAP, Fleet/CAP, and GDP/CAP all show a clear upward trend. The financial crisis around 2009 is clearly discernable in the time series of GDP and CO2 per capita. The energy intensity has a decreasing trend, i.e., cars got more efficient, although

the efficiency did not improve much prior to the 1980s. By inspecting the time series on international oil prices, one can clearly see a stark increase in prices during the first and second oil crises, starting in 1973 and 1979, respectively.

Table 4: Summary Statistics of Variables

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
CO2/CAP	55	0.981	0.321	0.344	0.728	1.250	1.365
EI	55	204.994	22.368	168.038	188.258	225.730	237.198
Fleet/CAP	55	372.211	145.580	102.328	258.820	506.959	564.342
GDP/CAP	55	28,972.920	8,957.980	12,964.250	22,032.390	37,761.610	42,139.200
Oil	55	89.790	56.120	26.730	49.994	122.567	227.909

3.2 General Model Framework

The STIRPAT model takes the variables from the IPAT identity as logarithms, and by adding an error term, the model we get has a typical regression-type form:

$$I_t = \alpha + \beta_1 P_t + \beta_2 A_t + \beta_3 T_t + u_t, \tag{1}$$

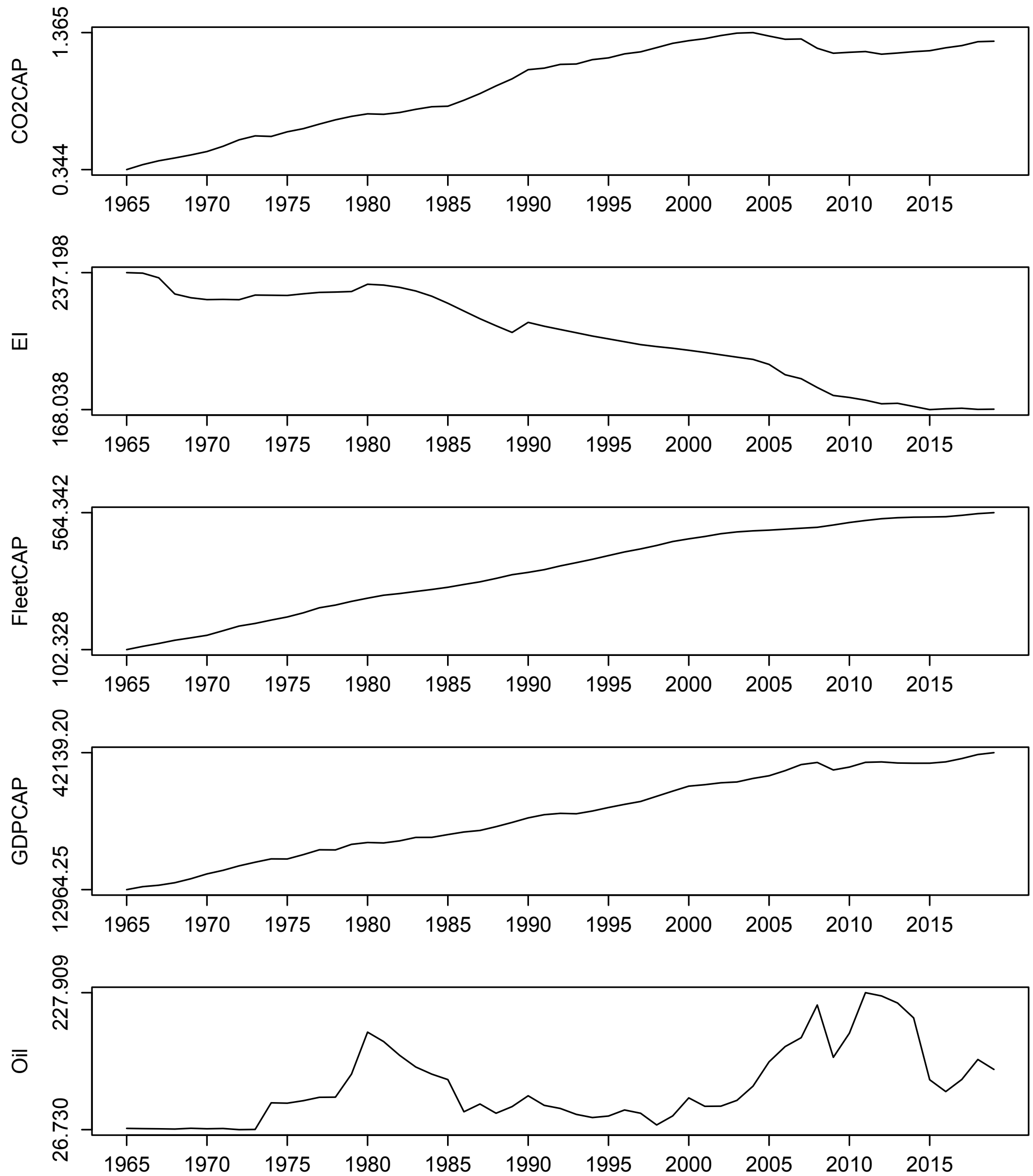
where α and the β_i are the usual regression coefficients, I is the environmental impact, which we capture by CO2 emissions, P stands for population, A for affluence, usually measured by per capita GDP, T is a technology term, u the error term, and the subindex indicates the year of observation.

For the purpose of our analysis, we reformulate and extend the model as follows. We focus on passenger transport related CO2 emissions per capita (CO2/CAP) and drop the population parameter. We also measure affluence in GDP per capita terms (GDP/CAP). Technology is proxied by energy intensity (EI), given by gCO2/100km. Additionally, we include the passenger car fleet in per capita terms (Fleet/CAP) as well as international oil prices (Oil) in the model. Finally, we include the different policy sub-indexes as we are interested in their effect on CO2 emissions. The baseline model for CO2 emissions per capita then becomes:

$$\begin{aligned} CO2/CAP_t =& \alpha + \beta_1 Comp_t + \beta_2 EI_t + \beta_3 Fleet/CAP_t \\ &+ \beta_4 GDP/CAP_t + \beta_5 Oil_t + u_t, \end{aligned} \tag{2}$$

where $Comp_t$ stands for the composite index containing the policies outlined in Table 1. This model forms the basis for our specification. We can disaggregate $Comp_t$ to get model

Figure 2: Time Series in Levels, 1965-2019



specifications that allow for a more fine-grained policy analysis. In a first step, we can disaggregate the composite index into the two main sub-indexes: $Invest$ and $Usage$. We modify the structural baseline model motivated by equation (2) to obtain:

$$\begin{aligned} CO2/CAP_t =& \alpha + \beta_1 Invest_t + \beta_2 Usage_t \\ & + \beta_3 EI_t + \beta_4 Fleet/CAP_t + \beta_5 GDP/CAP_t + \beta_6 Oil_t + u_t. \end{aligned} \tag{3}$$

In a next step, we can disaggregate the two main policy categories. We modify the baseline model to obtain the two following models:

$$\begin{aligned} CO2/CAP_t = & \alpha + \beta_1 Insurance\ Tax_t + \beta_2 SFC\ Tax_t + \beta_3 Usage_t \\ & + \beta_4 EI_t + \beta_5 Fleet/CAP_t + \beta_6 GDP/CAP_t + \beta_7 Oil_t + u_t, \end{aligned} \tag{4}$$

and

$$\begin{aligned} CO2/CAP_t = & \alpha + \beta_1 Fuel\ Tax_t + \beta_2 Use\ Qual_t + \beta_3 Invest_t \\ & + \beta_4 EI_t + \beta_5 Fleet/CAP_t + \beta_6 GDP/CAP_t + \beta_7 Oil_t + u_t. \end{aligned} \tag{5}$$

In equation (4), we disaggregate the policy category $Invest$ into its subcomponents: engine-related insurance tax ($Insurance\ Tax$) and standard fuel consumption tax ($SFC\ Tax$). The policy category $Usage$ contains too many individual policies to fully disaggregate it. In equation (5), we thus disaggregate the policy category $Usage$ into the mineral oil tax ($Use\ Tax$) and gather the remaining policies in the new category qualitative usage ($Use\ Qual$).

All of these specifications share the same drawbacks that (i) they are likely to suffer from endogeneity and (ii) they are static models, whereas we are interested in dynamic effects. The next section describes our modeling approach to accommodate these complications.

3.3 VAR Analysis

Most variables in equation (2) are likely to be endogenous. These include the composite index and CO2/CAP, EI, and Fleet/CAP. Real GDP/CAP and real oil prices are likely to be determined outside this system and we treat them as exogenous. Vector autoregressive (VAR) type models with exogenous variables are an appropriate model class for our analysis (Sims, 1980, Lütkepohl, 2005). Due to potential nonstationarity of most variables, we have to test the variables for unit roots and for cointegrating relations in order to establish which model form is most suitable.

Figure 2 clearly shows that the variables included in our model exhibit some kind of trend. For the econometric analysis, it is important to establish whether the variables are characterized by a stochastic trend (i.e. a unit root) or a deterministic one. Several tests have been proposed to test the presence of a unit root, but many unit root tests suffer from low power when applied to near-unit processes; see, e.g., Kilian and Lütkepohl (2017). Elliott, Rothenberg, and Stock (1996) propose a unit root test that dominates other tests in terms of small sample properties and power. It is based on the Augmented-Dickey-Fuller test (ADF) and tests the null hypothesis of a unit root. We apply the test to the variables in equation (2).

The resulting test statistics are shown in Table B.1 in Appendix B. The results for the variables in levels and first differences based on models with a constant only as well as a constant plus trend specification are given. The results reveal that the null hypothesis of a unit root cannot be rejected at the 10% significance level in the tests with only a constant as well as a constant and trend for all variables in levels. The series in first differences appear to be stationary, as the null can be rejected at the 5% level for both models (trend and constant as well as constant only). We can thus conclude that the variables in level form are I(1).

Next, we test for a cointegrating relation between the endogenous variables. The results of the Johansen cointegration trace test for CO2/CAP, EI, and Fleet/CAP are shown in Table B.2 in Appendix B[8]. The test cannot reject the null hypothesis of a cointegration rank of zero (i.e. no cointegration) at the 10% level. We further confirm this result by analyzing all pairwise cointegrating relations, where we find no evidence for cointegration (results available upon request). We thus conclude that there is no evidence in favor of a cointegrating relation between the variables.

Consequently, we adopt a (structural) VAR model for the first differences of the variables for our analyses. The model treats all variables as endogenous and each variable is determined by lagged values of all other variables. As mentioned above, we include GDP per capita and international oil prices as exogenous variables in the model as they are likely important drivers of CO2 emissions. Such a VARX model with p lags of the endogenous and q lags of the exogenous variables in its structural form is given by:

$$\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{\mu} + \textstyle\sum_{i=1}^{p} \boldsymbol{B}_i\boldsymbol{y}_{t-i} + \sum_{j=0}^{q} \boldsymbol{\vartheta}_j\boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \tag{6}$$

where $t = 1, \ldots, T$, $\boldsymbol{y}_t$ is a $K \times 1$ vector containing the endogenous time series and $\boldsymbol{x}_t$ is an $M \times 1$ vector containing the exogenous time series. $\boldsymbol{\mu}$ is a vector of intercepts, $\boldsymbol{B}_0$ is a $K \times K$ parameter matrix containing the contemporaneous interactions, $\boldsymbol{B}_i$ are $K \times K$ matrices containing the coefficients of the lagged endogenous variables, $\boldsymbol{\vartheta}_j$ are $M \times K$ matrices containing the coefficients of the exogenous variables, and $\boldsymbol{u}_t$ is the $K \times 1$ vector of structural errors, which are assumed to be independent of each other. Note that without prior restrictions the model is not identified.

[8] We do not include the policy stringency variables in the test because these are naturally bounded.

Applying the model to the variables in equation (2) and taking first differences we obtain: $\boldsymbol{y}_t = [\Delta Comp_t, \Delta EI_t, \Delta Fleet/CAP_t, \Delta CO2/CAP_t]'$ and $\boldsymbol{x}_t = [\Delta log(GDP/CAP_t), \Delta log(Oil_t)]'$. Note that the endogenous variables are taken in first differences, whereas the endogenous ones are taken in log-differences. The estimation of the model is based on its reduced form:

$$\boldsymbol{B}_0^{-1}\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{B}_0^{-1}\boldsymbol{\mu} + \textstyle\sum_{i=1}^{p} \boldsymbol{B}_0^{-1}\boldsymbol{B}_i\boldsymbol{y}_{t-i} + \sum_{j=0}^{q} \boldsymbol{B}_0^{-1}\boldsymbol{\vartheta}_j\boldsymbol{x}_{t-j} + \boldsymbol{B}_0^{-1}\boldsymbol{u}_t, \quad (7)$$

which can be rewritten more compactly as:

$$\boldsymbol{y}_t = \tilde{\boldsymbol{\mu}} + \textstyle\sum_{i=1}^{p} \boldsymbol{\phi}_i\boldsymbol{y}_{t-i} + \sum_{j=0}^{q} \boldsymbol{\theta}_j\boldsymbol{x}_{t-j} + \boldsymbol{v}_t, \quad (8)$$

where $\tilde{\boldsymbol{\mu}} = \boldsymbol{B}_0^{-1}\boldsymbol{\mu}$, $\boldsymbol{\phi}_i = \boldsymbol{B}_0^{-1}\boldsymbol{B}_i$, $\boldsymbol{\theta}_j = \boldsymbol{B}_0^{-1}\boldsymbol{\vartheta}_j$, and $\boldsymbol{v}_t = \boldsymbol{B}_0^{-1}\boldsymbol{u}_t$.

The reduced form can be estimated by simple OLS, and a specific structure can be imposed on $\boldsymbol{B}_0$ to recover the structural parameters and interpret the results.[9] In order to identify the system, we place specific short run restrictions on the coefficient matrix $\boldsymbol{B}_0$ as shown in Table 5. The columns contain the shocks to each variable, and the rows indicate which variables are affected by this shock. The identification is justified as follows. It is reasonable to assume that policies influence CO2 emission contemporaneously, but higher emissions may translate into stricter policies with a delay. Similarly, this holds also for EI and Fleet/CAP. EI can influence both the fleet and emission contemporaneously, whereas the fleet only has an immediate effect on emissions. We exclude contemporaneous interactions among the policy categories, as these may be difficult to order and justify. Additionally, we postulate that policies affect energy intensity with a delay.

Table 5: Identification of VARX(1,1) model with non-recursive short-run restrictions.

	Comp	EI	Fleet/CAP	CO2/CAP
Comp	1	0	0	0
EI	0	1	0	0
Fleet/CAP	*	0	1	0
CO2/CAP	*	*	*	1

Note: The * indicates a possible contemporaneous interaction, whereas a 0 stands for a restriction, i.e. a coefficient of zero.

One drawback of the VAR framework is its high data intensity. Therefore, the length of the

[9] The most popular structure is a triangular one based on the Cholesky decomposition. However, this implies that the results depend on the ordering of the variables and the restrictions are not always economically meaningful.

lags of the variables have to be chosen carefully. To choose this optimally, we run a series of specification tests. For these tests, we specify a VAR model with one lag for the endogenous as well as exogenous variables (i.e., a VARX(1,1) model), which we choose to maximizes the degrees of freedom. The series of model adequacy tests confirm that a lag selection of one for both the endogenous and exogenous variables is valid. Various test statistics for lag-length selection shown in Table B.3 in Appendix B select a lag length of 1 for the endogenous variables. The statistics include the Akaike information criterion (AIC), the Schwarz criterion (SC), the Hannan-Quinn (HQ) information criterion, and the final prediction error (FPE). While these criteria do not explicitly select a lag-length for the exogenous variables, the remaining adequacy tests show positive results for a VARX(1,1) specification.

The autocorrelation properties of the residuals of the VARX(1,1) model are shown in Table B.4 in Appendix B. It shows the results from the test proposed by Edgerton and Shukur (1999). The test is based on a VAR model of the error vector and tests the null hypothesis of no residual autocorrelation, i.e., all coefficients of the h orders of the VAR process are equal to zero. The results show that we are not able to reject the null at any meaningful significance level. We also test for ARCH effects in the residuals with a multivariate LM-type test from Doornik and Hendry (1997). Test results are shown in Table B.5 in Appendix B and show no sign of ARCH effects in the residuals. Given the test results, we model a structural VARX(1,1) with the chosen short run restrictions. The empirical results will be discussed in the following section.

3.4 Impulse Response Analysis and Dynamic Multipliers

Due to the interdependence of the variables, the coefficients of the VAR are difficult to interpret directly. Therefore, other concepts have been proposed to analyse such a system. One popular type of analysis for such models is the study of impulse response functions (IRFs). The basic idea of an impulse response analysis is to consider the vector moving average representation of the VAR to express model in terms of past shocks, specifically its structural errors u_t. This enables us to study how the system responds to structural shocks (impulses) related to the individual endogenous variables. Responses to shocks to exogenous variables, in contrast, can be studied with dynamic multipliers (DMs), which follow a standard ceteris-paribus interpretation. The interpretation is still similar to those of IRFs but without a dynamic feedback mechanism.

In the next subsection, we study the responses of CO2/CAP to shocks to the composite index. Then we go on to break down the index into its two main categories: $Invest$ and $Usage$. We then further disaggregate these and study specific policies contained in these sub-indices in more detail.

3.4.1 A Shock to the Composite Index

We start by analyzing the effect of a shock to the composite index on CO2 emissions from passenger cars. The VARX(1,1) in this setting is motivated by the model defined in equation (2). Figure 3 shows the cumulated impulse response of $CO2/CAP$ from passenger cars to a structural shock to the composite index ($Comp$), energy intensity (EI), and fleet/cap ($Fleet/CAP$) over time (years). The solid curves show the IRFs over time, the dashed curves provide a bootstrapped 90% confidence interval (CI), and the solid lines are plotted at zero to distinguish significant responses. The effect of a shock to a specific variable on $CO2/CAP$ is considered statistically significant at the 90% CI whenever both confidence bands are either below or above the zero line. The labels on the y-axis indicate the minimum and maximum values of the lower and upper CIs, respectively. Additionally, the estimated long-run responses are given.

The shock to the composite index is of size 6. This equals the maximum stringency the index can take if every quantitative policy is at its most stringent level and every qualitative policy is in effect. In other words, it is a 100% increase in the maximum stringency the index can theoretically take. Recall that the stringency index shown in Figure 1 reaches a maximum stringency of 4.5. The shock is thus of substantial size. As the variables in the structural VARX model are taken in first differences, the associated (cumulated) impulse responses to those shocks tend towards a long-run equilibrium. The long-run response of $CO2/CAP$ to a shock to $Comp$ of size 6 settles at -0.49 kt. This is a significant effect, given that the maximum amount of emissions in our data is at 1.365 kt (see Table 4). Converted into percentages this means that a 100% increase in the theoretical maximum stringency of the index reduces passenger transport CO2 emissions per capita by around 36% relative to its highest value.

The impulse responses of $CO2/CAP$ to shocks to EI and $Fleet/CAP$ are also shown in Figure 3. We consider negative shocks to these variables, meaning an improvement in energy intensity and a decrease in the degree of motorization. For the shock sizes we decided to use economically/technically meaningful values, in contrast to the usual choice of one standard deviation shocks. Qualitatively, both shocks decrease emissions as to be expected. The shock size to EI is set to -25 gCO2/100km. This equals around 15% of the minimum (most efficient) value of EI over our sample period. The long-run effect on passenger transport CO2 emissions per capita to this shock settles at a about -0.14 kt. In the long-run, a 15% improvement in EI relative to its minimum reduces CO2 emission per capita by around 10% relative to its maximum. The effect stays statistically significant for around seven years. The shock to $Fleet/CAP$ is set to -50 vehicles per 1000 person. This relates to roughly a 9% reduction relative to its highest value. The reaction of $CO2/CAP$ is quite stark: it decreases by about -0.90 kt (around 66% relative to its highest value). The effect is statistically highly significant for the entire period. We attribute this strong response to the dynamic feedback mechanism in the VAR system. The shock to the fleet can lead to a reinforcing dynamic that further reduces the fleet in the following periods. If this effect is strong enough, this can justify the impulse response.

Figure 3: Cumulated impulse responses for $CO2/CAP$ (1965-2019). Responses to a shock of 6 to $Comp$, -25 to EI, and -50 to $Fleet/CAP$. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.

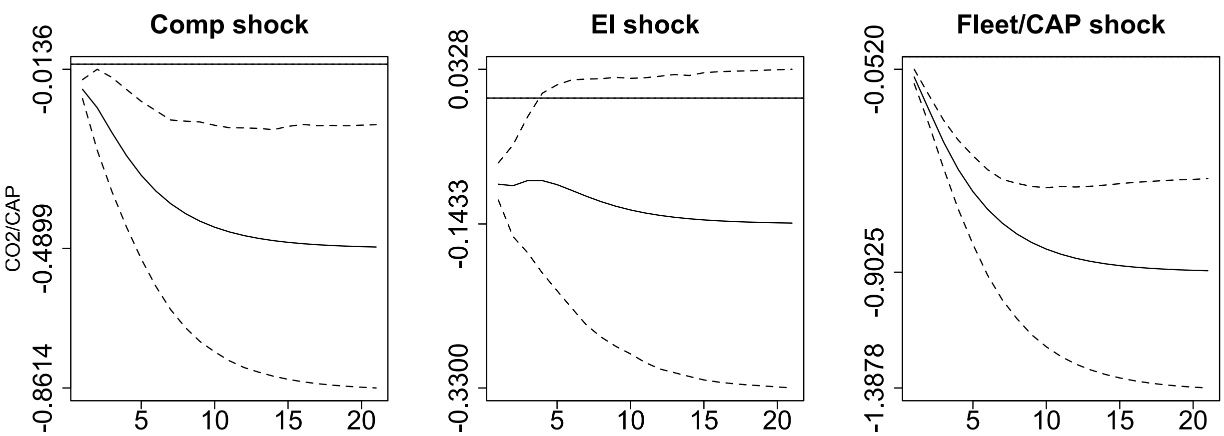
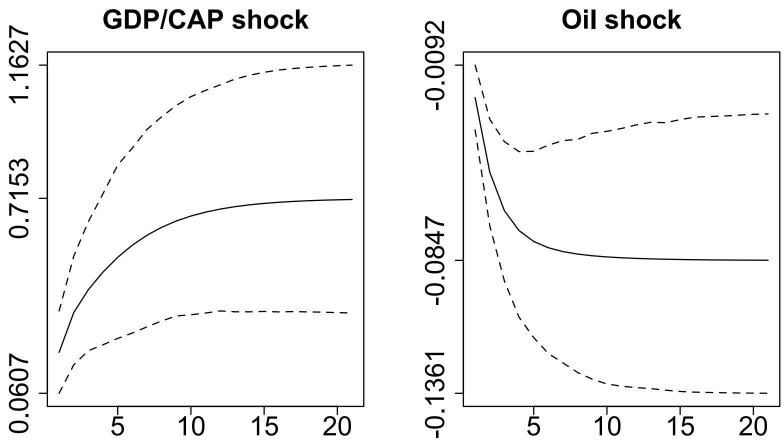


Figure 4 shows the cumulated dynamic multipliers (DMs) of $CO2/CAP$ to shocks to the exogenous variables, GDP/CAP and Oil. The shocks are of unit size and constant, and we see that the effects are highly significant. The exogenous variables are taken in log-scales. The interpretation thus follows a level-log model: an increase in the exogenous variable by 100% leads to a unit change in $CO2/CAP$ as given by the solid line in Figure 4. Therefore, an increase in GDP/CAP by 100% then leads to an increase in $CO2/CAP$ by 0.7153 kt. The effect is thus quite strong. An increase in international oil prices is associated with a decrease in (per capita) passenger transport CO2 emissions, but the effect is markedly weaker compared to GDP/CAP. Increasing Oil by 100% in the long-run reduces $CO2/CAP$ by around 0.085 kt, which amounts roughly to a 6% decrease in emissions relative to their highest value.

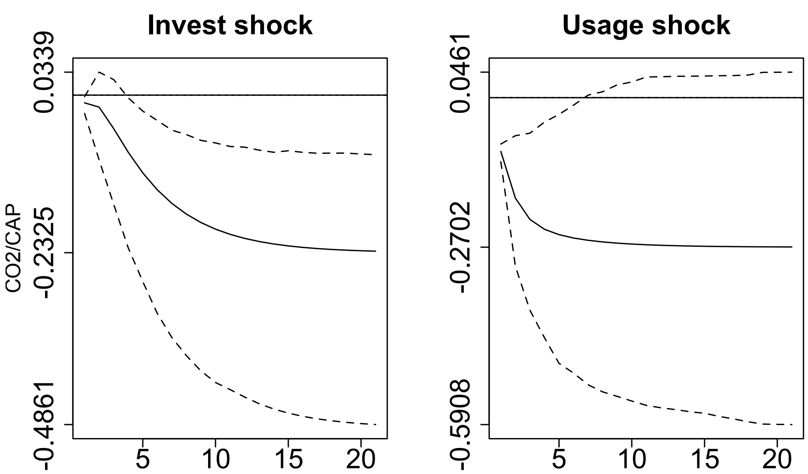
Figure 4: Dynamic multipliers for $CO2/CAP$ (1965-2019). Response to a 100%-shock to GDP/CAP and Oil. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



3.4.2 A Shock to the Sub-Indexes

We now go on to provide a more fine-grained analysis of the disaggregated policy categories. We start by decomposing the composite index into its two main sub-indexes: $Invest$ and $Usage$. To study the effect of shocks to these policy categories, we model a VARX(1,1) based on equation (3). Figure 5 contains the cumulated impulse responses to structural shocks to the two main policy categories. Shocks to the policy variables are chosen such that they represent a 100% increase in the maximum stringency (i.e. 3). Qualitatively, a shock to each of the policy categories shows a negative effect on per capita passenger transport CO2 emissions. The response of $CO2/CAP$ to a shock to $Invest$ settles at -0.2325 kt. Thus, a 100% increase in the maximum stringency of the category $Invest$ in the long-run reduces passenger transport CO2 emissions per capita by around 17% relative to its highest value. The effect of a shock to $Invest$ starts close to the zero-line and gets statistically significant only after around 5 years. This seems intuitive given that policies in this category affect the purchase behavior of new vehicles. Purchases may either not be undertaken or altered towards more efficient vehicles. Either way, it will take time for this effect to materialize in a significant reduction in emissions over the entire fleet. A shock to $Usage$ reduces emissions by about 0.2702 kt in the long-run (around 20% relative to their highest value). The effect thus seems to be a bit stronger than that of a shock to the invest category. The effect of a shock to $Usage$ significantly reduces emissions from period 0 on and remains statistically significant for around 7 years.

Figure 5: Impulse responses for $CO2/CAP$ (1965-2019). Responses to a shock of 3 to $Invest$ and $Usage$. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



Next, we disaggregate the $Invest$-category into its sub-components: $Insurance\ Tax$ and $SFC\ Tax$. To analyze the effect of a shock to these policies on per capita CO2 emissions from passenger cars, we study a VARX(1,1) based on to equation (4). Figure 6 shows the corresponding impulse responses. It depicts the response of $CO2/CAP$ to shocks to the insurance tax and standard fuel consumption tax, which together make up the $Invest$ category. Shocks are again chosen to double the maximum stringency of each policy (i.e. 1.5). Qualitatively, we can see that both policies exhibit a negative effect on CO2 emissions per capita. The shocks become significant after a few years, which seems consistent with the overall effect of $Invest$ shown in Figure 6. Quantitatively, a shock to $Insurance\ Tax$ reduces emissions by approximately 0.1586kt, which amounts to a 12% reduction relative to the highest emission value. A shock to $SFC\ Tax$ reduces emissions by about -0.0989 kt per 1000 persons in the long-run (around a 7% reduction relative to the highest emission value). Both policies significantly reduce emissions in our sample period. While the effect of $Insurance\ Tax$ is stronger, the effect of $SFC\ Tax$ overall shows stronger statistical significance.

In a final step, we disaggregate the sub-index $Usage$ into its components. Impulse responses corresponding to equation (5) are shown in Figure 7. It shows the response of $CO2/CAP$ to shocks to the mineral oil tax ($Use\ Tax$) and the remaining qualitative usage-related policies ($Use\ Qual$). Together these two categories constitute the $Usage$ sub-index. Shocks are again chosen to increase the maximum stringency of each policy by 100%. Each policy within this category can contribute a maximum of 0.75 to the index. This means that $Use\ Tax$ is shocked with 0.75, while the remaining three policies of the usage-related category are gathered in $Use\ Qual$ and are shocked with 0.75 each. $Use\ Qual$ is thus shocked by $0.75 \cdot 3 = 2.25$. Qualitatively, we can see that both policies are less significant compared to the investment-related polices. $Use\ Tax$ is only briefly significant, whereas qualitative usage-related measures appear to be highly insignificant. Quantitatively, a shock to $Use\ Tax$ reduces emissions by approximately 0.1341kt, which amounts to a 10% reduction in emissions relative to their highest value. A shock to $Use\ Qual$ reduces emissions by about -0.1950 kt per 1000 persons in the long-run (around a 14% reduction relative to their highest value).

Figure 6: Impulse responses for $CO2/CAP$ (1965-2019). Responses to shocks of size 1.5 to $Ins\ Tax$ and SFC (doubling the maximum stringency). Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.

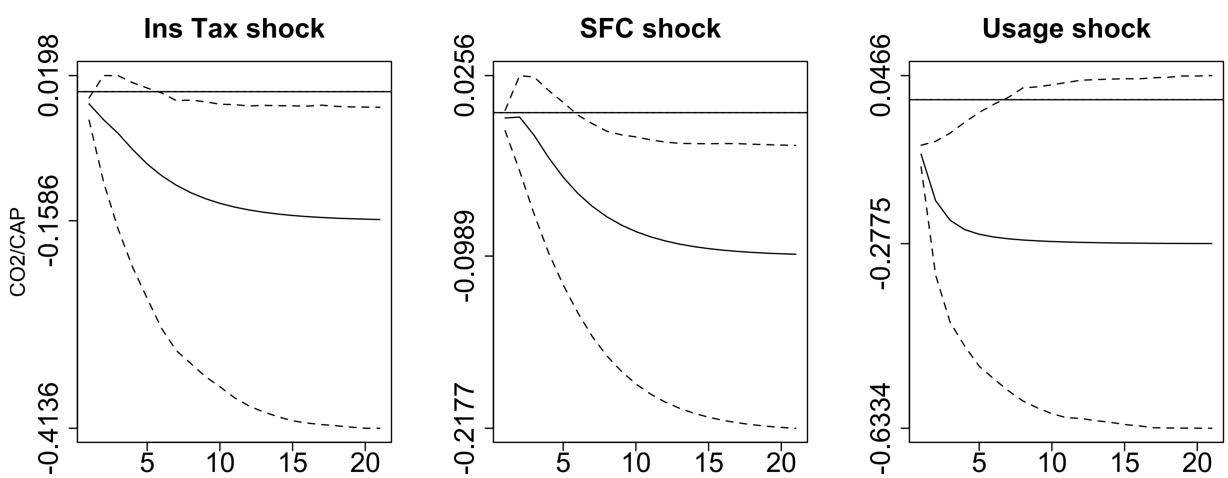
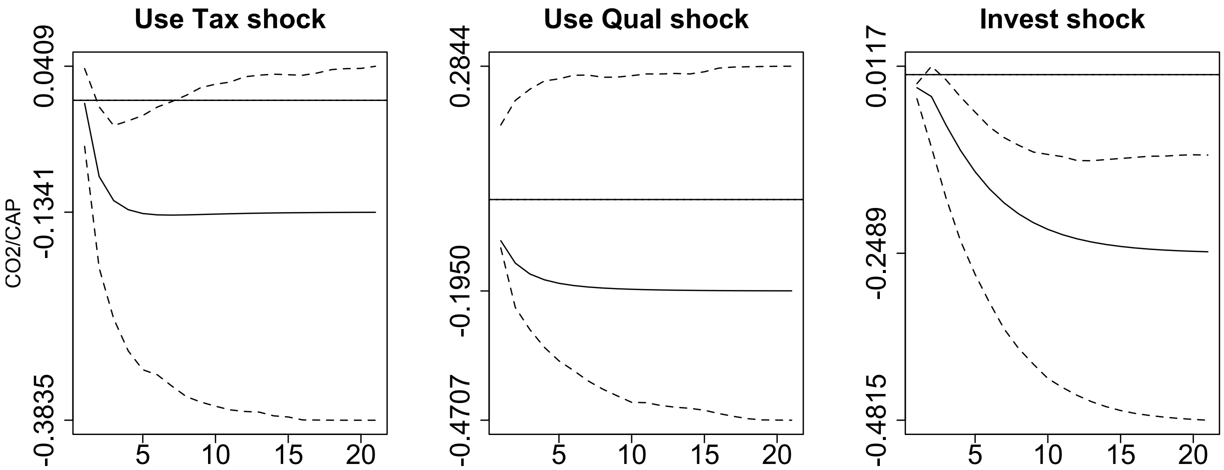


Figure 7: Impulse responses for $CO2/CAP$ (1965-2019). Responses to shock of size 0.75 to $Use\ Tax$ and 2.25 to $Use\ Qual$ (doubling the maximum stringency of each). Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



3.4.3 Robustness

Equations (4) and (5) are disaggregated forms of equation (3). Equation (4) disaggregates $Invest$ into its subcomponents. The remaining variables in equations (3) and (4) remain the same. Similarly, equation (5) disaggregates $Usage$ in (3) and the remaining variables are again the same in the two models. We can utilize this structure for robustness checks. Ideally, a shock to the same variables in the three models should show very similar responses in $CO2/CAP$ across all three models. For example, we can see from Figure 6 (corresponding to equation (4)) that the effect of a shock to $Usage$ is very similar to the effect shown in Figure 5 (corresponding to equation (3)). By comparing Figure 7 (equation (5)) to Figure 5, we see very similar effects of a shock to $Invest$ on $CO2/CAP$. These results are reassuring and add credibility to the robustness of the different specifications motivated by equations (3)-(5). Additionally, remaining impulse responses of EI and $Fleet/CAP$) as well as the remaining dynamic multipliers of GDP/CAP and Oil show very similar results. They are qualitatively identical to those reported above and quantitatively they differ only marginally, adding further credibility to the robustness of our model specifications.

The policy stringency index is calculated from nominal values whenever policy stringency is determined by price changes. The reasoning is that if we calculated the index based on real terms, it would simply change in stringency whenever prices change - even though the policy itself did not change. In this, we follow the methodology of the OECD environmental policy stringency index. However, to address this issue, we re-calculate the impulse-responses based on equations (3)-(5) extended by the consumer price index as an additional exogenous variable. This approach ensures that the stringency index remains unaffected by price changes. At the same time, the effect of changing price levels is controlled for. The IRFs remain consistent across all specifications.

4 Policy Discussion

In this section, we provide a policy discussion that focuses on three key areas. First, we discuss the impact of changes in policy stringency on CO2 emissions based on the results of the econometric analysis from Section 3.4. Second, we put these results in a wider context to explore policy options for Austria to achieve its national target to achieve net-zero GHG emissions by 2040 considering legal and economic aspects. Third, we assess the external validity of our insights for other EU countries with similar or differing policy and economic environments.

4.1 Emissions reacting to Changes in Policy Stringency

Our first interest is in the comparative effectiveness of different observed policies on reducing CO2 emissions. Table 6 concisely summarizes the effect of changes in the policy stringency index on passenger transport CO2 emissions in Austria based on the impulse response functions (IRFs) from Section 3.4. The first column shows different aggregation levels of the index. Composite is the overall index. Invest and Usage are the two main sub-indexes, which can be further disaggregated into their respective components. The level of aggregation is indicated by a slight indentation of the index components. Columns 2-4 are associated with increases in policy stringency. Column 2 shows by how many index-points an index component is increased. All stringency increases are chosen to represent a 100% increase in policy stringency. Whenever possible, this increase is stated in monetary or percentage terms for single policies. Columns 5-7 show the effect of the associated stringency increase. Column 5 shows the reduction in kt CO2 per capita from passenger cars. Column 6 shows the reduction in these emissions relative to 2019 emissions in percentage terms. The statistical significance of the emission impacts due to stringency increases is shown in Column 7.

Consider, for example, the first row of Table 6. The composite index is increased by 6 index

Table 6: Changes in policy stringency and effects on passenger transport CO2 emissions

	Policy Stringency Increase			Effect on CO2 Emissions		
	(2)	(3)	(4)	(5)	(6)	(7)
	Index-Points	Change	Single policy	kt CO2	Relative to 2019	Statistically significant?
Composite	6	100%		−0.49	−36%	yes
Invest	3	100%		−0.23	−14%	after 5 years
Ins. Tax	1.5	100%	272 EUR	−0.16	−12%	after 5 years
SFC	1.5	100%	14 p.p.	−0.10	−7%	after 5 years
Usage	3	100%		−0.27	−16.5%	up to 7 years
Fuel Tax	0.75	100%	0.45 EUR	−0.13	−10%	btw. 1-6 years
Use Qual	2.25	100%		−0.20	−12%	no

Note: Results are based on the impulse response function (IRF) results reported in Section 3. Statistical significance is based on a 10% confidence interval. The policy stringency increase is reported in monetary terms or percentage points when possible, with associated values based on 2019 levels of stringency. Statistical significance remains throughout the rest of the time horizon studied, i.e., up to 20 years, if not stated otherwise.

points. This is equivalent to a 100%-increase in its theoretical maximum value, which can only be reached when all policies are in effect and at their most stringent level ever chosen within the time period of analysis. The composite index actually takes on a maximum value of 4.5, which is lower than its theoretical maximum value of 6. Increasing the stringency of the composite index by 6 (100%) thus represents a stronger change in policy stringency than actually observed between 1965 and 2019. This change would reduce CO2/CAP from passenger cars by ∼0.49 kt, which is a reduction of ∼36% relative to 2019 emission levels. The effect is highly statistically significant throughout its contemporaneous effect (time period 0) up to 20 years after the change in stringency.

Overall, we find that policies affecting the investment decision to buy new cars have been implemented at stringency levels that were more effective in Austria than the ones of instruments affecting the usage of vehicles. The engine-related insurance tax showed the strongest quantitative impact. It increased the price of emission-intensive vehicles and is charged on a yearly basis, which can incentivise individuals to shift to more efficient efficient vehicles. In this regard, it can also serve as a push measure to promote the electrification of the vehicle fleet. In this framework, the standard fuel consumption tax can have similar effects. We find this effect to be smaller compared to the insurance tax, which may be because the standard fuel consumption tax affects new registrations only, while the insurance tax is levied on the entire fleet. We further find that the second main policy category - limiting the usage of combustion-engine vehicles - was an effective policy category to reduce emissions in the short run. This category includes the fuel tax and qualitative measures (speed limits and car-free days). However, we find these latter measures to be statistically insignificant.

These results are consistent with the notion that the transport sector is characterized by persistence. Especially policies that address the acquisition of cars and thus the development of the fleet composition will result in emissions reacting with a time lag. We can see this effect in the responses of CO2 emission to changes in the stringency of the standard fuel consumption or engine-related insurance tax. Conversely, policies targeting the usage of vehicles have been shown to have an imminent effect, but this effect seems to get watered down in the long-run. This may be attributable to people getting accustomed to the increase in, for example, fuel prices and revert to old driving habits with a time lag. Another possible explanation is that monetary stringency increases are usually not indexed to inflation, which reduces the real price of the tax increase over time. Considering their divergent time impact profile the two policy categories, focusing on influencing investment versus usage decisions, may thus well complement each other.

4.2 Implications for Austrian Policies

Austria set the ambitious goal to become carbon-neutral by 2040. For the passenger transport sector this could be ensured in the long term by a sufficiently early enforced requirement in new car registrations of zero-emission vehicles only, and by a complementary set of measures to guide the development in the short and medium term. As the transformation to a carbon-neutral transport system is not the only objective to be tackled, the policy package will need to be more comprehensive. Passenger transport in its current form is associated with a range of particular further challenges, including noise, local air pollution, geographical sprawl, affordability, safety and health issues (Dugan et al., 2022; Jochem et al., 2016; Santos et al., 2010; Steg & Gifford, 2005). The switch in engine technology from combustion to electric alone,i.e., the requirement of zero-emissions engine technology, will not suffice to address all of them.

To achieve such GHG emission reduction targets in passenger car transport over time, as discussed above, countries have instruments at their discretion that either work via incentives for or regulation of the use of cars ("usage" indicators) or via incentives or regulation of what type of car (and engine) the users acquire and thus what cars make up the national fleet, including the dynamics of the fleet development over time ("invest" indicators). Austrian transport policies between 1965-2019 included a range of instruments of both types. A structured empirical analysis of the short term and long term effects on passenger transport CO2 emissions of each of these policies at their respective stringency levels revealed that "invest" policies were the ones with stronger emission reduction implications.

In achieving a zero-emission requirement in the future itself, Austria, as a Member State of the European Union, has to act according to European law. With the European Union's 'Fit for 55' package – aiming at reducing GHG emissions by 55% by 2030 – the EU has implemented an EU-wide 'fleet target value' to reduce CO2 emissions by 100% from 1 January 2035 and on, de facto establishing an admission ban for new passenger cars and light commercial vehicles equipped with combustion engines from 2035 onwards. The Council in March 2023 has further specified that vehicles powered by CO2-neutral synthetic fuels, also known as 'e-fuels', will be exempt from this. An EU wide date in admission restrictions from 2035 onwards, however, would not ensure carbon neutrality of the private vehicle transport sector by 2040, given an average lifetime of passenger cars in Austria of 15 years (EAA, 2019).

Could Austria unilaterally restrict registrations earlier? Regulation 2018/858/EU of the European Union lays down "harmonised rules and principles for the type-approval of motor vehicles" and explicitly obliges the member states to register and operate all vehicles covered by it: According to Art 6 (5) leg cit, "they shall not, among other things, restrict or impede the placing on the market, registration or entry into service of vehicles that comply with this regulation" (Steininger, Posch, et al., 2024). Also, such de facto usage restrictions would impose an obstacle to sales and thus interfere with the EU principle of free movement of goods. While a national admission ban of passenger cars with internal combustion engines would therefore not be compatible with current EU law, it possibly could still be justified on the basis of Art. 114 (5) of the Treaty on the Functioning of the European Union, which enables national action to be taken if a 'specific' environmental problem arises in the member state. Austria would need to prove that its conditions are particular and different than in EU Member States in general, requiring such a unilateral measure. One could think of arguments, such as a particularly high sprawl in settlement structures or its alpine topography, but it would remain very uncertain whether these arguments would be sufficiently strong to justify such a unilateral intervention.

The transition in actual registrations, however, need not to be governed by registration bans of combustion engines, but could be enhanced and especially started earlier by respective economic incentives, e.g., with registration fees differentiating between combustion and other engines. Equivalently, the standard fuel consumption tax - as found effective in our analysis, see Section 4.1 - could be differentiated much more significantly by engine type. If such differentiation is sufficiently strong, registrations will shift (BMK, 2021). EU Member States do have own decision power in this field. Achieving an adequate fleet composition in the net zero target year is not the only concern of countries. For the example, in the EU, national greenhouse gas emission targets are set for both specific points in time (in particular 2030 and 2050) and for the path to get there. Up to 2030, a target path of linear emission reduction is specified for each member state for the emissions in the "effort sharing" system, i.e., all emissions outside the EU Emissions Trading System (ETS) that is operated at the overall European level. Exceeding this path is sanctioned by asking countries to acquire emission reductions of countries that lower their emissions more than they are required to.

Consequently, nations are not only concerned with the year to reach carbon neutrality, but also with emission reductions throughout the period until they reach carbon neutrality. Therefore, it is not the admission regulation alone that is of interest, but also other complementary policy measures influencing transport emissions well before the year carbon neutrality is sought to be achieved. The broad range of policies reflected in Sections 2 and 3 and synthesized in Table 6 thus remains crucial also throughout the period of transition to carbon neutrality, with e.g., economic instruments complementing technological standard setting, in particular for EU member states as they do have more individual leeway with the former than with some variants of the latter.

In our analysis of the "Usage"-type instruments, fuel taxes turned out effective. As an instrument in that spirit, Austria in 2021 has implemented a national carbon tax, effective also for the transport sector. The feature that the rate is increasing by 10 €/ton each year, addresses our finding that without such a rise the emission-reduction effect would fade out. Given that this instrument is already established, the current discussion in Austria in the context of its update of the National Energy and Climate Plan to be submitted to the European Commission focuses on other additional usage instruments: both kilometre based road pricing and reducing the speed limit are found significantly effective (Steininger, Riahi, et al., 2024). The former instrument works very similar to the fuel tax analysed above (but in this case also for alternative fuel vehicles, such as electric vehicles). While speed limits turned out not statistically significant in the past in our analysis above, the much stricter and more widely applied levels now discussed (30/80/100 kilometres/hour for municipal/countryside/highway) are broadly assessed to be of significant impact (Steininger, Riahi, et al., 2024).

4.3 External Validity

Austria presents an interesting case to study because it implemented a wide variety of policies over the past decades. These include policies targeted at the purchasing behavior of vehicles and the usage of vehicles. For the case of Austria, we find that policies targeting the purchasing behavior (the household permanent consumption good, i.e., investment decision), have been introduced in a way that they were more effective than policies addressing usage, but that this stronger effect comes with a time lag. The explanation for this stronger relevance may be a historic one. Environmental regulation started out as a field of foremost legal administration, largely resorting to command and control instruments. While in the Anglo-Saxon regions economic environmental policy instruments addressing usage were present at least over the last half century, countries such as Austria started to expand their regulatory toolbox to include them much later, and still make use of them on a comparatively smaller scale.

We believe our results externally validate because of the microeconomic principle that price changes and other policy measures generally impact consumer utility and thereby influence more sustainable transport choices. This economic rationale reinforces the broad applicability of our analysis in achieving environmental objectives through targeted policy interventions to different countries. The exact degree of applicability, however, depends on macroeconomic parallels as well as the respective policy environment of these countries over time. We will discuss these aspects in more detail below. Furthermore, we believe that our results validate not only between countries but also for specific policy goals not historically targeted by the policies we study. An example can be an accelerated switch to a more environmentally friendly engine technology, such as battery electric vehicles.

Macroeconomic factors that influence the applicability of our results to other countries include GDP per capita, population density, the geographical landscape, and energy sources. These elements collectively shape the feasibility and public reception of specific policy interventions. Economic strength may impact the viability of specific policy measures as well as their public acceptance. Population density and the distribution of population centers affects commuting habits and distances driven. Austria's geographical landscape allows it to harness renewable energy from hydroelectric power, which can be vital for supporting battery electric vehicles and to reduce emissions from a transition to more sustainable engine technologies. Countries comparable to Austria in these respects include several countries in Scandinavia - namely Sweden, Norway, Finland, and Denmark. However, Belgium, Czechia, Slovenia, Germany, and Switzerland also share numerous characteristics with Austria, making them relevant for the extrapolation of our results.

Regarding the policy environment, the Austrian experience is one of a balanced policy approach, combining both investment and usage strategies that the literature indicates to be crucial in general. Our findings on Austria's transport policies first offer insights relevant and valid for countries with similar policy environments. For example, France, Ireland, Belgium, Denmark, and Sweden introduced taxes on new vehicle registration and ownership that are directly or indirectly based on CO2 emissions and have similar or higher fuel taxes. Our results indicate that such a policy combination can be particularly effective in accelerating a transition away form combustion-engine vehicle towards zero-emission vehicles as well as other modes of transport. The latter three countries share similarities with Austria in terms of economic size and structure, further strengthening our believe of external validity in these cases.

Second, our results offer insights for countries such as Bulgaria, Croatia, Czechia, Estonia, and Poland who all lack CO2-based vehicle taxes and have lower fuel taxes. Among these, Czechia shows the closest macro-level resemblance to Austria. Nevertheless, we believe our results possess a degree of external validity for all mentioned countries, which is anchored in the micro-foundation previously discussed. The Austrian experience across more than five decades analysed here shows that both types of policies could well complement each other for achieving the now increasingly more relevant carbon neutrality target in passenger transport. Especially instruments that affect investment decisions could introduce the more long-term effective component to the national transport policy instrument package. Results also indicate that policy types do not substitute for each other, but each have their merits and contribute to achieving the emission targets. Thus we consider our results to underscore the importance of the broader principle of balancing investment and usage policies in national transport policy design.

5 Conclusion

In this paper, we introduce a new environmental policy stringency index targeted to the Austrian transport sector for the period 1950-2019. The index encompasses two main policy categories: Investment-related policies and policies that directly or indirectly limit the usage of vehicles. We then incorporate this index in an econometric model to study the efficacy of these policies in reducing CO2 emissions in the Austrian passenger transport sector. Our results can help policy makers design balanced policy packages to accelerate the transition towards a carbon-neutral transport sector. Moreover, our results are not only relevant to the Austrian transport sector, but provide policy conclusions and recommendations for a broader set of countries.

We find that for the Austrian case stringent taxes affecting the investment decision to buy a new car show the strongest effect on passenger transport CO2 emissions out of the two main policy categories. Among these policies, the engine-related insurance tax quantitatively shows the strongest impact. Doubling the stringency reduces emissions by about 0.16 kt per 1,000 persons and year. Whereas the standard fuel consumption tax (an emission-based tax on newly registered vehicles) shows the strongest statistical significance and a 100% increase in its stringency (that is the maximum divergence in stringency observed bewteen any two points in time within the period of analysis) reduces emissions by about 0.10 kt per 1000 persons and year. Both policies take a few years to show a significant impact on emissions. This is to be expected given that it takes time for newly registered vehicles to disseminate broader and only then to impact fleet emissions.

Targeting the usage significantly reduces emissions only in the short run. Among these policies, the mineral oil tax (a tax on fuel consumption) is found to be most effective. Doubling the stringency of this policy reduces CO2 emissions from passenger cars in the long-run by about 0.13 kt per 1000 persons and year. Note that its impact is smaller in magnitude compared to the investment-related policies and it is only statistically significant for a short period. The remaining usage-related policies are found to be statistically insignificant during our sample period.

Our study opens several avenues for future research. The policy stringency index for the transport sector, tailored to a specific country, is a novel approach. This methodology can be applied to other countries or a group of countries to study the external validity of results. Another avenue is the development of theoretical models and empirical study of micropanels to provide a microfoundation for policy effects and a more detailed understanding of these at the individual level. Another extension is an updated dataset that includes more recent information regarding the adoption of electric vehicles and associated policies, such as subsidies. Finally, policies could further be disaggregated to study their specific effect on different propulsion technologies, e.g., petrol and diesel. This approach might offer a clearer view of how different policies influence the transition to more sustainable transportation options.

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Declaration of interest

None.

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Appendix A

Table A.1: Policy costs and scores

Year	Ins Tax		SFC Tax		Fuel Tax		Speed Limit		Car-Free Days		IG-L	
	Cost	Scr.	Cost	Scr.	Cost	Scr.	Cost	Scr.	Cost	Scr.	Cost	Scr.
1950	NA	0	NA	0	0.0114	1	NA	0	NA	0	NA	0
1952	34.88	1	NA	0	0.0114	1	NA	0	NA	0	NA	0
1960	34.88	1	NA	0	0.0202	1	NA	0	NA	0	NA	0
1961	34.88	1	NA	0	0.1140	2	NA	0	NA	0	NA	0
1966	34.88	1	NA	0	0.1284	2	NA	0	NA	0	NA	0
1971	34.88	1	NA	0	0.1455	2	NA	0	NA	0	NA	0
1973	34.88	1	NA	0	0.1455	2	0.25	1.5	NA	0	NA	0
1974	34.88	1	NA	0	0.1455	2	0.25	1.5	0.0833	0.5	NA	0
1975	34.88	1	NA	0	0.1455	2	NA	0	NA	0	NA	0
1977	104.65	2	NA	0	0.1455	2	NA	0	NA	0	NA	0
1978	104.65	2	0.12	4	0.1455	2	NA	0	NA	0	NA	0
1980	104.65	2	0.12	4	0.2186	3	NA	0	NA	0	NA	0
1981	104.65	2	0.12	4	0.2333	3	NA	0	NA	0	NA	0
1984	156.97	3	0.12	4	0.2333	3	NA	0	NA	0	NA	0
1985	156.97	3	0.12	4	0.2262	3	NA	0	NA	0	NA	0
1987	156.97	3	0.12	4	0.2338	3	NA	0	NA	0	NA	0
1992	156.97	3	0.09	1	0.2668	3	NA	0	NA	0	NA	0
1993	180.04	4	0.09	1	0.2668	3	NA	0	NA	0	NA	0

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Table A.1 – continued from previous page

Year	Ins Tax		SFC Tax		Fuel Tax		Speed Limit		Car-Free Days		IG-L	
	Cost	Scr.	Cost	Scr.	Cost	Scr.	Cost	Scr.	Cost	Scr.	Cost	Scr.
1994	180.04	4	0.09	1	0.2906	4	NA	0	NA	0	NA	0
1995	180.04	4	0.09	1	0.3641	4	NA	0	NA	0	NA	0
1997	180.04	4	0.09	1	0.3641	4	NA	0	NA	0	1	6
2000	272.58	6	0.09	1	0.3641	4	NA	0	NA	0	1	6
2004	272.58	6	0.09	1	0.3769	5	NA	0	NA	0	1	6
2005	272.58	6	0.09	1	0.3752	5	NA	0	NA	0	1	6
2007	272.58	6	0.09	1	0.4089	5	NA	0	NA	0	1	6
2010	272.58	6	0.11	3	0.4089	5	NA	0	NA	0	1	6
2011	272.58	6	0.11	3	0.4524	6	NA	0	NA	0	1	6
2013	272.58	6	0.12	4	0.4524	6	NA	0	NA	0	1	6
2014	310.06	6	0.14	6	0.4524	6	NA	0	NA	0	1	6
2016	310.06	6	0.15	6	0.4524	6	NA	0	NA	0	1	6

Note: Only years in which policy changes took place are shown. Costs for Ins Tax and Fuel Tax are in EUR and for SFC Tax in percent of the price of the average new vehicle. Costs for qualitative measures (Speed Limit, Car-Free Days, IG-L) are indicated by a dummy variable. This dummy takes a value of 1 if the policy was in effect throughout an entire year and is otherwise weighted according to the fraction of a year that it was in force. Only the IG-L legislation is in full effect since its introduction in 1997 and receives a cost of 1 and score of 6. Speed limits were in effect for one quarter in 1973 and 1974, respectively. Car-free days were in effect for only one month in 1973.

Appendix B

Table B.1: Elliott, Rothenberg, and Stock (1996) Unit Root Test (DF-GLS)

	Levels		Differenced	
Variable	trend	constant	trend	constant
EI	−1.850	0.700	−3.700***	−3.430***
Fleet/CAP	−0.640	−0.020	−3.420**	−2.090**
CO2/CAP	−0.460	0.280	−3.210**	−2.480**
GDP/CAP	−0.630	0.680	−5.110***	−3.890***
Oil	−2.190	−1.240	−5.480***	−5.270***
Comp	−2.470	0.660	−5.710***	−5.440***
Invest	−2.070	0.160	−5.310***	−5.170***
Use	−1.870	−0.030	−5.800***	−5.660***

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$; Null hypothesis: unit root.

Table B.2: Johansen trace test, with 2 lags and linear trend

cointegrating vectors r	test	p-value
r <= 2	3.34	0.8264
r <= 1	10.99	0.8707
r = 0	27.91	0.6311

Note: Null hypothesis: number of cointegrating vectors is r.

Table B.3: VAR Order Selection Criteria

	Eq. (2)	Eq. (3)	Eq. (4)	Eq. (5)
AIC	2	1	3	1
HQ	1	1	1	1
SC	1	1	1	1
FPE	2	1	1	1

Note: The VAR order selected by the respective information criteria are shown for model specifications based on the respective Eq. numbers.

Table B.4: Edgerton and Shukur (1999) test for residual autocorrelation

	Eq. (2)	Eq. (3)	Eq. (4)	Eq. (5)
Order	P-Value			
1	0.0745	0.3333	0.7749	0.1360
2	0.1050	0.2070	0.4168	0.2769
3	0.3672	0.3828	0.2952	0.0963
4	0.5257	0.8202	0.7327	0.3823
5	0.4486	0.4537	0.3783	0.3853

Note: P-values are shown for model specifications based on the respective Eq. numbers. Null hypothesis: no residual autocorrelation.

Table B.5: Doornik and Hendry (1997) multivariate LM-test for ARCH effects in residuals

	Eq. (2)	Eq. (3)	Eq. (4)	Eq. (5)
Order	P-Value			
1	0.9189	0.9504	0.8354	0.8436
2	0.6279	0.4348	0.5714	0.559
3	0.5087	0.4098	1.0000	1.0000
4	0.6808	0.9999	1.0000	1.0000
5	0.6169	1.0000	1.0000	1.0000

Note: P-values are shown for model specifications based on the respective Eq. numbers. Null hypothesis: no ARCH in residuals.