Policy Stringency and Drivers of CO2 Emissions from Passenger Cars in Austria over the period 1950-2019

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1 Introduction

The Paris Agreement in 2015 marks the commitment of the international community to a carbon-free society by setting the target to stay well below +2°C of global warming (IPCC, 2018). In 2019, the EU released the European Green Deal, a roadmap on how to achieve climate-neutrality by 2050. The transport sector plays an instrumental role on the way towards achieving this goal. Overall greenhouse-gas (GHG) emissions decreased from 1990 to 2018 in the EU-27. Many sectors contributed to this development – with one marked exception. GHG-emissions from the transport sector increased by 29% in the period 1990-2017. The largest share of transport-related emissions (mostly CO2) stems from road transport (72%), and cars make up the largest share within road transport (IPCC, 2018).

One crucial element to achieve climate neutrality in the transport sector is to promote the switch to electric vehicles (IEA, 2019). But to achieve the target set in the Paris Agreement, it is more likely that a differentiated set of policies will be required rather than a single policy, such as a switch to low carbon technologies. Such 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 and noise.

To devise effective policy mixes, 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 would provide policy makers with a guide on which measures to include in a policy package to achieve the global target. In this paper, we analyse transport related policies in Austria from 1950-2019 in a dynamic econometric framework. We thereby recognize that transport sector is governed by systemic delays. These are, in part, governed by the fact that vehicles have a relatively long lifetime. Policies aimed at influencing the existing vehicle stock thus come with a delay. To devise effective policy measures to reduce transport related emissions, policy makers have to be aware of this delay.

We focus our analysis on Austria, which poses a particularly interesting case for analysis. It is among the most ambitious countries with respect to their climate targets. It was one of the first countries to ratify the Paris Agreement. It recently even set itself a stricter goal than that outlined the EU's Green Deal, that is, Austria aims to become carbon-neutral by 2040. Here again, the transport sector will play a crucial role in achieving this goal. Transport emissions in Austria have grown significantly and, in 2017, amounted to 29.5% of overall GHG-emissions (Anderl et al., 2019). Policy instrument packages to meet Austria's environmental target are yet to be implemented. Existing policy measures in Austria are not expected to achieve a significant reduction in motorized individual transport. They are also expected to be insufficient in reaching Austria's contribution in the EU effort sharing, i.e. cutting CO2 emissions by 36% in 2030 relative to 2005 (Heinfellner et al., 2019).

To evaluate transport related policies in Austria, we employ a two-step procedure. In a first step, we construct a policy stringency index. This index captures the stringency of various policies over time. 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. We consider 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. These issues are only rarely addressed in the literature. A notable

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exception is the paper by Xu and Lin, 2015.

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. The closest concept would be the OECD Environmental Policy Stringency Index, proposed by Botta and Koźluk, 2014. The index focuses on energy-related policies as well as economy-wide aspects. 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. Additionally, 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.

The remainder of the paper is organised as follows. Section 2 is dedicated to the index. It starts with a short literature overview and then explains the construction of the policy stringency index. Section 3 establishes the econometric model used to analyse the determinants of transport related 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 discusses the empirical results. Section 4 ends with concluding remarks.

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. We focus our analysis on policies that directly impact combustion engine vehicles. We exclude subsidies on electric vehicles, because we want to focus on complementary measures to reduce emissions from combustion vehicles in addition to switch to zero emission vehicles.[1]

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	

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 (Federal Law Gazette No, 140/1949). In its current version, the law on the mineral oil tax was implemented in 1995 (Federal Law Gazette II No, 630/1994). The Standard Fuel Consumption Tax (commonly referred to as NoVA - Normverbrauchsabgabe) is a tax on new cars; it was introduced in 1992 (Federal Law Gazette No, 695/1991). However, it can be seen as a direct successor to the Luxury Tax, which was introduced in 1978 (Federal Law Gazette No, 645/1977). 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 (Federal Law Gazette No, 110/1952), and from 1993 onwards based on engine power (Federal Law Gazette No, 449/1992).

The Vignette was a way to implement a collective road tax for the usage of motorways and express roads; it was introduced in 1997 (Federal Law Gazette No, 201/1996). The Air Pollution Control Act allows provincial governors to enact speed limits in areas with strong air pollution since 1997 (Federal Law Gazette I No, 115/1997). As a response to the oil crisis and higher fuel prices, Austria enacted a temporary speed limit of 100

[1]Additionally, electric vehicles in Austria were almost non-existant 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.

km/h from November 1973 to March 1974 (Federal Law Gazette No, 562/1973). In 1974, Austria additionally implemented car-free days (Federal Law Gazette No, 5/1974). 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 (Federal Law Gazette II No, 417/2004), and stricter targets were set in 2012 (Federal Law Gazette II No, 398/2012).

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 lower emission standards and 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, which makes sense 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 $6 * 1/3 = 2$ to the composite index.

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, e.g., the fuel tax 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 theses 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. But it gets more complicated with other taxes, as these include different tax rates for different 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 calculated based on fuel consumption and 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 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 measures do not change. This is because the attributes of cars change over time. Moreover, this can even lead to decreases in stringency. 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 over the period 1970-2019.[2] 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 Federal Ministry for Digital and Transport (BMDV), 2019.[3] The Standard Fuel Consumption Tax is calculated based on attributes of new cars. Data on average emissions has 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

[2] We chose this time period mainly due to data availability reasons.

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

average net price of new cars with the price index for new vehicles for Germany.[4]

Qualitative instruments have to be treated slightly differently. Usually, these measures do not change in stringency over time. They are either in force or not. Whenever such instruments 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 0.01471.[5] The weighted average gives 0.0114. The maximum value for diesel is its current amount at EUR 0.397, for petrol at 0.482. The weighted average is 0.4524. For a 7-step scale, $k = |0.4524 - 0.0114|/6 = 0.0735$. An increase of EUR 0.0735 would lead to a one-step increase in the stringency of the tax.

The thresholds calculated as linearly increasing by $k = 0.0735$ are given in Table 3. The lowest threshold for a existing policy is calculated as the sum of its mimimal numeric realization plus k. The remaining steps are linearly increasing by 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

	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

2.4 The Final Index

The final index for a 7-step scale (0-6) is shown in Figure 2. The composite index is given by the solid line. Taxes on emissions are 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. This 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, i.e., the car-free day and the temporary speed limits. Each of these two measures can reach a maximum 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.

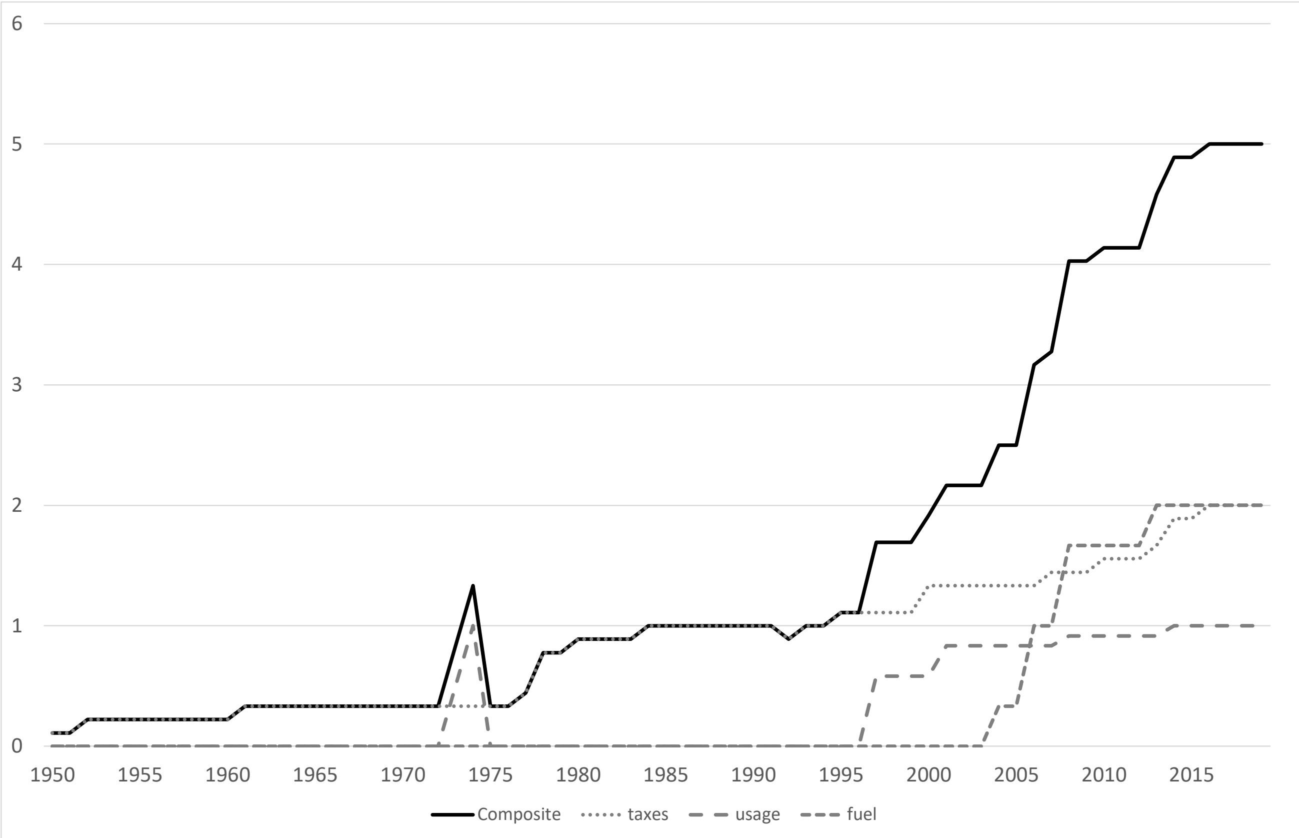
3 A Dynamic Econometric Analysis

To study the effect of the instruments captured by the transport related environmental policy stringency index, we develop an appropriate econometric model in this section. As policies aimed at influencing emissions from the transport sector, be that directly or indirectly, endogeneity issues have to be considered. To address this,

[4] The relevant attributes for the fleet are: 1660 ccm, 69 kW, and for new registrations: 7.1 l/100km, 173 gCO2/100km, and 18,650 EUR net for a new car

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

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



we employ a vector autoregressive (VAR) model that, by construction, treats all variables as endogenous. This approach additionally allows us to control for possible interdependency of other variables included in the model.

3.1 Determinants of Transport Emissions

In a first step, we will define the determinants of transport related 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 transformed the identity into an econometric model called Stochastic Impact by Regression on Population, Affluence, and Technology (the STIRPAT model). Taking the variables as logarithms and adding an error term, the model becomes:

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

where α and the βs are 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 emission 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 transport related environmental policy stringency index for Austria in the model (Comp). Rearranging the order of the variables, the model becomes:

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

To facilitate a more differentiated analysis of the different policy categories, the composite index can be decomposed into its three subindices. The model then becomes:

$$
\begin{aligned}
CO2/CAP_t = \alpha + \beta_1 Tax_t + \beta_2 Use_t + \beta_3 Fuel_t \\
+\beta_4 EI_t + \beta_5 Fleet/CAP_t \\
+\beta_6 GDP/CAP_t + \beta 7 Oil_t \\
+u_t,
\end{aligned}
\tag{3}
$$

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.

3.2 Data and Descriptive Statistics

Data on CO2, EI, and Fleet have 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 is measured in 1000t, EI by gCO2/100km, and Fleet contains the total fleet of petrol and diesel powered cars in a given year, including hybrid and plug-in hybrid vehicles. Population statistics have been extracted from Statistik Austria, 2021. 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 1966-2019. Table 3 summarizes and describes the variables.

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).

The time series of these variables are shown in Figure 5 in Appendix A for the period 1965-2019. 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.

3.3 Econometric Methodology

Some variables in Equation (3) are likely to be interdependent to some degree. These include the policy categories (Tax, Use, Fuel) and CO2/CAP, EI, and Fleet/CAP. Real GDP/CAP and real oil prices are more likely to be determined outside this system, we therefore treat these as unmodelled variables. We consequently want to apply a model that accounts for these characteristics. Vector autoregressive (VAR) type models with unmodelled variables are suitable choices. To establish which model in what form is most suitable, we have to test the variables for nonstationarity as well as for cointegrating relations.

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 or deterministic trend. Several tests have been proposed to test the presence of a unit root, i.e., a stochastic trend. But many unit root tests suffer from low power when applied to near-unit processes (for example, Kilian and Lütkepohl, 2017).

Elliott, Rothenberg, and Stock (1996), henceforth referred to as ERS, proposed a unit root test that dominate other tests in terms of power. It is based on the Augmented-Dickey-Fuller test (ADF) and tests the null hypothesis of the presence of a unit root. We applied the test to the variables in Eq. (3). The resulting test statistics and critical values are shown in Table 4. The results for both the models with a constant and a trend (second column) and a constant only (third column) are included. Table 4 shows 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. Thus, we continue by testing for a cointegrating relation between the endogenous variables.

Table 4: ERS: ADF-Type Unit Root Test

	trend	const
Tax	−2.170	1.220
Use	−2.520	−0.890
Fuel	−0.720	1.010
EI	−1.850	0.700
Fleet/CAP	−0.620	−0.050
CO2/CAP	−0.850	0.140
GDP/CAP	−0.630	0.680
Oil	−2.190	−1.240

Null hypothesis: unit root

The results of the Johansen cointegration trace test for CO2/CAP, EI, Fleet/CAP, and the policy categories are shown in Table 5. The test cannot reject the null hypothesis cointegration rank of zero at the 5% level. We further confirm this result by analyzing all pairwise cointegrating relations, where we can clearly reject the null hypothesis cointegration rank of zero at the 10% level for every pair. We thus conclude that there is not sufficient evidence in favor of a cointegrating relation between the variables.

Table 5: Johansen trace test, with 2 lags and linear trend

	test	p-value
r <= 5	3.56	0.7986
r <= 4	12.07	0.8053
r <= 3	26.06	0.7353
r <= 2	51.96	0.3337
r <= 1	81.33	0.1525
r = 0	116.21	0.0601

Null hypothesis: number of cointegrating vectors is r

3.4 VAR Model

Given the lack of evidence in favor of cointegration, a VAR model is well suited to capture these dynamics. Such a model imposes minimal structure on the data. This aspect intrigued Sims, 1980, who developed VAR models as a response to the "incredible identification" in macroeconometric models at the time. In a VAR model, each variable is determined by lagged values of all other variables. However, in some instances, it seems useful to define exogenous variable nonetheless. In our case, it can be argued that GDP per capita and international oil prices are likely determined outside of the system outlined in Equation (3). Such a VARX model with p lags of the endogenous and q lags of the exogenous variables in its structural form is given by:

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

where $t = 1, ..., T$, $\boldsymbol{y}_t$ is a $Kx1$ vector containing the endogenous time series, $\boldsymbol{x}_t$ is a $Mx1$ vector containing the exogenous time series. $\boldsymbol{B}_0$ is a KxK parameter matrix containing the contemporaneous interactions, $\boldsymbol{B}_i$

are KxK matrices containing the interactions between the lagged endogenous variables. $\boldsymbol{\vartheta}_j$ are MxK matrices containing the interactions between the exogenous variables. $\boldsymbol{\mu}$ is the $Kx1$ vector representing the structural error term.

Applying the model to Equation (3) and taking GDP/CAP and international oil prices as exogenous variables, we have: $\boldsymbol{y}_t = [Tax_t, Use_t, Fuel_t, EI_t, Fleet/CAP_t, CO2/CAP_t]'$ and $\boldsymbol{x}_t = [GDP/CAP_t, Oil_t]'$. The endogenous variables are taken in 1st differences, whereas the unmodelled variables are taken in log-diffs. Such a structural model cannot be estimated directly. More precisely, the contemporaneous interactions cannot be directly estimated. Therefore, the model has to be transformed into its reduced form:

$$\begin{aligned} \boldsymbol{B}_0^{-1}\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{B}_0^{-1}\boldsymbol{\mu} + \textstyle\sum_{i=1}^{p} \boldsymbol{B}_0^{-1}\boldsymbol{B}_i\boldsymbol{y}_{t-i} \\ + \textstyle\sum_{j=0}^{q} \boldsymbol{B}_0^{-1}\boldsymbol{\vartheta}_j\boldsymbol{x}_{t-j} + \boldsymbol{B}_0^{-1}\boldsymbol{u}_t, \end{aligned} \tag{5}$$

which can be rewritten more compactly as:

$$\boldsymbol{y}_t = \tilde{\boldsymbol{\mu}} + \textstyle\sum_{i=1}^{p} \boldsymbol{\phi}_i\boldsymbol{y}_{t-i} + \textstyle\sum_{j=0}^{q} \boldsymbol{\theta}_j\boldsymbol{x}_{t-j} + \boldsymbol{v}_t, \tag{6}$$

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. To identify the system, the we placed custom short run restrictions the endogenous variables $\boldsymbol{B}_0$, as shown in Table 6. The columns contain the shocks to each variable, and the rows indicate which variables are afffected by this shock. In this identification strategy, the ordering of the variables plays a crucial role. The first variable in the system affects all other variables contemporaneously, but is unaffected by the other variables. The second variable affects all variables that it precedes contemporaneously and so on.

The ordering 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. Thus, the policy categories are ordered first. EI follows next, as it 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 EI do not contemporaneously affect the fleet.

Table 6: 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

3.5 Model Adequacy Tests

We again start with inspecting the variables in first differences for stationarity. Table 7 shows that the null hypothesis of a unit root can be rejected at the 5% significance level in the test with only a constant for all variables.

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 8, 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 9 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.

Table 7: ERS: ADF-Type Unit Root Test

	trend	const
Tax	-4.720^{***}	-4.370^{***}
Use	-7.370^{***}	-7.300^{***}
Fuel	-2.920^{*}	-2.670^{***}
EI	-3.650^{***}	-3.320^{***}
Fleet/CAP	-3.400^{**}	-2.050^{**}
CO2/CAP	-3.210^{**}	-2.480^{**}
GDP/CAP	-5.110^{***}	-3.890^{***}
Oil	-5.480^{***}	-5.270^{***}

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$

Null hypothesis: unit root

Table 8: VAR Order Selection Criteria

Lag	AIC	HQ	SC	FPE
1	$-1.745076e+01^{*}$	$-1.7437^{9}5e+01^{*}$	$-1.697723e+01^{*}$	$-1.677841e+01^{*}$
2	$-1.666913e+01$	$-1.6135^{2}3e+01$	$-1.515343e+01$	$-1.443352e+01$
3	$-1.540530e+01$	$-1.4028^{8}5e+01$	$-1.220449e+01$	$-1.064202e+01$
4	$2.697487e-08$	$2.974663e-08$	$5.783935e-08$	$1.060428e-07$

* indicates chosen lag order selection criteria

Table 9: Edgerton and Shukur (1999) test for residual autocorrelation

Order	P-Value
1	0.2688
2	0.1513
3	0.657
4	0.6498
5	0.0979

Null hypothesis: no residual autocorrelation

3.6 Results and Discussion

Following the model adequacy results, we model a structural VARX(1,1) model with custom short run restrictions. Due to the interdependency of the variables, the coefficients in standard regression output tables would be very hard to interpret. Therefore, other concepts have been proposed to analyse such a system.

3.6.1 Impulse Response Analysis and Dynamic Multipliers

One popular type of analysis for such a model is the study of impulse response functions (IRFs). The basic idea is to express the VARX model in terms of past shocks, i.e., its uncorrelated error terms, u_t. This enables us to study how the system responds to structural shocks (impulses) related to the variables. IRFs are suited to study the dynamic feedback mechanism between the variables. The results can not be interpreted as ceteris paribus, rather the IRFs consider the interdependency of all endogenous variables.

Figure 2 contains the cumulated impulse responses of CO2/CAP to structural one-standard-deviation shocks of the other endogenous variables. For the exogenous variables, Figure 3 shows the cumulated dynamic multipliers (DMs), i.e. the effect of changes in GDP/CAP and Oil on CO2/CAP. The solid curves show the IRFs and DMs over time. The solid line shows the final (long-run) responses, the dotted line indicates zero, and the dashed lines provide a bootstrapped 95% confidence interval (CI). The effect of a shock to a specific variable on CO2/CAP is statistically significant at the 95% CI whenever both confidence bands are either below or above the zero line.

We can see that a one standard-deviation shock to each of the policy categories significantly reduces CO2 emissions per capita. Although the upper confidence interval of the effect of fuels on emissions crosses the zero line after a few years. A shock to EI (implying less efficient cars) tends to increase emissions, but the effect is statistically not significant. An increase in Fleet/CAP is associated with a significant increase in CO2 emissions per capita. A shock to GDP/CAP also shows a strong positive effect on CO2 emissions per capita. Whereas an increase in international oil prices is associated with a decrease in CO2/CAP. Overall, the results are in line with our expectations.

The IRFs and DMs in Figures 2 and 3, respectively, have to be interpreted carefully. The impulse responses are obtained from the endogenous variables, which are all taken in first differences of their level form. The impulse responses are then simply the response to a one-standard-deviation shock of the respective variables. The exogenous variables are taken in log-differences. The interpretation of the dynamic multipliers thus follows a level-log structure. The impulse responses and dynamic multipliers for EI and Fleet/CAP in addition to CO2/CAP are shown in Figures 6 and 7 in Appendix B.

Figure 2: Impulse responses for CO2/CAP (1965-2019). Hall's percentile intervals are at 5% significance level with 2000 bootstrap replications.

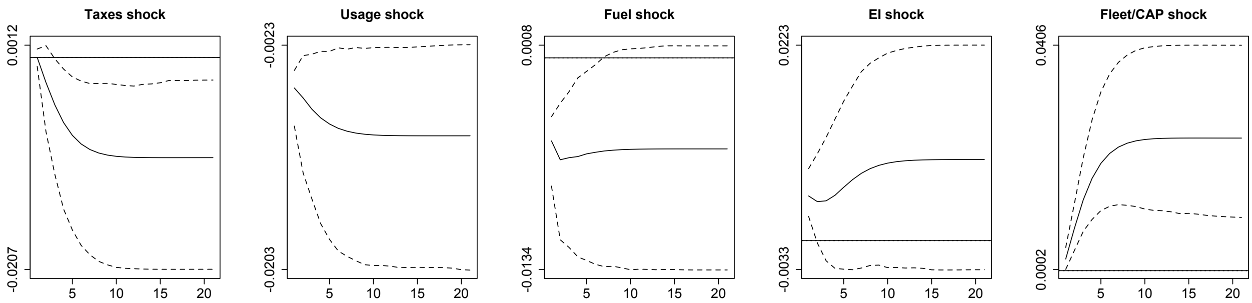
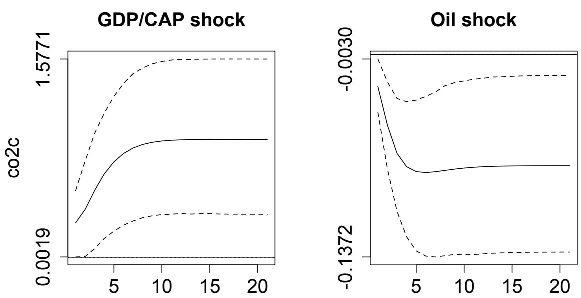


Figure 3: Dynamic multipliers for CO2/CAP (1965-2019). Hall's percentile intervals are at 5% significance level with 2000 bootstrap replications.



3.6.2 Forecast Error Variance Decomposition Analysis

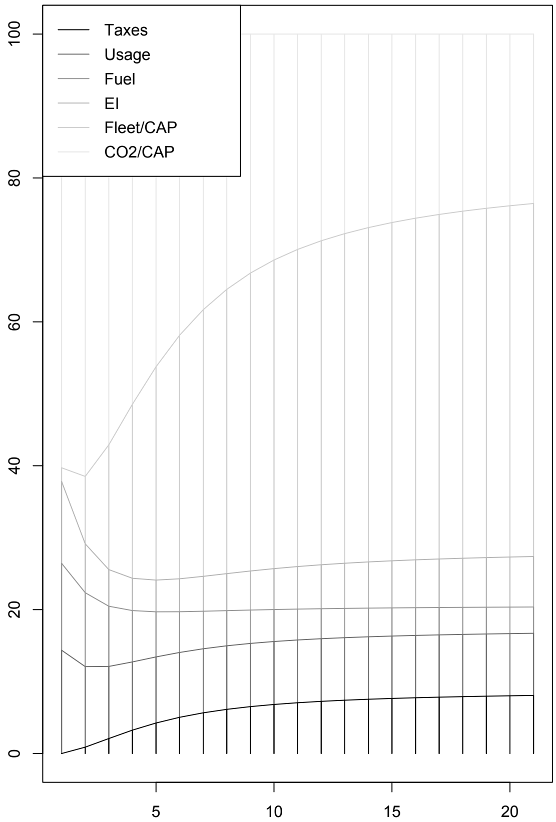
Another instrument to analyse VAR models is forecast error variance decomposition (FEVD) analysis. This type of analysis decomposes the forecast error variance and shows how much of the forecast error variance in one variable can be explained by other endogenous variables in the system. The FEVD analysis thus provides insight into the importance of endogenous variables in explaining a specific variable. Figure 4 shows the results of the FEVD analysis for CO2/CAP for a period of 10 years.

From Figure 4, we can see that the three policy categories account for about 30% of the forecast error variance in CO2/CAP. Taxes on emissions only become a relevant factor after several years, while the importance of policies aimed at influencing the usage of cars slightly decrease in magnitude. Energy intensity plays only a marginal role in explaining the forecast error variance. The importance of the fleet per capital increasing strongly with time, while CO2/CAP itself becomes less important.

4 Discussion and Conclusion

The analysis of the determinants of passenger car related CO2 emissions in Austria show that these emissions are significantly determined by both endogenous and exogenous factors. The exogenous factors include GDP

Figure 4: Forecast error variance decomposition for CO2/CAP



per capita, which exhibits a strong positive influence on emissions, and international oil prices, which exhibit a significant negative impact on emissions. Among the endogenous variables, the IRFs and FEVD indicate that the degree of motorization, i.e. fleet per capita, is the main driving factor behind th emissions. Furthermore, we can also conclude that the three policy categories that we studied show a significant effect on emissions.

This finding is particularly relevant for policy makers in the context of reaching the goal of a carbon neutral transport fleet. While zero carbon vehicles will play a crucial role in achieving this goal, it is likely not sufficient in itself. In the Mobility Master Plan 2030, Austria set the target to completely phase out new registrations of non zero emission vehicles (Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation, Technology (BMK), 2021). Austria also set the target to become climate-neutral by 2040. Considering that the average life-span of a car in Austria is estimated to be around 15 years (Environmental Agency Austria, 2019), complementary measures are needed to achieve a climate-neutral transport sector by 2040.

Our contribution thus suggests that policy makers devise a differentiated set of policy measures to decarbonise the transport sector. While the switch to zero emission vehicles is an important part to achieve this, this transition should be accompanied by complementary policy measures. We show that policy measures that tax passenger related transport emissions, instruments that influence the usage of cars, and those that improve the carbon intensity of fuels may be effective tools to achieve a faster transition towards a climate-neutral transport sector. Although these policies will have to be increased in their stringency drastically.

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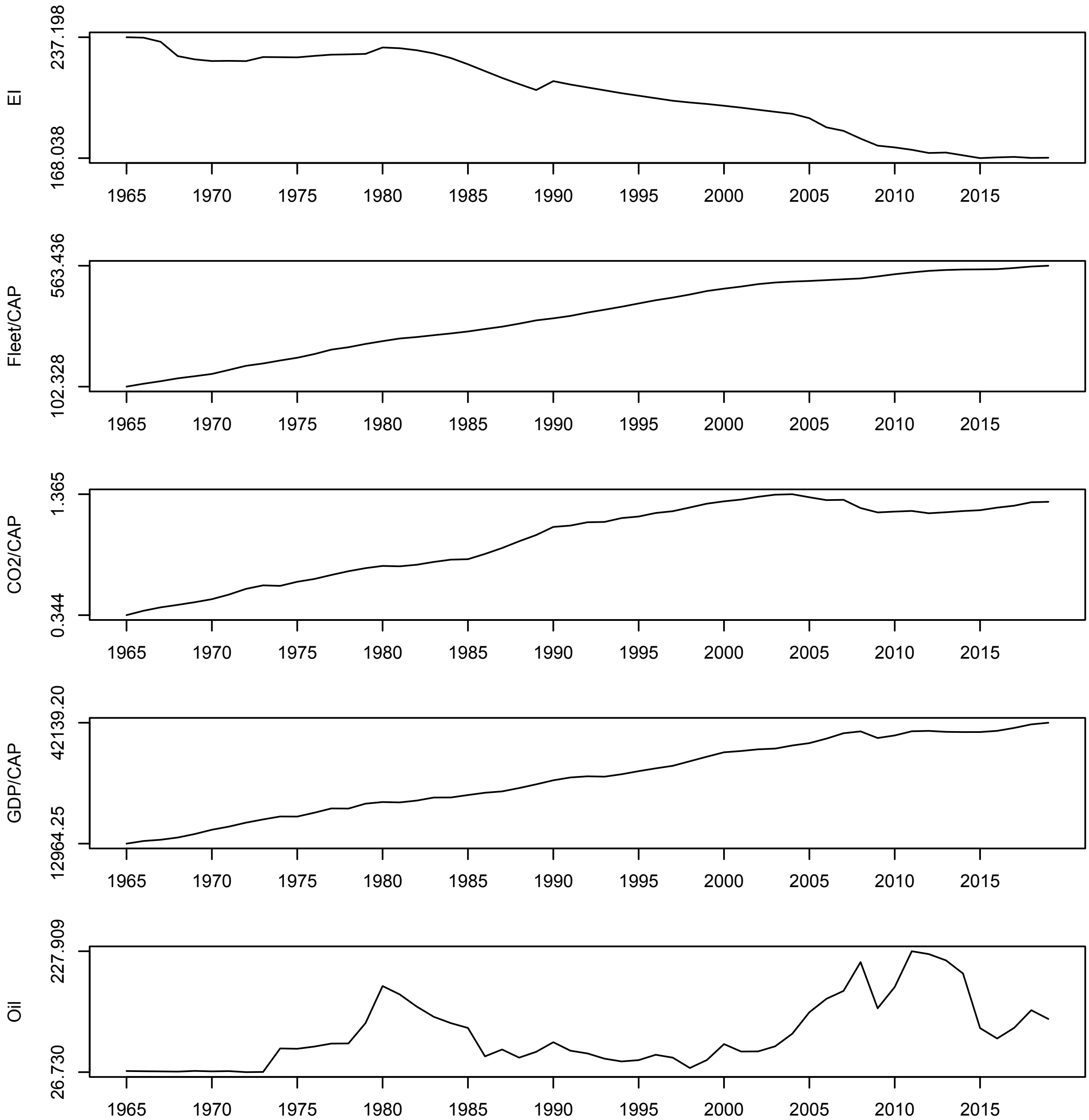
5 Appendix

5.1 Appendix A: Time Series Graph

Time Series of Variables in Levels from 1965-2019 are shown in Figure 5.

Figure 5: Time Series in Levels, 1965-2019



5.2 Appendix B: Impulse Responses and Dynamic Multipliers for EI, Fleet/CAP, CO2/CAP

Figure 6: Impulse responses for EI, Fleet/CAP, CO2/CAP (1965-2019). Hall's percentile intervals are at 5% significance level with 2000 bootstrap replications.

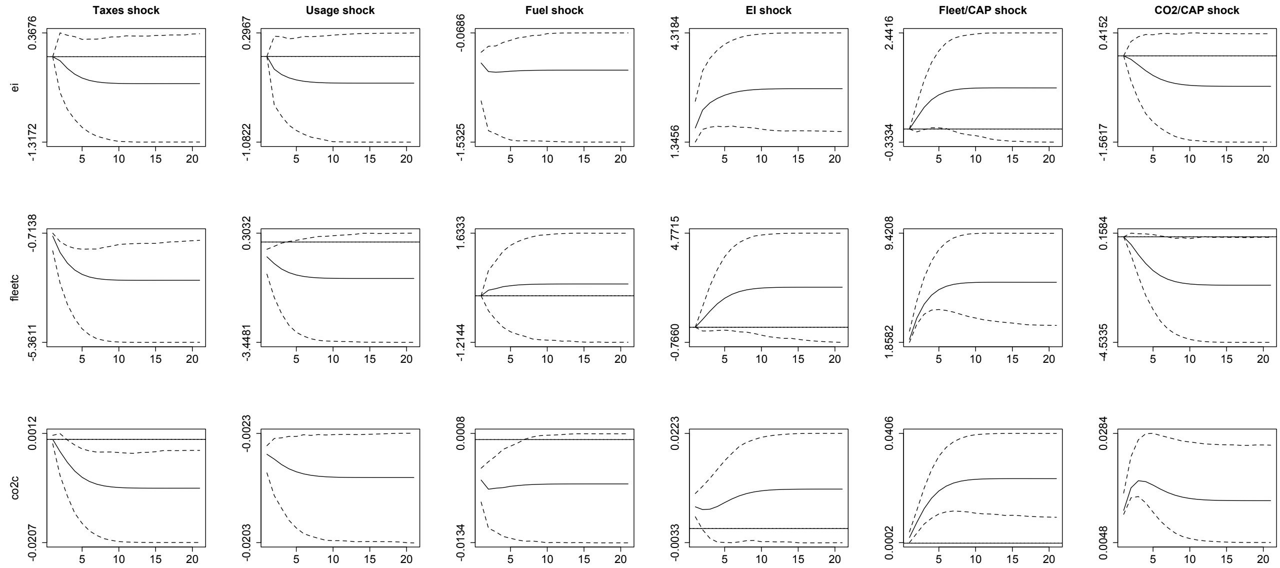


Figure 7: Dynamic Multipliers for EI, Fleet/CAP, CO2/CAP (1965-2019). Hall's percentile intervals are at 5% significance level with 2000 bootstrap replications.