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Abstract

Passenger transport plays a crucial role in achieving climate-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 climate-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 an environmental policy stringency index for 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 variables. We find that taxes on vehicle-related emissions and policies that influence the usage of cars (through, e.g., speed limits, car-free days, road pricing) can significantly reduce CO2 emissions and contribute to an accelerated transition towards a carbon-neutral society. Among tax-based policies, we find emission-based taxes on new vehicles to be most effective. Finally, our results indicate that more efficient fuels can reduce emissions from existing vehicles at a limited magnitude.

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). The EU set itself the target to become climate-neutral by 2050 (EC, 2021c). In the period 1990-2019, overall GHG emissions in the EU decreased by 28%. In the same period, emissions from the transport sector 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). The transport sector, and road transport in particular, thus plays an instrumental role on the way towards achieving climate goals.

While a switch to zero emission vehicles is a critical part in this process, policy makers likely have to resort to a differentiated mix of complementary policy measures to achieve global targets on climate-neutrality (Dugan et al., 2022). Policies may include mitigation pathways addressing vehicle efficiency, carbon intensity of fuels, and a reduction in overall travel (Axsen et al., 2020). Particularly, a set of complementary demand side policies aimed at reducing travel has the benefit of a possible reduction in overall transport activities, thus ameliorating non-climate related negative effects from transport, including congestion, noise or use of public space (Dugan et al., 2022).

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 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 analysis on Austria, which poses a particularly interesting case for analysis. Austria is among the most ambitious countries with respect to their climate targets. 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. 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 have increased by 74.4%. In 2019, the transport sector accounted for 30% of total GHG emissions. 19% of 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. 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 emission 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 we recognize that determinants of transport related 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.

Environmental policy stringency can be measured and proxied in various ways. One popular method is to compute composite indices. Botta and Koźluk (2014) developed a composite environmental policy stringency index for OECD countries for the period 1990-2015. The index is composed of several market-based and non-marked-based policies. It is regularly applied in empirical studies. Examples include, Georgatzi et al. (2020), Ahmed (2020), Wang et al. (2020), and Galeotti et al. (2020). For an overview of different variants of environmental stringency indicators, we refer to Botta and Koźluk (2014) and Galeotti et al. (2020). In this paper, we follow the spirit of Botta and Koźluk (2014) and create a composite stringency index for the Austrian transport sector.

The contribution of our paper to the literature is twofold. Firstly, a transport-specific policy stringency index does not exist to the best of our knowledge for any country, and the approach could be used to compute similar indices for other countries. Additionally, we compute the index for an extensive period (1950-2019), which is also a novelty. Secondly, we incorporate this index in a dynamic econometric framework that can deal with possible interdependencies between determinants of transport related emissions as well as policies related to the transport sector. The model allows us to study the diffusion of the effect of each variable over time. Such a comprehensive analysis seems to be novel in the literature. We find that an increase in environmental policy stringency in the transport sector has a negative effect on (i.e., reduces) CO2 emissions. In particular, tax-related policies and restrictions on the usage of vehicles show a strong and significant effect. Among tax-related policies, we find emission-based taxes on new vehicles most effective. Stricter standards on the usage of more efficient fuels can serve as an accompanying measure to reduce emissions.

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 and then explains the construction of the index. Section 3 establishes the econometric model used to analyse the determinants of transport related CO2 emissions. It starts with a short introduction to the related literature, lays out the basic model, explains the data used for analysis, shows some descriptive statistics, and finally discusses the empirical results. Section 4 provides a policy discussion, and Section 5 concludes.

2 A Policy Stringency Index for the Austrian Transport Sector

Indexes that measure the stringency of policies face several complications. Foremost, countries can draw on a plethora of different measures to address a specific issue. These may be characterized by varying degrees of efficacy and stringency. This aspect is commonly referred to as the problem of multidimensionality (e.g. Botta and Koźluk, 2014; Galeotti et al., 2020). Several approaches to compute such indexes have been promoted in the literature; for an overview, see Galeotti et al. (2020). We create a composite index, which simply aggregates individual indicators, and thereby closely follow the OECD environmental policy stringency index developed by Botta and Koźluk (2014).

2.1 Policies and Categorization of Policies

The policies under consideration as well as their categorizations have been established in accordance with experts from the Austrian Environmental Agency. We identified three broad categories: 1) Taxes directly affecting passenger transport related emissions, 2) measures affecting the usage of cars, and 3) regulations affecting the carbon intensity of fuels. 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 we want to

Table 1: Categorized Policy Instruments

Taxes on Emissions	Usage	Fuels
Excise Duty on Mineral Oils (Fuel Tax)	Vignette	EU Biofuel Directives
Standard Fuel Consumption Tax	Air Pollution Control Act	
Engine-Related Insurance Tax	Temporary Speed Limits	
	Car-Free Days	

focus on complementary measures to reduce emissions from combustion vehicles in addition to switch to zero emission vehicles.[1]

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 Standard Fuel Consumption Tax (commonly referred to as NoVA - Normverbrauchsabgabe) is a tax on new cars; it was introduced in 1992 (Normverbrauchsabgabegesetz, 1991). However, it can be seen as a direct successor to the Luxury Tax, which was introduced in 1978 (2. Abgabenänderungsgesetz, 1977). The NoVA, which superseded it, was calculated based on fuel consumption from 1992 to 2013, and based on CO2 emissions from 2014 onwards. The Engine-Related Insurance Tax 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 Vignette was a way to implement a collective road tax for the usage of motorways and express roads; it was introduced in 1997 (Bundesstraßenfinanzierungsgesetz, 1996). The Air Pollution Control Act 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). The EU Biofuel Directive (2003/30/EC) set minimum shares for the use of biofuels and other renewable fuel in the transport sector; it was implemented in national legislation in 2004 (Änderung der

[1] Additionally, until very recently electric vehicles in Austria were almost nonexistent relative to the diesel and petrol powered cars, making an analyses of the effect of policies directly promoting the switch to electric vehicles in our framework infeasible.

Kraftstoffverordnung 1999, 2004), and stricter targets were set in 2012 (Kraftstoffverordnung, 2012).

2.2 Computing the Stringency Index

In a next step, these categories can be combined into a composite index. The methodology thereby closely follows the OECD Environmental Policy Stringency Index developed by Botta and Koźluk (2014). The individual indicators of the composite index straightforwardly follow from the categories outlined in Table 1. The stringency of each indicator contributes to the composite stringency index. A more stringent indicator is defined as a stricter measure in an attempt to reduce passenger-transport related emissions. Environmental taxes increase in stringency with an increase in the cost of pollution. Non-market based measures (e.g. regulations) get more stringent with the increased presence of qualitative measures. The stringency in a given year is thus relative to the most stringent level of an indicator over the entire sample period. In most cases, this is 2019, the most recent year in our analysis. This seems intuitive, given that policy measures tend to increase in stringency rather than decrease (e.g. taxes tend to increase).

Following the OECD Stringency Index, a 7-step scale will be adopted. This is, of course, an arbitrary choice, and any scale may be chosen for the final version of the index. The scale goes from 0 to 6, where 0 indicates the absence of a policy, 1 the lowest stringency of a measure (e.g. when it is first introduced), and 6 indicates the most stringent realization of a policy measure. Each indicator will contribute equally to the composite index. This ensures that the effect of a given measure is not a priori influenced by different pre-determined weights. The three main categories each have a weight of 1/3 and can contribute up to a maximum of $6 \cdot 1/3 = 2$ to the composite index. Subindices are simply defined as the indices corresponding to the main categories and these will play a key role in the econometric analysis below.

The individual policies within each category are also weighted equally. The fuel tax, for example, can contribute a maximum of $6 \cdot 1/3 \cdot 1/3 = 2/3$ to the overall index. A one-step increase of it then contributes $6 \cdot 1/3 \cdot 1/3 \cdot 1/6 = 1/9$ to the index. Several instruments differentiate in their stringency between petrol and diesel cars. In these cases, we calculated weighted averages of the taxes based on the petrol and diesel shares in the relevant stocks (e.g. fleet and new registrations). In a final step, the thresholds for a one-step increase in stringency need to be calculated. These are crucial for determining by how much a given measure has to increase in stringency to warrant an increase in the 7-step scale. We employ simple linearly increasing thresholds, which are calculated by $k = |max(x) - min(x)|/h$, where k gives the linear difference from one threshold to the next, x stands for numeric realizations of a specific instrument in a given time period, and h gives the number of thresholds, i.e., 6.

Such calculations are rather straightforward for fuel taxes and the Vignette. They get more complicated with other taxes, as these include distinct tax rates for various characteristics of different categories of vehicles. As briefly mentioned above, the Engine-Related Insurance Tax was based on engine size (ccm) up to 1992. From 1993 on, it was based on engine power (kW). The Standard Fuel Consumption Tax was first calculated based on fuel consumption and later based on CO2 emissions. Additionally, in 2008 a bonus-malus regulation was implemented, which benefited low emission cars and applied additional costs to cars with high emissions.

To calculate the effective tax rates, one could resort to one of two approaches. One would be to 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. Take for example the Standard Fuel Consumption Tax from 2014 onward (when it was based on CO2 emissions). Cars have gotten more efficient (at least on paper), meaning that the tax would get less stringent over time. Therefore, we resort to constant attributes of cars for computing these components of the index. The Engine-Related Insurance Tax is based on attributes of cars in the existing fleet. Data on average attributes of the car fleet have been taken from "Verkehr in Zahlen", published by the German BMDV, 2019.[2] The Standard Fuel Consumption Tax, on the other hand, is calculated based on attributes of new cars. Data on average emissions have been extracted from the National Inventory Reports from the Austrian Environmental Agency. The bonus-malus system affects the tax in absolute terms. To convert these to percentages, we calculated the average net price of new cars with the price index for new vehicles for Germany.[3]

Qualitative instruments have to be treated slightly differently. Usually, these measures do not change in stringency over time, as they are either in force or not. Whenever such instruments

[2]We assume that characteristics from cars driven in Germany proxy attributes of cars driven Austria well enough for the purpose of the index.

[3]The relevant attributes for the existing fleet are: 1660 ccm, 69 kW. For new registrations we use: 7.1 l/100km, 173 gCO2/100km, and 18,650 EUR net price.

are implemented, they are indicated by a value of 1. This equals their most stringent level and is thus rescaled to equal the largest scale value (in this case 6). All qualitative measures are weighted equally.

2.3 The Fuel Tax as an Example

The Excise Duty on Mineral Oil (fuel tax) shall serve to exemplify the calculation of the index. The minimum value of the tax over the entire sample period for diesel was EUR 0.0061, for petrol it was EUR 0.01471.[4] The weighted average gives EUR 0.0114. The maximum value for diesel is EUR 0.397, and for petrol EUR 0.482. The weighted average is EUR 0.4524. For a 7-step scale, the step size is $k = |0.4524 - 0.0114|/6 = 0.0735$. An increase of EUR 0.0735 would thus lead to a one-step increase in the stringency of the tax.

The thresholds based on $k = 0.0735$ are given in Table 3. The lowest threshold for an existing policy is calculated as the sum of its mimimal numeric realization plus k. The remaining steps are linearly increasing by steps of k. Additionally, the corresponding scores (index scale) as well as the contribution of a given scale value to the overall index are shown. The most stringent fuel tax level is associated with a score of 6 and would contribute the maximum of 0.67 to the composite index. Similar calculations can be applied to all other non-qualitative instruments.

Table 2: Subindex for Fuel Tax. The fuel tax is calculated as a weighted average of taxes on diesel and petrol.

	range	score	contr.
=	0	0	0
<	0.0849	1	0.11
<	0.1584	2	0.22
<	0.2319	3	0.33
<	0.3054	4	0.44
<	0.3789	5	0.55
<	0.4524	6	0.67

[4]Taxes on diesel and petrol are based on fuels with sufficiently low sulfur and high biodiesel content to be eligible for reduced mineral oil tax rates.

2.4 The Final Index

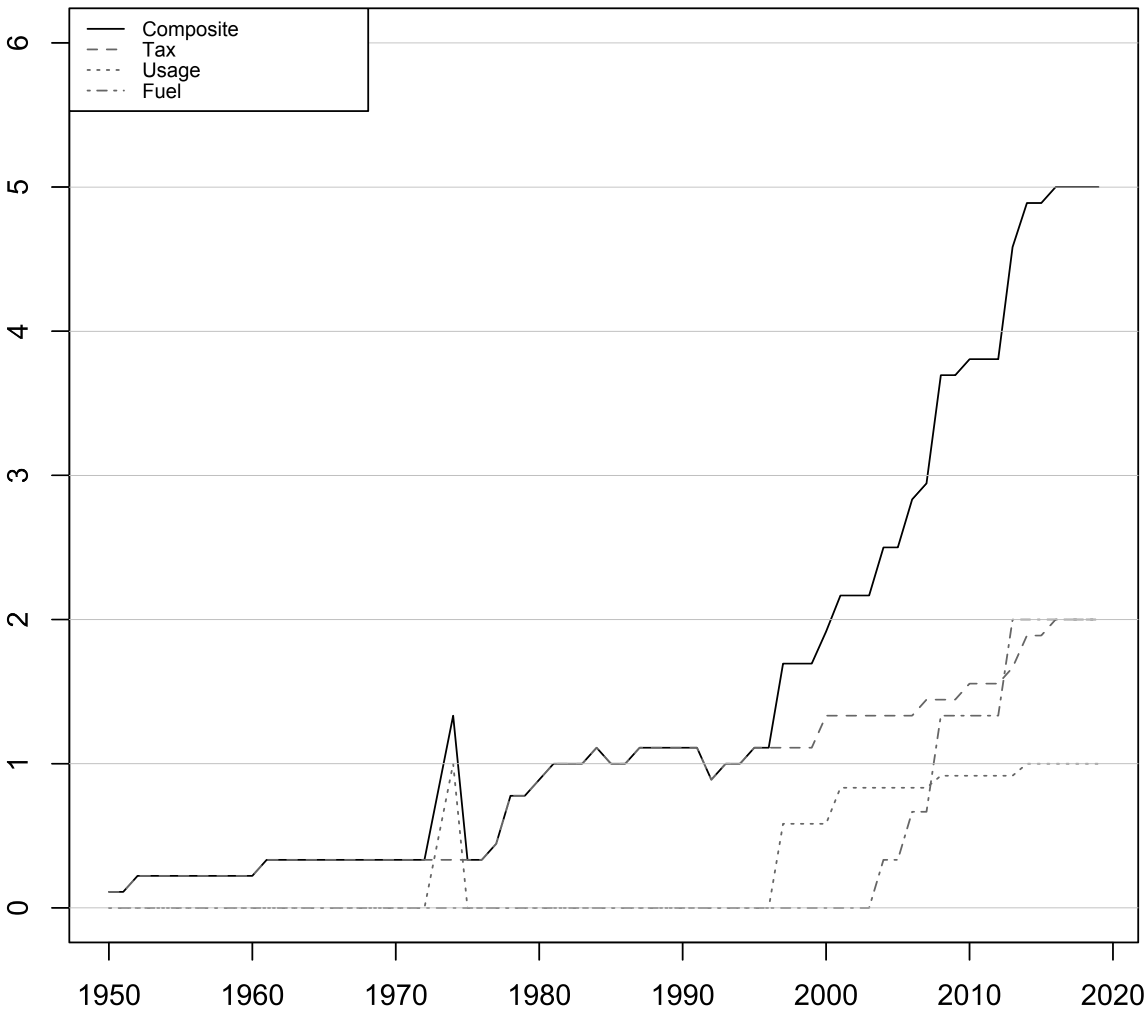
The final index for a 7-step scale (0-6) is shown in Figure 1. The composite index is given by the solid line. The index based on taxes on emissions is given by the dotted line, measures affecting the usage of cars by the loosely dashed line, and measures affecting fuel carbon intensity by the dashed line. The actual maximum value of the composite index is 5, which is 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, namely the car-free day and the temporary speed limits. Each of these two measures can reach a maximum contribution of 0.5.

During the first two decades in the sample period, the composite index is exclusively driven by taxes on emissions. Measures on the usage of cars spiked in 1973-1974 due to the introduction of the car-free day and temporary speed limits. Another steep increase can be noticed in 1997, which can be attributed to the implementation of the Vignette and the Air Pollution Control Act. In 2001, the price of the Vignette was significantly raised, it almost doubled. The Biofuel Directive and its amendment laid out benchmarks with increasing stringency starting in 2003. Increases can bee seen in 2006, 2008, and 2013. Overall, the composite index can be characterized by a spike in 1973-1974, a strong increase in stringency around 1997 and then again around 2005.

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 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)

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



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

Transport related data 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). Data on CO2, EI, and Fleet have been provided by the Austrian Environmental Agency. CO2 emissions are measured in 1000t, data on the vehicle fleet contain the total fleet of petrol and diesel powered cars (including hybrid and plug-in hybrid vehi-

Table 3: Description of Variables

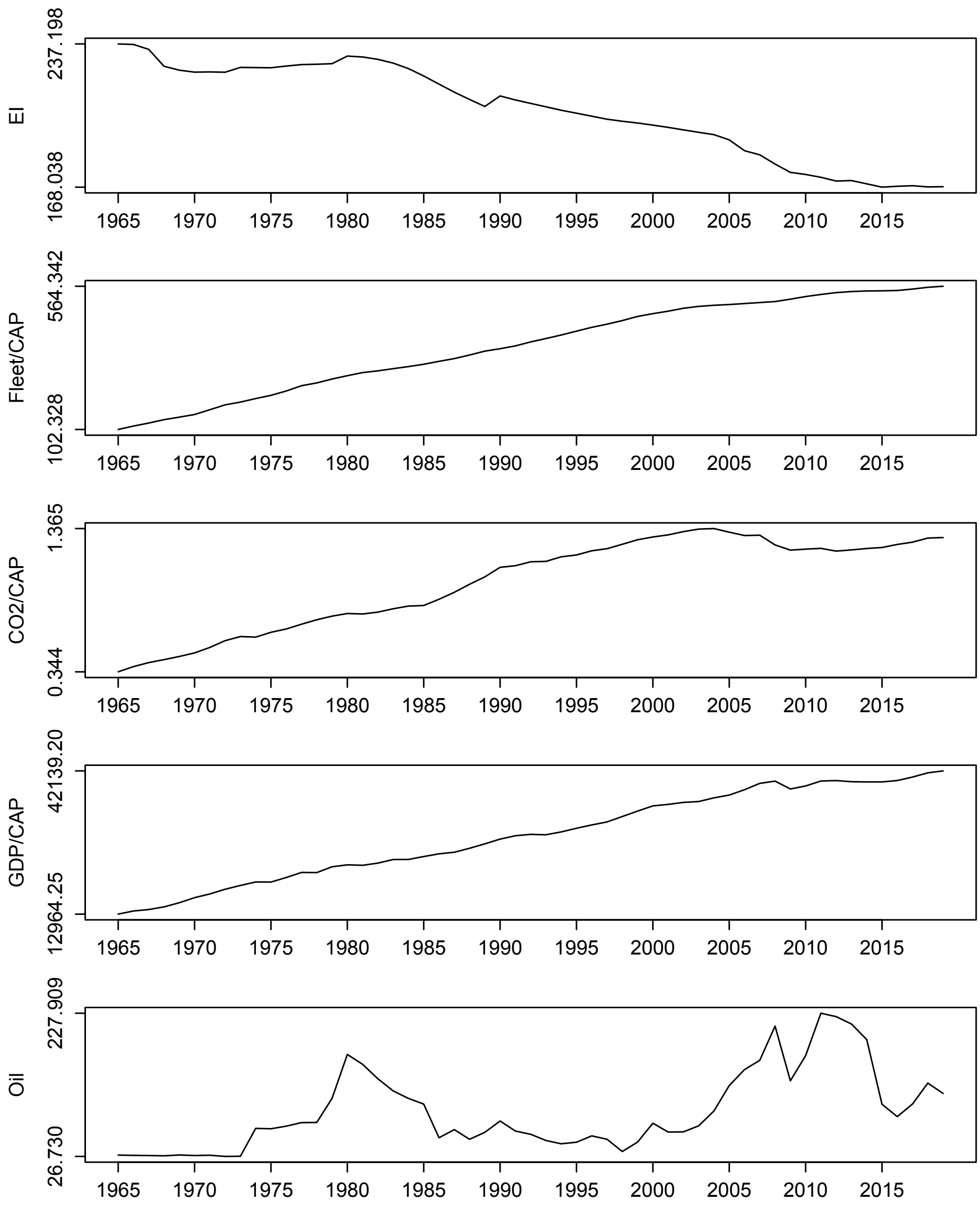
Variable	Description
CO2/CAP	CO2 emissions from combustion engine passenger cars (diesel, petrol, hybrids, and plug-in hybrids) in 1000t divided by the average population in a given year in 1000 persons.
EI	Energy intensity measured by grams CO2 emitted per 100km
Fleet/CAP	Total number of passenger cars 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).

cles) 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

Figure 2: Time Series in Levels, 1965-2019



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 categories as we are interested on their effect on CO2 emissions. The baseline model for CO2 emissions per capita then becomes:

$$\begin{aligned} CO2/CAP_t =& \alpha + \beta_1 Tax_t + \beta_2 Usage_t + \beta_3 Fuel_t + \beta_4 EI_t + \beta_5 Fleet/CAP_t \\ &+ \beta_6 GDP/CAP_t + \beta_7 Oil_t + u_t, \end{aligned} \tag{2}$$

where Tax_t stands for the subindex containing taxes on emission, Use_t for measures aimed at influencing the usage of cars, and $Fuel_t$ for measures that improve carbon intensity of fuels. This model forms the basis for our specification, but it has the drawbacks that (i) it is likely to suffer from endogeneity and (ii) is a static model, whereas we are interested in dynamic effects. The next section describes our modeling approach.

3.3 VAR Analysis

Most variables in Eq. (2) are likely to be endogenous. These include the policy categories (Tax, Use, Fuel) 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 nonstationarity as well as 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 dominate 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 Eq. 2.

The resulting test statistics are shown in Table A.1 in Appendix A. 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 A.2 in Appendix A[5]. 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:

$$\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{\mu} + \textstyle\sum_{i=1}^{p}\boldsymbol{B}_i\boldsymbol{y}_{t-i} + \sum_{j=0}^{q}\boldsymbol{\vartheta}_j\boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \tag{3}$$

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

where $t = 1, ..., T$, $\boldsymbol{y}_t$ 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 parameter matrix containing the contemporaneous interactions, $\boldsymbol{B}_i$ are K matrices containing the coefficients of the lagged endogenous variables, $\boldsymbol{\vartheta}_j$ are M matrices containing the coefficients of the exogenous variables, and $\boldsymbol{u}$ 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.

Applying the model to the variables in Eq. (2) and taking first differences we obtain:
$\boldsymbol{y}_t = [\Delta Tax_t, \Delta Use_t, \Delta Fuel_t, \Delta EI_t, \Delta Fleet/CAP_t, \Delta CO2/CAP_t]'$ 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:

$$\boldsymbol{B}_0^{-1}\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{B}_0^{-1}\boldsymbol{\mu} + \textstyle\sum_{i=1}^{p} \boldsymbol{B}_0^{-1}\boldsymbol{B}_i\boldsymbol{y}_{t-i} + \sum_{j=0}^{q} \boldsymbol{B}_0^{-1}\boldsymbol{\vartheta}_j\boldsymbol{x}_{t-j} + \boldsymbol{B}_0^{-1}\boldsymbol{u}_t, \tag{4}$$

which can be rewritten more compactly as:

$$\boldsymbol{y}_t = \tilde{\boldsymbol{\mu}} + \textstyle\sum_{i=1}^{p} \boldsymbol{\phi}_i\boldsymbol{y}_{t-i} + \sum_{j=0}^{q} \boldsymbol{\theta}_j\boldsymbol{x}_{t-j} + \boldsymbol{v}_t, \tag{5}$$

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.[6] In order to identify the system, we placed custom 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 taxes and usage related policies affect energy intensity with a delay, whereas more efficient fuels instantly improve energy intensity. Finally, more efficient fuels as well as an changes in

[6]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.

EI do not contemporaneously affect the fleet.

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

	Tax	Use	Fuel	EI	Fleet/CAP	CO2/CAP
Tax	1	0	0	0	0	0
Use	0	1	0	0	0	0
Fuel	0	0	1	0	0	0
EI	0	0	*	1	0	0
Fleet/CAP	*	*	0	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 lags of the variables have to be chosen carefully. According to various test statistics shown in Table A.3 in Appendix A, we choose lag length of 1. The statistics include the Akaike information criterion (AIC), the Schwarz criterion (SC), the Hannan-Quinn (HQ) information criterion, and the final prediction error (FPE).

If we are interested in inference, it is useful to analyse the autocorrelation properties of the residuals of the VAR model. Table A.4 in Appendix A 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.

3.4 Impulse Response Analysis and Dynamic Multipliers

Following the model adequacy results, we model a structural VARX(1,1) with the chosen short run restrictions. Due to the interdependency of the variables, the coefficients are very hard to interpret directly. Therefore, other concepts have been proposed to analyse such a system. One popular type of analysis for such a model 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, i.e., its structural errors u_t. This enables us to study how the system responds to structural shocks (impulses) related to the individual variables. IRFs are suited to study the dynamic feedback mechanism between the variables.

But the results cannot be interpreted as ceteris paribus, rather the IRFs consider the dynamic interdependency of all endogenous variables. In some instances it may be desirable to treat some variables as exogenous. These include variables that are determined outside of the system that is modelled. Although IRFs study the dynamic feedback between the endogenous variables and the effects can thus not be interpreted as ceteris paribus, these exogenous variables are held constant in the impulse response analysis. Responses to shocks to those variables can be studied with dynamic multipliers (DMs). The interpretation is similar to those of IRFs but without a dynamic feedback mechanism within these variables.

In the next subsection, we study the responses of CO2/CAP to shocks to the three main policy categories, to EI and Fleet/CAP. Dynamic multipliers are discussed for GDP/CAP and Oil. Then we go on to study the effect of tax-related policies contained in the category Tax in Section 3.4.2. This analysis additionally serves as a robustness check, in which we study the sensitivity to our previous results to alternative model specifications.

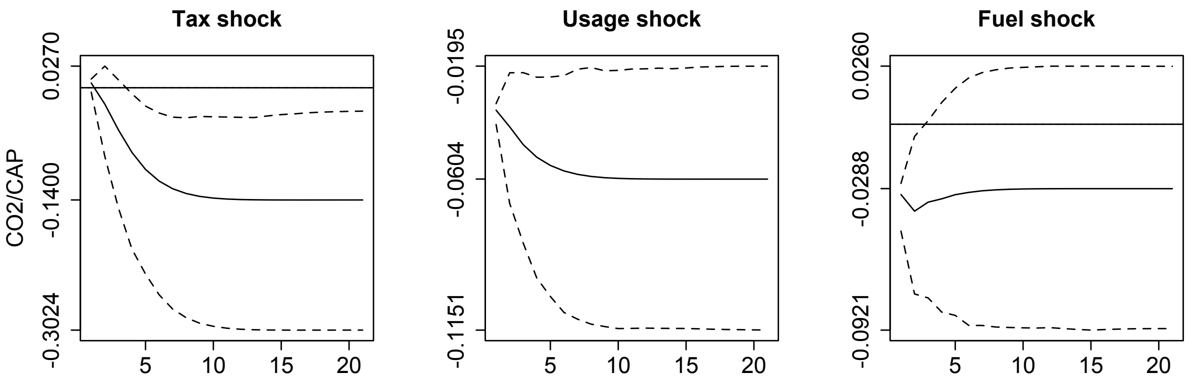
3.4.1 Main Policy Categories

Figure 3 contains the cumulated impulse responses to structural shocks to the three main policy categories over time (in 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 labeled.

Shocks to the policy variables are of unit size. This has the advantage that shocks to the policy variables are of comparable magnitudes. A unit shock to the policies is associated with an increase in the respective index category of one unit. Recall that the maximum value the three sub-indices can take is two. These shocks are thus of significant magnitude. Qualitatively, a shock to each of the three policy categories shows a negative effect on CO2 emissions. A shock to Tax is significant after a few years, whereas a shock to Usage is significant throughout the entire time period, and a shock to Fuel is only significant in the very short run.

The quantitative interpretation is a bit more complex. While the contemporaneous shocks to

Figure 3: Impulse responses for CO2/CAP (1965-2019). Responses to a unit shock in policy variables. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



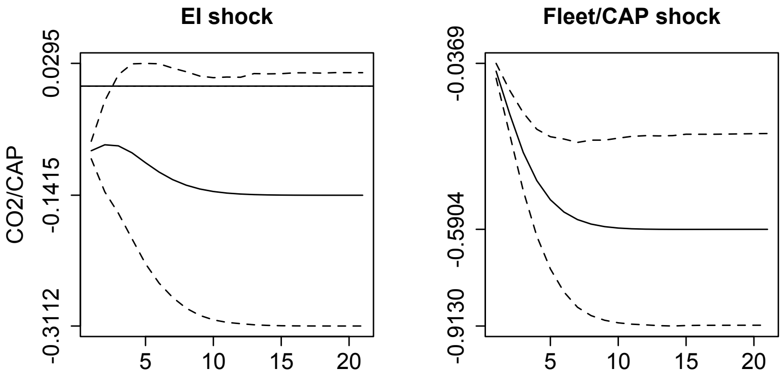
the policy categories are of unit size, this need not hold for consecutive time periods.[7] As the variables in the structural VARX model are taken in first differences, the shocks as well as the associated impulse responses to those shocks tend towards a long-run equilibrium. The unit shock to Tax settles at about 0.75. The response of CO2/CAP to this shock settles at 0.14. Thus, a unit shock to the category Tax gets slightly watered down and in the long-run reduces CO2 emissions per capita by 0.140 kt. This is a significant effect, given that the maximum amount of emissions in our data is at 1.365 kt (see Table 4 in Appendix A). A unit shock to Usage settles at about 0.85 and reduces emissions by about 0.6 kt in the long-run. The effect thus seems to be weaker than that of a shock to Tax. Finally, a shock to Fuel settles at about 0.74 and is associated with a long-run reduction in emissions of about 0.03 kt. It thus shows the weakest effect of the three policy categories.

The impulse responses of CO2/CAP to shocks to EI and Fleet/CAP are shown in Figure 4. 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 and in the long run, through the model dynamics, converges to an improvement of -40 gCO2/100km. The long-run effect on CO2 emissions per capita

[7]We interpret this in the sense that some policy measures may be reversed or weakened due to political pressure and the fact that these are typically not very popular. This effect is captured in the model and the interpretation of the estimated effect sizes.

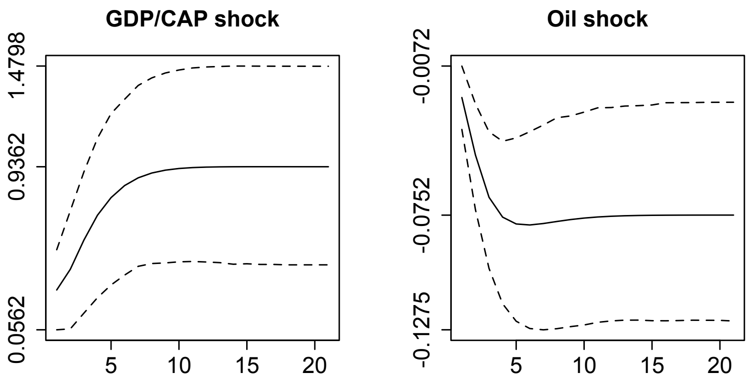
settles at a reduction of about -0.14 kt. However, the effect gets statistically insignificant after a few years. The shock to Fleet/CAP is set to -50 vehicles per 1000 person, and it settles at about -140 vehicles per 1000 person in the long run. The reaction of CO2/CAP is quite stark: it decreases by about -0.6 kt. The effect is statistically highly significant for the entire period.

Figure 4: Impulse responses for CO2/CAP (1965-2019). Responses to a shocks in EI and Fleet/CAP. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



For the exogenous variables, Figure 5 shows the cumulated dynamic multipliers (DMs) of CO2/CAP to shocks in GDP/CAP and Oil. The shocks are of unit size and constant, and we see that the effect 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 1% leads to a unit change in CO2/CAP as given by the solid line in Figure divided by 100. Therefore, a 1% increase in GDP/CAP in the long-run is estimated to lead to an increase in CO2/CAP of about 0.0094 kt. An increase by 100% then leads to an increase of 0.94. The effect of GDP/CAP on CO2/CAP is thus quite strong. An increase in international oil prices is associated with a decrease in CO2/CAP, but the effect is markedly weaker compared to GDP/CAP.

Figure 5: Dynamic multipliers for CO2/CAP (1965-2019). Response to a 1%-shock in GDP/CAP and Oil prices. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



3.4.2 Tax-Related Policies and Robustness

We saw that out of the three main policy categories, Tax and Usage seem to be more effective than Fuel. Moreover, Fuel gets statistically insignificant quickly. Therefore, we disaggregate the Tax index to study the efficacy of different tax-related policies in reducing CO2 emissions per capita. We modify the structural VARX motiviated by Eq. 2 as follows:

$$\begin{aligned} CO2/CAP_t =& \alpha + \beta_1 Fuel\ Tax_t + \beta_2 Insurance\ Tax + \beta_3 SFC\ Tax + \beta_4 Usage_t \\ &+ \beta_5 EI_t + \beta_6 Fleet/CAP_t + \beta_7 GDP/CAP_t + \beta_8 Oil_t + u_t. \end{aligned} \tag{6}$$

In Eq. (6) we thus substitute the main policy category Tax with the three tax-related policies contained within this category: we include the mineral oil tax (Fuel Tax), engine-related insurance tax (Insurance Tax), and the standard fuel consumption tax (SFC Tax). We exclude the main category Fuel from the model, but the rest of the model specification stays unchanged. All variables are again taken in first differences.[8]

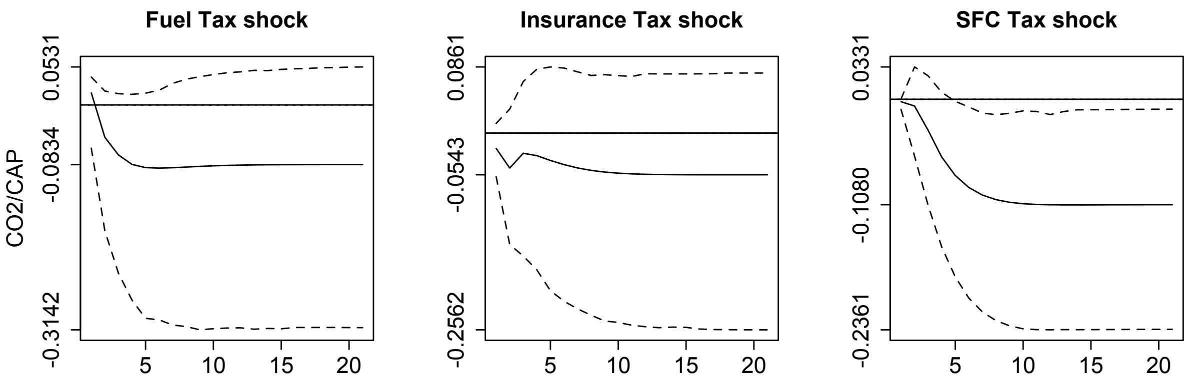
Figure 6 shows the impulse responses of CO2/CAP to shocks to the three tax-related policies. Shocks are of size $\frac{2}{3}$. This is related to the most stringent version of the policies in our

[8]The identification strategy is equivalent to that for the model with the three main policy categories. For the three tax-related policy variables, we adopt the same custom short-run restrictions as for the main category Tax. According to lag-selection criteria, the structural VARX is again modelled with one lag for both the endogenous and exogenous variables. Deterministic components include a constant but no trend. Tests for residual autocorrelation suggest an adequate model specification; test results are available on request.

sample period. The shock can thus be associated with doubling the stringency of each tax-related policy. Qualitatively, we can see that all of these policies exhibit a negative effect on CO2 emissions per capita, but only a shock to SFC Tax is statistically significant. Quantitatively, a shock to Fuel Tax settles at about 0.77 and reduces CO2 emission per 1000 persons by about 0.083kt. A shock to Insurance Tax settles at about 0.56 and reduces emissions by approximately 0.054kt. Finally, a shock to SFC Tax settles at about 0.63 and reduces emissions by about -0.11 kt per 1000 persons in the long-run. We can thus conclude that a shock to SFC Tax has the strongest impact on CO2 emissions per capita for the sample period. It is also the only tax-related category that is statistically significant. Although Fuel Tax and Insurance Tax are statistically not significant, the former shows a stronger impact on emissions, and the confidence band is closer to the zero-line. Overall, we attribute the statistical insignificance to the limited data availability and are quite confident that all three policies would show statistical significance given a larger sample size.

The impulse responses and dynamic multipliers for the other variables in Eq. (6) can be considered as a robustness check, but they are not included explicitly to save space. Overall, we find very similar results. The response of CO2/CAP to Usage is nearly indistinguishable to that in the previous section. The remaining impulse responses and dynamic multipliers are qualitatively identical to those reported above and quantitatively they differ only marginally. This indicates that our model specification shows robustness, at least to a certain degree, to alternate model specifications.

Figure 6: Impulse responses for CO2/CAP (1965-2019). Responses to shocks of size 2/3 to tax-related policy variables. Hall's percentile intervals are at 10% significance level with 1000 bootstrap replications.



4 Policy Discussion

Austria set the ambitious goal to become climate-neutral by 2040. To this end, it proposed to completely phase out new registrations of non-zero-emission vehicles by 2030 in its Mobility Master Plan 2030 (BMK, 2021). Considering that the average life-span of a car is estimated to be around 15 years (EAA, 2019), even this drastic measure will not be sufficient to decarbonise the transport sector by 2040. Additionally, an increasing electrification of the vehicle fleet is still associated with adverse effects, e.g., noise, congestion, and use of limited public space (Dugan et al., 2022). Thus, scientists highlight demand-side concepts, such as "avoid-shift-improve" (e.g., Creutzig et al., 2018). Also, Dugan et al. (2022) emphasize the importance of a diversified set of policy measures to meet climate goals in the transport sector.

The "avoid-shift-improve" framework incorporates measures to *avoid* trips, *shift* to more sustainable modes, and *improve* the efficiency of remaining transport activities. Our results can be discussed within this framework as well. We analysed the effect of various transport-related policies in Austria from 1965-2019. The three main policy categories are: tax-related policies, policies that impact the usage of vehicles, and stricter biofuel regulations. Tax-related policies showed the strongest effect on emissions.

The emission-based tax on new vehicles (SFC tax) proved to be most effective. It increased the price of emission-intensive vehicles, which can incentive individuals to avoid motorized individual transport altogether and to shift to more sustainable transport modes (e.g., public transport). It can also serve as a push measure to promote the electrification of the vehicle fleet (improve). Push measures can complement pull measures - financial incentives to accelerate the transition to a zero-emission vehicle fleet. In this framework, the engine-related insurance tax and mineral oil tax (a tax on fuel consumption) can have similar effects, albeit that we find them to be less effective and less significant compared to the SFC tax.

We further find that limiting the usage of combustion-engine vehicles was an effective policy category to reduce emissions. This category includes speed limits, car-free days, and road pricing. Speed limits can reduce emissions as well as noise and congestion (Nitzsche & Tscharaktschiew, 2013). Road pricing can help to internalize external costs associated with motorized individual transport (Eliasson, 2021). It can also help to reduce the rebound effect from more efficient vehicles, e.g., more trips due to lower trip costs associated with more efficient vehicles (EEA, 2022). Car-free days can also help avoid trips and promote a shift to more sustainable transport modes and active mobility.

Overall, we find that a combination of tax-based policies and limiting the usage of vehicles can be effective measures in reducing CO2 emissions. Our results also indicate that more efficient fuels (biofuels) can be utilized as accompanying measures, although we find their effect to be limited. Combining these strategies with mandates on the promotion of electric vehicles may be a particularly effective mix to accelerate the transition towards a climate-neutral transport sector. These findings are in line with other studies, such as Lam and Mercure (2021), who recommend a policy mix of taxes, mandates on electric vehicles, and regulations on non-zero-emission vehicles to effectively reduce emission in the transport sector.

From an international perspective, our findings are relevant as well. In the EU, CO2 emissions from transport are expected to only drop by 41% by 2050 compared to 2015 (EC, 2021a). Recently, the EU pushed a plan to ban non-zero-emission vehicles 2035 (EC, 2021b). But rebound effects and other adverse effects of individual motorized transport (e.g., noise, congestion, traffic accidents, extended use of limited public) remain (EEA, 2022). This is particularly relevant because overall transport activity is projected to increase until 2050 in the EU (EC, 2021a).

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 three main policy categories: Tax-related policies, policies that directly or indirectly limit the usage of vehicles, and regulations on the usage of more efficient fuels (biofuels). We then incorporate this index in an econometric model to study the efficacy of these policies in reducing CO2 emissions in the Austrian transport sector. Our results can help policy makers design balanced policy packages to accelerate the transition towards a climate neutral transport sector. Moreover, our results are not only relevant to the Austrian transport sector, but provide policy options for a broader set of countries.

Our analysis is in line with other studies that suggest a differentiated set of policy measures to decarbonise the transport sector. We find that stringent taxes show the strongest effect on CO2 emissions out of the three main policy categories. Among the tax-related policies, the standard fuel consumption tax (an emission-based tax on newly registered vehicles) shows the strongest emission-reduction potential. The mineral oil tax (a tax on fuel consumption) and the engine-related insurance tax also show a negative effect on emissions, albeit a weaker one. Limiting the usage of combustion-engine vehicles (through, e.g., speed limits, car-free days, or road pricing) is another viable option to reduce emissions. Lastly, our results suggest that more efficient fuels can also play a role in reducing CO2 emissions, although at a limited magnitude.

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Declaration of interest

None.

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Appendix A

Table A.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	-0.850	0.140	-3.210^{**}	-2.480^{**}
GDP/CAP	-0.630	0.680	-5.110^{***}	-3.890^{***}
Oil	-2.190	-1.240	-5.480^{***}	-5.270^{***}
Tax	-2.060	1.060	-5.030^{***}	-4.720^{***}
Use	-2.520	-0.890	-7.370^{***}	-7.300^{***}
Fuel	-0.640	1.170	-4.520^{***}	-3.950^{***}

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

Table A.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

Null hypothesis: number of cointegrating vectors is r

Table A.3: VAR Order Selection Criteria

Lag	AIC	HQ	SC	FPE
1	$-1.703826e+01^{*}$	$-1.625663e+01^{*}$	$-1.499280e+01^{*}$	$4.074810e-08^{*}$
2	$-1.684367e+01$	$-1.554095e+01$	$-1.343457e+01$	$5.389282e-08$
3	$-1.645181e+01$	$-1.462801e+01$	$-1.167907e+01$	$9.781592e-08$
4	$-1.626550e+01$	$-1.392061e+01$	$-1.012911e+01$	$1.771067e-07$

* indicates chosen lag order selection criteria

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

Order	P-Value
1	0.3427
2	0.1889
3	0.6928
4	0.8645

Null hypothesis: no residual autocorrelation

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