Publizierbarer Endbericht

Gilt für Studien aus der Programmlinie Forschung

A) Projektdaten

Allgemeines zum Projekt	
Kurztitel:	PETRA
Langtitel:	The role of persistence in tackling Austria's climate target: Policies for the transport sector
Zitiervorschlag:	Jonas, M., T. Eibinger, S. Lambert, P. Żebrowski, H. Manner, H. Heinfellner, and K. Steininger (2022): The role of persistence in tackling Austria's climate target: Policies for the transport sector. Final Report, Austrian Climate Research Programme, Vienna, Austria.
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Schlagwörter:	Transport, passenger cars, reduction of emissions, infrastructure longevity, policy stringency, memory, persistence

Allgemeines zum Projekt	
Projektgesamtkosten:	249,988 €
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B) Project Overview

1 Kurzfassung

Österreichs Emissionen haben insbesondere im Transportsektor stark zugenommen. 2020 machten sie (exklusive Emissionshandel) fast 45% der österreichischen THG- (Treibhausgas)-Emissionen aus. Trotz seiner Dynamik wird der Transportsektor dennoch wesentlich von systemischen Verzögerungen bestimmt, hervorgerufen durch Langlebigkeit von Infrastruktur und Fahrzeugbestand. Politische Maßnahmen können gegenwärtige Investitionen beeinflussen, aber gegenwärtige Emissionen werden ganz wesentlich von früheren Investmententscheidungen beeinflusst. Der Fokus des PETRA-Projektes liegt auf dem Sektor Pkw-Transport in Österreich.

Die Aufmerksamkeit von PETRA richtet sich insbesondere auf das unzureichend verstandene Zusammenwirken politischer Maßnahmen und System-bedingter Verzögerungen – bis zum heutigen Tage weder explizit modelliert noch quantifiziert. Ein besseres Verständnis dieses Zusammenwirkens wird als wesentlich bei der Ausgestaltung effektiver Maßnahmen zur Verringerung der Emissionen erachtet, insbesondere vor dem Hintergrund, dass das Übereinkommen von Paris faktisch eine sofortige und nachhaltige Reduktion der Emissionen verlangt. PETRA evaluiert die Verzögerung der Wirksamkeit politischer Maßnahmen, die die THG-Emissionen des Pkw-Transports zu verringern suchen, und untersucht, wie der Verzögerungseffekt quantifiziert und vom Network Emission Model (NEMO) genutzt werden kann, welches beim österreichischen Umweltbundesamt (EAA) zum Einsatz kommt.

Die Entwicklung von PETRA erfolgte in drei sich gegenseitig ergänzenden Ausrichtungen: eine sozioökonomische, eine physikalische und eine Modell-orientierte. Die sozioökonomische Ausrichtung strebte ein anwendbares Konzept an, welches politischen Maßnahmen einen Stringenzindex zuordnet und auf der Analyse ökonometrischer Zeitreihen basiert. Die physikalische Ausrichtung verfolgte das Ziel einer wissenschaftlichen Methodik, welche das Gedächtnis und die Pfadabhängigkeit (Memory und Persistenz) aus der Dynamik von Pkw-Daten herauszuarbeiten erlaubt. Das in den Daten enthaltene Memory nimmt Gauss-artig in die Vergangenheit hin ab und verlangte einen neuartigen Ansatz, um Ergebnisse für Modellierer und Anwender zu erlangen, die greifbar sind. Die dritte, die Modell-orientierte Ausrichtung, verfolgte den Nutzen, der sich aus der Zusammenschau der beiden vorherigen Ausrichtungen für NEMO ergibt. Dieser resultiert aus einer neuartigen Daten-basierten, retrospektiven, qualitativ-quantitativen Maßnahmen-Response-Analyse.

Die Untersuchung struktureller Umbrüche in Zeitreihen zwischen 1950–2019 erlaubt die Erstellung einer plausiblen Abfolge von Ursache und Wirkung. Diese beginnt beim Stringenzindex, der die relevanten politischen Maßnahmen österreichische (Otto- und Diesel-) Pkws betreffend aggregiert, und erstreckt sich über die CO_2-Emissionen, die aus dem Einsatz der Pkw-Flotte resultieren, bis hin zu ihrem gesamtheitlichen dynamischen Verhalten aus Sicht von Memory und Persistenz entsprechend ihrer geringeren zeitlichen Auflösung. Die strukturellen Umbrüche – sie finden zwischen 1996 und 2002 statt – können mit einer Unsicherheit von ungefähr sechs Jahren einander zugeordnet werden und erwirken eine Kaskade an Auswirkungen. Eine Zunahme des Stringenzindex um den Faktor 3 – 8 resultierte in einer um etwa 30% verringerten jährlichen Zunahme des Pkws-Bestandes – dies ist gleichbedeutend mit einer Verringerung der jährlichen Zunahme der Emissionen um etwa 92% (von 216 auf 18, also um 198 $ktCO_2$ y^{-1} jährlich). Gleichzeitig verringern sich Memory und Persistenz, allerdings mit geringerer Ausprägung, was die Schwierigkeit widerspiegelt, die Trägheit des Pkw-Sektors zu überwinden. Das Memory nahm insgesamt um etwa 10% ab (seine Reichweite nahm währenddessen sogar um etwa 13% zu), während die Persistenz, gleichbedeutend mit der Pfadabhängigkeit des Systems, um etwa 15% abnahm.

Die Größenordnung dieser strukturellen Umbrüche mag beeindruckend erscheinen. Tatsächlich ist sie es aber bei weitem nicht, wenn man einen Vergleich mit in der Zukunft erforderlichen Umbrüchen anstellt. Auf der Grundlage eines Sets von sechs prospektiven Szenarien für 2021–2050 haben wir untersucht, wie sensitiv NEMO auf die Änderung kritischer Parameter (Pkw-Bestand, -Neuzulassungen und -Stilllegungen) reagiert. Diese Szenarien simulieren Änderungen, die über bestehende Maßnahmen bzw. Österreichs („with existing measures“) WEM19-Szenario von 2019 hinausgehen. Die Intention der Szenarien ist es allerdings nicht zu untersuchen, wie Klimaneutralität vor oder bis 2050 erreicht werden kann.

Bereits Österreichs WEM19-Szenario verlangt eine Verringerung der Emissionen zwischen 2021–2050 von etwa 43% (oder 168 $ktCO_2$ y^{-1} jährlich bzw. 186 $ktCO_2$ y^{-1} jährlich, falls die Zunahme von 18 $ktCO_2$ y^{-1} jährlich bis 2021 berücksichtigt wird). Dies impliziert eine Gesamtänderung, welche in etwa vergleichbar ist mit der Verringerung von Österreichs Emissionen in der Vergangenheit (198 $ktCO_2$ y^{-1}/y) vor zu nach 1996–2002. Im Vergleich dazu verlangt das stringenteste (Scen4) der sechs untersuchten Szenarien – dieses sieht eine Vervierfachung der neuzugelassenen elektrisch betriebenen Pkws bis 2031 vor und eine ausschließliche Zulassung dieser danach – eine Abnahme der Emissionen von 94% (oder 360 $ktCO_2$ y^{-1} jährlich bzw. 378 $ktCO_2$ y^{-1} jährlich, falls die Zunahme von 18 $ktCO_2$ y^{-1} jährlich bis 2021 berücksichtigt wird). Dies impliziert eine Gesamtänderung, welche etwa um den Faktor 2 (bezogen auf 198 $ktCO_2$ y^{-1}/y) grösser ausfällt. Daher ist unsere Schlussfolgerung die, dass unsere retrospektive Analyse sehr wohl als wertvolle Referenz dienen kann, allerdings nicht als Blaupause für die Zukunft dahingehend, welche politischen Maßnahmen oder Kombinationen von Maßnahmen zu ergreifen sind. Diese müssen sehr viel progressiver ausfallen.

Unsere Forschung bedarf weiterer Anstrengungen. Zum einen, um die sechsjährige Unsicherheit in den strukturellen Umbrüchen zu reduzieren, die der zuvor genannten Ursache-Wirkungs-Abfolge zugrunde liegt, beginnend beim Stringenzindex bis hin zur Auswirkung politischer Maßnahmen auf Pkws mit Blick auf ihr Memory-Persistenz-Verhalten. Zum anderen weitere Grundlagenforschung, um Abweichungen von der klassischen (Newtonschen) Mechanik hin zu einer „nicht-Newtonschen" Mechanik besser zu verstehen (nicht mit Blick auf zeitliche Verzögerungen wohl aber) mit Blick auf Memory und Persistenz. Es sind diese beiden Systemcharakteristika, die uns im Allgemeinen interessieren und die wir aus Beobachtungen extrahieren müssen.

2 Executive Summary

Austria's transport emissions had grown significantly, in 2020 amounting to almost 45% of Austria's greenhouse gas (GHG) emissions (without emission trading). Despite its considerable dynamics, however, the transport sector is crucially governed by systemic delays caused by long-lasting infrastructure and vehicle stocks in operation for multiple years. Policies can influence current investments, but current emissions are governed substantially also by earlier investment decisions. The focus of the PETRA project is on Austria's sector of transport by passenger cars.

PETRA centers on the insufficient understanding of the interaction between policy measures and systemic delays – neither explicitly modelled nor quantified up to that day. A better understanding of this interaction had been considered essential for the design of effective emission reduction policies by taking into consideration that the Paris Agreement requires emissions to be reduced de facto immediately and sustainably. PETRA evaluates the delay in the effectiveness of policies in reducing GHG emissions of passenger-car transport and explores how this delay effect can be quantified and made available to the Network Emission Model (NEMO) applied by the Environment Agency Austria (EAA).

Work under PETRA developed along three perspectives which complement each other: a socioeconomic, a physical and a modeling perspective. The socioeconomic perspective aimed at an operational concept to assign a stringency index to policy measures and is based on econometric time-series analyses. The physical perspective aimed at a scientific methodology allowing memory and persistence in the dynamics of the passenger-car data to be quantified. Memory in these data decays Gaussian backward in time and required a novel approach to achieve tangible results relevant to modelers and practitioners. The third, the modeling perspective, aimed at taking advantage of the two previous perspectives which, when combined, allow a novel data-based, retrospective qualitative-quantitative policy-response analysis to be conducted for the support of NEMO.

By assessing structural breaks in time series between 1950–2019, a plausible cause-effect relationship could be established ranging from the stringency index aggregating relevant policies affecting Austria's passenger cars (Otto and Diesel) to CO_2 emissions from the use of these cars (fleet in use) to their overall

medium-term dynamical behavior in terms of memory and persistence. The structural breaks come with an uncertainty of about six years – they took place between 1996 and 2002 – and result in a cascade of effects. An increase in the policy stringency index by a factor of 3 – 8 led to a reduction in the annual increase in passenger cars of about 30% – equivalent to a reduction in the annual increase in emissions of about 92% (from 216 to 18, or 198, $ktCO_2$ y^{-1} annually). Concomitantly, memory and persistence of the Austrian passenger-car system decreased but only little, reflecting the difficulty in overcoming the inertia of the passenger-car sector. Memory decreased overall by about 10% (the extent of memory even increased by about 13%), while persistence, equivalent to the system's path dependency, decreased by about 15%.

The order of magnitude of these structural changes may appear impressive but they are more than insufficient when compared to the changes needed in the near future. We explored, on the basis of an agreed set of six prospective scenarios for 2021–2050, how sensitive NEMO responds to changes in crucial parameters (stock, new registrations, and drop-out rates of passenger cars). These scenarios simulate changes above and beyond Austria's with-existing-measures scenario from 2019 (WEM19) in terms of CO_2 emissions. However, the scenarios are not meant to assess how to achieve climate neutrality before or until 2050.

Austria's WEM19 scenario alone foresees a reduction in emissions between 2021–2050 of about 43% (or 168 $ktCO_2$ y^{-1} annually; or 186 $ktCO_2$ y^{-1} annually if the increase of 18 $ktCO_2$ y^{-1} annually prior to 2021 is also considered), implying a total change comparable to the reduction Austria had experienced in the past (198 $ktCO_2$ y^{-1} annually) before versus after 1996–2002. By way of comparison, the most stringent scenario (Scen4) of the six scenarios we investigated – this scenario prescribes a quadrupling of newly registered electric passenger cars until 2031 from when on only electric vehicles are allowed to be registered – foresees a reduction in emissions of about 94% (or 360 $ktCO_2$ y^{-1} annually; or 378 $ktCO_2$ y^{-1} annually if the increase of 18 $ktCO_2$ y^{-1} annually prior to 2021 is also considered), implying a total change greater (than 198 $ktCO_2$ y^{-1}/y) by a factor of about 2. We, therefore, conclude that our retrospective analysis can serve as a valuable reference but not as a blueprint for the future in terms of measures, or combination of measures, which need to be taken. These must be exceedingly more progressive.

Our research requires further efforts. First, to reduce the six-year uncertainty in the structural breaks underling the aforementioned cause-effect relationship ranging from a policy stringency index to the response of passenger cars to these policies in terms memory and persistence. Secondly, more basic research to better understand deviations from classical (Newton's) mechanics to a "non-Newton" mechanics (not in terms of time delays but) in terms of memory and persistence. It is these two system characteristics which we are usually interested in and which we need to extract from observations.

3 Background und Objective

The global transport sector is described and documented by the IPCC, the Intergovernmental Panel on Climate Change (Doblas-Reyes et al., 2021). In 2019, direct greenhouse gas (GHG) emissions from the transport sector were 8.7 Gt CO_2-eq (up from 5.0 Gt CO_2-eq in 1990) and accounted for 23% of global energy-related CO_2 emissions. 70% of the direct transport emissions came from road vehicles. Since the last (fifth) assessment report of the IPCC, a growing need for systemic infrastructure changes became obvious to enable behavioral modifications and reductions in demand for transport services that can, in turn, reduce energy demand. Against this backdrop, fuel and technology shifts are considered crucial to reducing emissions to meet global temperature goals. At the same time, legislated climate strategies are emerging at all levels of government, which can spur the deployment of demand and supply-side transport mitigation strategies.

The PETRA project is embedded in this global context. Its focus is on Austria’s sector of transport by passenger cars. It had been motivated by the insufficient understanding of the interaction between policy measures and systemic delays – neither explicitly modelled nor quantified up to that day – while realizing that the Paris Agreement requires emissions to be reduced de facto immediately and sustainably. A better understanding of this interaction is considered essential for the design of effective emission reduction policies in the future.

Austria’s transport sector is of particular and growing concern. Transport emissions had grown significantly, in 2020 amounting to almost 45% (without emission trading) of Austria’s GHG emissions (EAA, 2021). Despite its considerable dynamics, however, the transport sector is crucially governed by systemic delays caused by long-lasting infrastructure and vehicle stocks in operation for multiple years. Trains and even some vehicles have a lifetime of decades. That is, policies can influence current investments, but current emissions are governed substantially also by earlier investment decisions (causing the memory of the system). It is argued that, for a reliable policy analysis prospective in time, the proper quantification of the system’s memory and persistence characteristics is of core importance.

The ambitious objective of PETRA is to evaluate the delay in the effectiveness of policies in reducing GHG emissions in the transport sector, here with the focus on Austria’s passenger cars (Otto and Diesel); and to explore how this delay effect can be quantified and made available to the Network Emission Model (NEMO) applied by the Environment Agency Austria (EAA).

PETRA is novel in that it aims **1)** at establishing a robust relationship between relevant (national and international) policies and the diffusion of their impact (as reflected, e.g., by the phase-in of new vehicles in the market); and **2)** at quantifying the memory-persistence effect caused by the “remainder” of the system (as reflected, e.g., by the share of old vehicles in the fleet). Such a data-based, retrospective qualitative-quantitative policy-response analysis has not yet been carried out, neither in Austria nor elsewhere.

This analysis offers two important benefits which, together, render PETRA in connection with NEMO novel as well: The analysis helps **(i)** to model-generate more robust prospective emission scenarios (ideally for use as reference scenarios) and to test existing ones in terms of plausibility; and **(ii)** decision-makers to better understand the effectiveness of their emission reduction policies over time and vis-à-vis uncertainty.

An operational concept for assigning a stringency index to policy measures: This sub-objective captures the socioeconomic perspective of PETRA. It aims at quantifying the dynamics of policy effects which bring about changes in memory and persistence of transport-related stocks. The main methodology to be applied in this context is based on econometric time-series analyses. To analyze the dynamic effect of policies, it must be considered that these depend on the size and composition of the overall stock of vehicles. These quantities, in turn, depend on socioeconomic variables and events, and policies aimed at influencing them. Econometric models can disentangle these effects and allow the effects of policies implemented over time to be quantified. To capture the effect of various policies, a policy stringency index had been composed which groups policies by category.

A scientific methodology to quantify memory and persistence: This sub-objective captures the physical perspective of PETRA. It aims at quantifying memory and persistence as exhibited by the dynamics of the sector of transport by passenger cars. An in-depth inspection shows that the time series of new registrations and total fleet of passenger cars can be considered piecewise linear, prior to and after 2002. It is this feature that facilitates determining memory and persistence in the two intervals. The piecewise linear behavior points strongly at a weighting of memory inherent in the passenger-car system which decays Gaussian backward in time. But knowledge of how to extract memory and persistence from data exhibiting Gaussian behavior did/does not exist. PETRA overcomes this problem by way of analogy with and learning from a pertinent system exhibiting memory decaying exponentially backward in time.

Combining the socio-economic and physical perspective to support NEMO: This sub-objective captures the modeling perspective of PETRA. It aims at taking advantage from the two sub-objectives mentioned before which, together, allow a novel data-based, retrospective qualitative-quantitative policy-response analysis to be conducted. With the focus of this model-advancement process is on passenger cars, this sub-objective is extremely ambitious because the delay effect intrinsic in NEMO plays out at a temporal resolution which is lower than the (annual) resolution NEMO operates at. Nonetheless, the retrospective analysis allowed the robustness of scenarios of emissions from passenger cars to be perceived from a new perspective.

4 Project Content and Results

PETRA evaluates the delay in the effectiveness of policies in reducing GHG emissions in the transport sector and explores how this delay effect can be quantified and also made available in the context of the Network Emission Model (NEMO) applied by the Environment Agency Austria (EAA), a schematic picture of which is shown in Figure 1. Figure 2 resolves Figure 1 in a greater context as well as in greater detail to facilitate monitoring where activities interact with NEMO. The core activities performed under PETRA

- capture memory and persistence theoretically and describe a way forward to isolate these system characteristics quantitatively by way of processing passenger-car data for 1950–2019.
- identify the most relevant policies affecting the Austrian passenger-car transport sector in the period 1950–2019.
- devise an index to capture the stringency of these policies over that period. And
- explore ways to make NEMO benefit from the application of insights on memory and persistence in combination with those on policies aggregated in a stringency index.

Table A1 lists the main documents (DOC) and data (Dat) files generated over the course of the PETRA project. Table 1 and Figure 3 provide additional information of general nature: Table 1 a summary of characteristics pertinent to PETRA, NEMO and to the analysis of both the policy stringency index and the memory-persistence effect; while Figure 3 recalls that processing data requires robustness to be kept in the focus. It compares the detectability of structural changes (signals) that we expect to be confronted with in working across various thematic data levels.

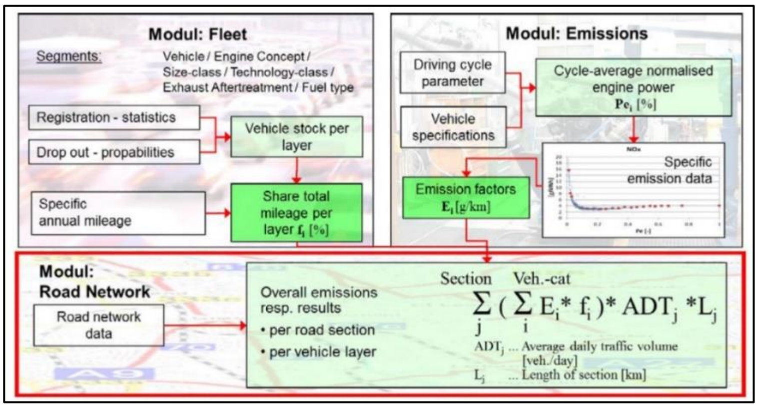


Fig. 1: Schematic picture of the Network Emission Model (NEMO). The model is maintained by the Graz University of Technology and applied by the Environment Agency Austria (EAA). Source: Rexeis et al. (2022)

PETRA is structured into six interlinked work packages (WPs).

WP1: Developing the conceptual data set-up and structure to capture the memory-persistence effect of the transport sector

In WP1 we capture memory and persistence theoretically and describe a way forward to isolate these system characteristics quantitatively by way of data processing. Both memory and persistence are perceived as system characteristics which come with a (medium-term) temporal resolution which is lower than the (here) annual resolution of the data at hand (surveyed and/or model-generated) (see Fig. 2: boxes *NEMO Module: Fleet* and *Medium Term Assessment*). That is, memory and persistence are hidden characteristics; they need to be uncovered before we can take advantage of them. Knowing memory and persistence comes with a benefit which is unexplored so far. This knowledge allows the underlying system to be understood better in terms of path dependency including potential system failures (see WP6). Also will this knowledge provide a reference against which the (undoubtedly valuable) "knob-turning experience" of modelers can be scaled. In the long(-er) run, it will help to model-generate more robust prospective emission scenarios or to test existing ones in terms of plausibility.

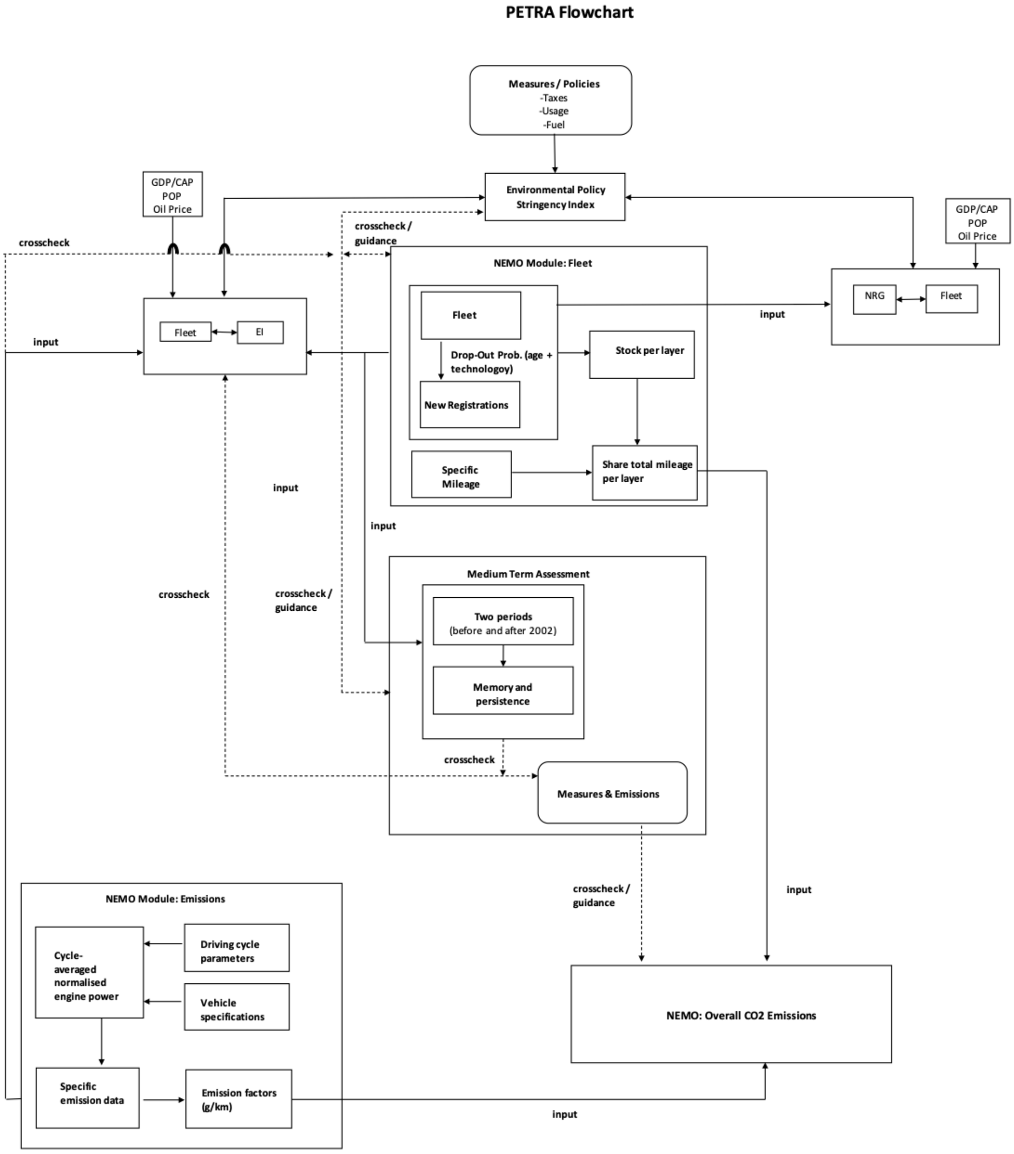


Fig. 2: Like Figure 1 but resolved in a greater context as well as in greater detail.

Tab. 1: Summary of characteristics pertinent to PETRA, NEMO and to the analysis of both the policy stringency index and the memory-persistence effect.

PETRA:	
Thematic Coverage	Passenger cars
Thematic Resolution	Propulsion technology (Otto and Diesel)
Spatial Reference	Austria
Network Emission Model (NEMO)	
Thematic Level	Passenger cars ↔ GHG emissions (esp. CO_2), air pollutants (esp. NO_x)
Temporal Coverage / Origin of Data	1. 1950 – 1989: WEM13 (historical data; based on OLI 2012) 2. 1990 – 2017: WEM19 (historical data; based on OLI 2019) 3. 2018 – 2050: WEM19 (predicted)
Temporal Resolution:	Annual
Policy Stringency Index:	
Thematic Level	Policy measures (by category: taxes on emissions, usage, fuels) ↔ CO_2 emissions
Temporal Coverage	1950 – 2019
Temporal Resolution	Annual
Key Assumption	Policies are weighted equally to construct composite index
Key Limitation	Index qualitative by nature reflecting a selected range of policies
Memory–Persistence Analysis:	
Thematic Level	Fleet (in use) and newly registered cars
Temporal Coverage	1950 – 2019
Temporal Resolution	10 – 20 y
Key Assumption	Memory decays Gaussian backward in time
Key Limitation	Memory must be "visible" in the data

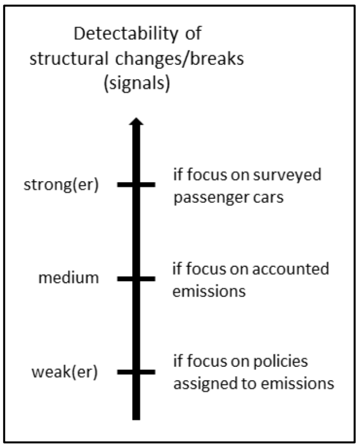


Fig. 3: Anticipated detectability of structural changes (signals) qualitatively across various thematic data levels ranging from the number of surveyed passenger cars to the emissions caused by their use to the policies influencing emissions.

Thematically, the level of surveyed passenger cars was chosen as the appropriate (skillful) scale for determining memory and persistence (see Fig. 3). When inspecting Austria's passenger car data for 1950–2019 (see Dat1.3 and Dat2.1, respectively), it can be observed that the data exhibit a linear behavior versus time piecewise over wide intervals. This points strongly at a weighting of memory inherent in the passenger-car system which decays Gaussian (or sufficiently close to Gaussian), not exponentially, backward in time (see WP5). But knowledge of how to extract these memory characteristics from data did/does **not** exist. This explains why we produced the following series of three documents (Doc2.1–Doc2.3):

<u>Document Doc2.1 (Learning Phase):</u> This document focuses on a pertinent (here the atmosphere–land and ocean carbon) system exhibiting memory with a weighting which decays exponentially backward in time. There are several good reasons why this type of memory should be studied initially. Generating this document may appear as a detour but can be considered an extremely useful exercise. It allowed a deep understanding of memory and persistence to be achieved which, to the best of our knowledge, goes beyond of what was known about memory and persistence so far (see Tab. 2). The detour also allowed memory and persistence to be defined analytically. In addition, we attained a

valuable guide of how to approach memory with a weighting decaying **Gaussian** backward in time.

<u>Document Doc2.2 (Expansion Phase):</u> This document provides a 1:1 comparison of memories with weightings which decay exponentially and Gaussian backward in time – in terms of definitions, characteristics, behaviors, etc. It thus provides the theoretical basis for the Gaussian memory concept (not yet, though, how it can be applied). Without this comparison (i.e., Document Doc2.1), we wouldn't have been able to gain an equally thorough understanding of Gaussian memory.

Tab. 2: Guide on how to go about memory and persistence contained in a system/an observed time series and on how to understand memory and persistence systemically.

1. When and where to search for memory and persistence:	
1.1	It needs to be known whether the system exhibits memory (thus, persistence). This is typically the case when the system includes/reflects processes which come with a lag-time.
1.2	It must be judged whether conditions for detecting memory (thus, persistence) are favorable. This is typically the case, when memory becomes "visible" at a temporal resolution which is lower than the resolution of the data in the time series.
1.2	In the case memory is present, its weighting backward in time can be carved out by way of testing (e.g., for exponential or Gaussian weighting).
2. How to define and derive memory and persistence:	
2.1	We assume that memory and persistence are contained in the dynamics of the time series. (Memory and persistence cannot be determined unambiguously anymore if the time series is detrended).
2.2	Thus, memory and persistence are defined with the help of the system's dynamic characteristics. (Meaning that memory and persistence are defined other than statistically and interlinked other than via correlation.)
2.3	De facto, memory and persistence should be defined with the help of the system's delay time (see Doc2.3: Eq. 9, 11 and 18) which is derived by solving the system's characteristic partial differential equation (see Doc2.2: Tab. 4).
2.4	As expected, memory and persistence are not independent of each other.
2.5	Memory and persistence come in units of dimensionless time.
3. How to understand memory and persistence systemically:	
3.1	Memory is a retrospective characteristic. By way of contrast, persistence perpetuates long-term historical conditions, but it is not a prospective characteristic.
3.2	Memory implies persistence which, in turn, can be understood as the system's path dependency.
3.3	Memory and persistence are additive and independent of the system's initial conditions. (These only specify the point in time from when on memory and persistence start accruing.)

<u>Document Doc2.3 (Applicational Phase):</u> Document Doc2.3 goes beyond Document Doc2.2. It describes how the Gaussian memory concept can be applied to the Austrian passenger-car system and tangible results relevant to modelers and practitioners be achieved. In contrast to applying the exponential memory concept, the application of the Gaussian memory concept requires additional knowledge. Weighting and extent of memory are not linked unambiguously (see Doc.2.2).

There exist many scientific disciplines and research areas where memory and persistence had been defined and determined. Instead of providing an overview of these historical achievements, we put together a comprehensive list of how we characterize and define memory and persistence in the PETRA project. This "counter-list" in its entirety justifies why memory and persistence had to be perceived in a novel way (see Table 2).

WP2: Identification of drivers: Trends and policies

To connect memory and persistence to policies that may influence them, we identified policies of relevance to the Austrian sector of transport by passenger cars. In WP2 we identify the most important policies affecting that sector in the period 1950–2019. This served as the basis for the development of a policy stringency index (see WP3) and the consequent utilization of that index in conducting an empirical policy analysis that links policies to memory and persistence (see WP5 and WP6).

Overall, more than 150 policies (including amendments) related to the Austrian passenger-car transport sector had been identified (see Dat1.1). Both the University of Graz and EAA collaborated closely in the creation of this policy list. To facilitate a meaningful analysis of the policies, the policies most relevant for PETRA had been recognized beforehand. This was accomplished in accordance with expert judgement from EAA. The remaining policies were grouped and assigned to the following 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. The three categories are listed in Table 3 together with the individual policies assigned to each category.

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

Tab. 3: Categorized policies.

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. The Standard Fuel Consumption Tax (commonly referred to as NoVA – *Normverbrauchsabgabe*) is a tax on new cars; it was introduced in 1992. However, it can be seen as a direct successor to the Luxury Tax, which was introduced in 1978. For the purpose of this categorization, the two policies were regarded as one. The Engine-Related Insurance Tax was introduced in 1952. The Vignette was a way to implement a collective road tax for the usage of motorways and express roads; it was introduced in 1997. The Air Pollution Control Act allows provincial governors to enact speed limits in areas with strong air pollution since 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. In 1974, Austria additionally implemented car-free days. The EU Biofuel Directive set minimum shares for the use of biofuels and other renewable fuels in the transport sector; it was implemented in national legislation in 2004.

WP3: Parameter analysis and uncertainty ranges

The policies listed in Table 3 incorporate several amendments over the period 1950–2019, defining varying stringencies in the policies which are, in turn, relevant to the policy analysis conducted in WP5 and WP6. In WP3 we devise a policy relevant index to capture changes in the stringency of policies. The resulting index could then be used in an econometric analysis linking policies to memory and persistence. To the best of our knowledge, such an index has not yet been implemented for the Austrian transport sector at a level this disaggregated and spanning the entire period 1950–2019.

We designed a composite index which aggregates individual indicators. It closely follows the OECD environmental policy stringency index (Botta and Koźluk, 2014). The individual indicators of the composite index follow directly from the categories outlined in Table 3. The stringency of each indicator contributes to the composite stringency index. It can be understood in terms of strictness of a measure aiming at the reduction of emissions from the passenger-transport sector.

Environmental taxes increase in stringency with an increase in the cost of pollution. The stringency in a given year is relative to the most stringent level of an indicator over the entire sample period. Following the OECD Stringency Index, a 7-step scale had been adopted. This choice is arbitrary; that is, any other scale can be chosen as well for the final version of the index. In our case, 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 contributes equally to the composite index.

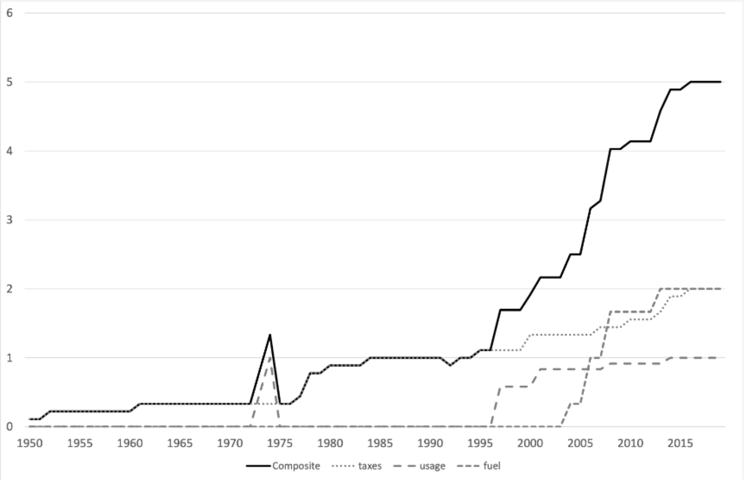


Fig. 4: Composite policy stringency index and its categories for 1950–2019. For details see Dat3.1.

The final index is depicted in Figure 4. The composite index is given by the solid line, taxes are given by the dotted line, measures affecting the usage of cars by the broadly dashed line, and measures affecting fuel carbon intensity by the narrowly dashed line. The actual maximum value of the composite index is 5. This is lower than the theoretical maximum of 6, the reason being that 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. Data on the policy stringency index can be found in Dat3.1.

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 be 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.

The policies under consideration pose several complications to the creation of a stringency index. Therefore, several assumptions had to be made:

- Several policies have been based on various attributes of cars over time. However, car attributes change over time. To capture actual changes in the stringency of policies and not changes in car attributes, we created an average car on which we based our calculations of policy stringency.
- Some policies are in nominal terms (e.g., the fuel tax is given in Euro-cents), while others are given in real terms (e.g., the tax on new cars is given in percentages of the price of a new car). It would probably be preferable to harmonize these. But prices for new cars are not available for the entire sample period; and adjusting the policies given in nominal terms to real terms, by, e.g., adjusting them for inflation, would distort the index again. We would see changes in the index purely related to price changes and not related to the stringency of policies.
- Policies are weighted equally. This assumption is justifiable because, in the end, the index will be part of an appropriate econometric framework accounting for this weighting.

WP4: Scenario simulation: Base case

NEMO, the Network Emission Model used by the PETRA consortium, had been developed at the Institute of Thermodynamics and Sustainable Propulsion Systems at the Graz University of Technology (GUT) as a tool for simulating traffic related emissions in road networks. NEMO was used in version 4.0.4 (GUT, 2019). A schematic overview of the model is given in Figure 1. It consists of three modules:

- The *Fleet* module determines the size and composition of the fleet in a given year. The composition is modeled as cohorts. A cohort can be characterized by vehicle category (e.g., passenger car, heavy duty vehicle, …), propulsion technology (e.g., petrol, diesel, electricity, gas, …), size, emissions, and fuels. The fleet in a given year is determined by statistical data. New registrations are determined by the difference between the entire stock of vehicles and existing older vehicles (determined by drop-out probabilities) in a given year.
- The *Emissions* module determines specific emission factors for vehicles in a specific cohort. Specific emission factors are calculated as a function of the effective power consumption of a vehicle in a cohort which is, in turn, determined by several factors, including rolling resistance, air resistance, gradient resistance, braking losses, etc. The emission factors for passenger

cars and the regarding subcategories are taken from the Handbook Emission Factors for Road Transport (HBEFA, 2019).
- The *Road Network* module calculates overall emissions from road transport. In PETRA we focused on overall emissions from road transport by passenger cars. Overall emissions are calculated by specific emissions (*Emissions* module) and total mileage of cohorts (determined in the *Fleet* module).

Further information on NEMO can be found in Dippold (2016). For PETRA, we required complete datasets (PC fleet, newly registered PCs, etc.) for the period 1950–2019. For details, we refer to Doc1.1.

WP5: Scenario simulation: Policies

In WP5 we explore how NEMO can benefit from applying insights on memory and persistence in combination with those on policies aggregated in a stringency index. This we did in three parts. The first part focuses on memory and persistence and the insights that could be gained and are of relevance to NEMO. Changes in memory and persistence were brought about (at least partly) by more stringent policy measures affecting the Austrian transport sector. In the second part, this link was explored in a dynamic econometric analysis of policies embedded in the policy stringency index. This analysis controls for socioeconomic factors that are believed to also influence memory and persistence, allows for a dynamic diffusion of the effect of policies on the transport sector, considers interdependencies between policies and other transport related variables, and allows insights to be gained that are also of relevance to NEMO. The third part pulls together the insights gained in Parts 1 and 2 and evaluates their usefulness from the perspective of NEMO.

<u>Part 1: The memory and persistence perspective.</u> Austria’s passenger-car data for 1950–2019 exhibit a linear behavior versus time piecewise over wide intervals (see Fig. 5a,b). As mentioned in the context of WP1, this points strongly at a weighting of memory inherent in the passenger-car system which decays **Gaussian** (or sufficiently close to Gaussian), **not exponentially**, backward in time. The difference between the two – visualized in Figures 6a,b – appears small but could not be greater. Exponential memory (as, e.g., exhibited by Earth under pressure of GHGs emitted into the atmosphere) is limited, while Gaussian memory is not (see Doc2.1 and Doc2.2). Figures 6a also shows that the decrease of Gaussian memory weights backward in time is rather sluggish and can be approximated well by polynomials.

	Interval 1 1958 – 2002	Interval 2 2002 – 2019
Memory (Gaussian)	11.7 y	10.5 y
Extent of memory	12.8 y	14.4 y
Persistence	$0.15\ y^{-1}$	$0.13\ y^{-1}$

Tab. 4: Passenger cars (Otto and Diesel) 1958–2019: Results pertinent to memory and persistence. These are derived (see Dat2.1) according to Doc2.3 (see Eq., 9, 11 and 18). Note: [y] stands for year-equivalent units (dimensionless time).

Table 4 summarizes the results pertinent to memory and persistence with the focus on passenger cars. *It can be observed* that, going from Interval 1 to Interval 2, the extent of memory backward in time increases; the explanation being that older cars are kept longer in use. Despite the increase in the extent of memory, a slight decrease in the memory itself can be observed, which can be readily understood if memory is perceived as a moving average. (A straight line with a lower slope exhibits a smaller moving average than a straight line with a greater slope.) Finally, a decrease in persistence (to be understood as the fleets path dependency) occurs, which can be attributed to the decrease in newly registered cars taking place during Interval 2.

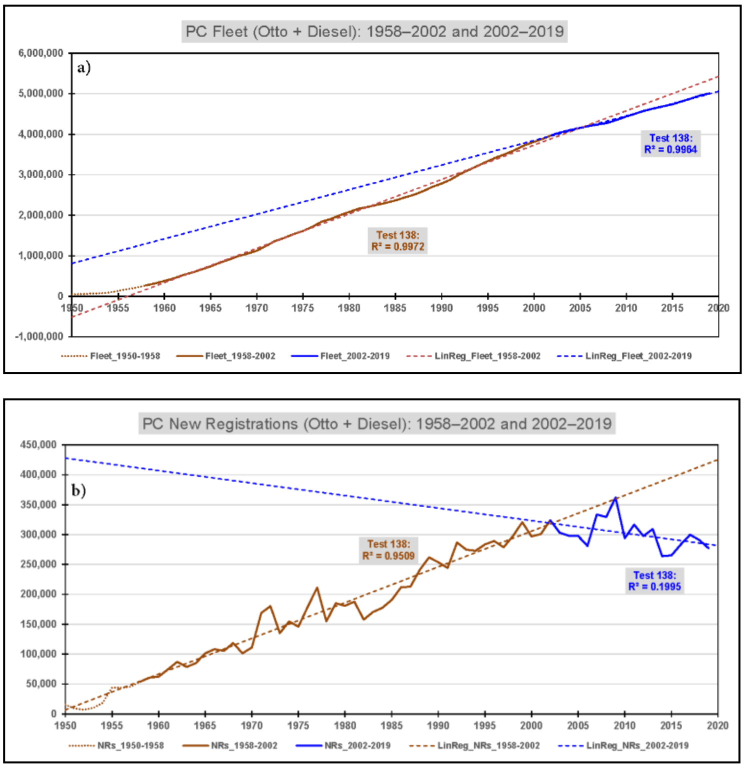


Fig. 5: Number of passenger cars (PCs: Otto and Diesel) for 1950–2019: a) fleet (PCs in use) and b) new registrations. The data were linearized for 1958–2002 (Interval 1) and 2002–2019 (Interval 2). In optimizing the linear regressions (i.e., their coefficients of determination, R^2) for Interval 1, the data prior to 1958 were excluded. For details see Dat2.1.

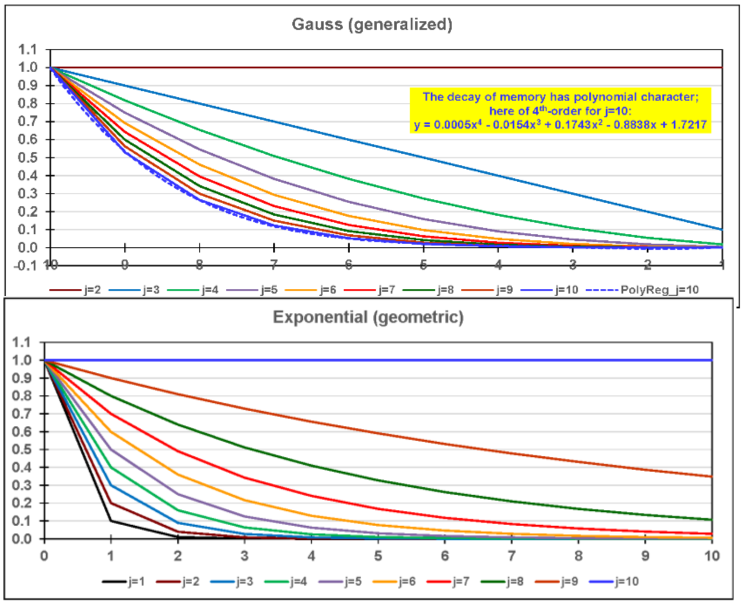


Fig. 6: Memory weights 17odell-sing ten years backward in time (dimensionless): a) Gaussian (weights are normalized) and b) exponential. The accounting of historical time is opposite (Gauss: 10 refers to today; exponential: 0 refers to today) but the curves are comparable. They show the decrease in weights relative to 1 (at the left) assigned to today. For details see Doc2.2.

Part 2: Econometric Analysis. Changes in memory and persistence are hypothesized to reflect Austria's efforts to mitigate emissions from the transport sector. We rendered this link more precisely in an econometric analysis. We employed a dynamic time-series model that captures the diffusion of the effect of policies on various transport-related variables of interest, e.g., new registrations, total fleet (PCs in use), and its CO_2 emissions. In doing so, we recognized that policies and transport-related variables may be interdependent. Also, we controlled for socioeconomic factors that influence various development-related variables of interest. These include economic growth, international oil prices, and population growth. An adequate econometric model to capture these development-related aspects is a vector autoregressive (VAR) model, which considers all variables to some degree interdependent to each other. Additionally, we controlled for socioeconomic factors which are determined outside of the system. These we included as exogenous variables.

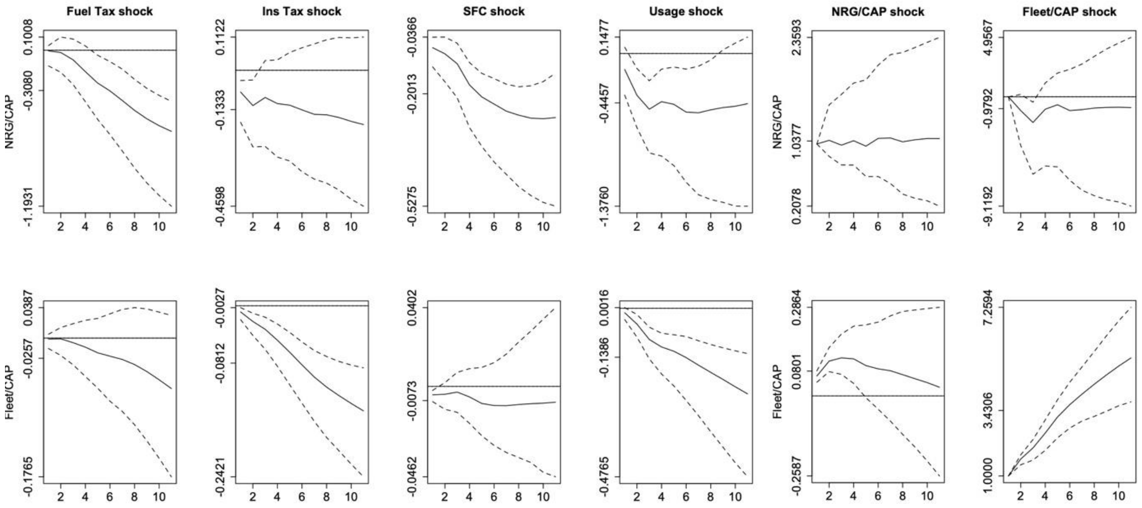
In a first step, we analyzed the effect of policies on both new registrations and fleet. This has several advantages: (i) Studying a sub-system of Figure 1 enabled us to conduct a more fine-grained analysis; that is, we were able to disaggregate the policy stringency index to some degree. (ii) This approach is closely linked with the analysis of memory and persistence which focuses on the same sub-system. In a second step, we analyzed the effect of policies on overall CO_2 emissions. This approach allowed the effect of policies to be linked directly to emissions, which is of prime relevance for policy conclusions.

Step 1: The policy-stringency-index perspective: New registrations and fleet. We employed the policy stringency index (see WP3) in an econometric analysis of policies, allowing the effect of policies on new registrations and the fleet to be studied by propulsion technology (Diesel + Otto). In this VAR setup, we disentangled the first category of the policy stringency index (fuel taxes) but excluded the last category (biofuels; see Table 3) as it neither affects new registrations nor the fleet. The VAR system included the following endogenous variables: Excise Duty on Mineral Oils (Fuel Tax), Engine Related Insurance Tax (Ins Tax), Standard Fuel Consumption Tax (SFC), policies affecting the usage of vehicles (Usage), new registrations per capita (NRG/CAP), and the fleet per capita (Fleet/CAP). Variables not modelled included: real gross domestic product per capita (GDP/CAP) and international oil prices (Oil). New registrations and the fleet were studied in terms of per-capita to control for population growth. The data can be found in Dat3.2.

The effect of shocks in each variable is shown in Figure 8. The figure shows the response of NRG/CAP and Fleet/CAP, respectively, to a shock in a specific variable as a function of time: endogenous tax policy variables per one-step increase in stringency (1/9), usage per one-unit increase, other endogenous and exogenous variables (log-scaled) per shock of 1%. The response is given by the solid curve, the dashed lines show the upper and lower bounds of the confidence interval (95%), and the straight line shows the zero line. An effect is said to be statistically significant when both confidence interval bounds are above or below the zero line. It is crucial to note that the system is interdependent and cannot be interpreted as ceteris paribus. Shocks to endogenous variables are thus not constant. But the exogenous variables are held constant in the analysis. This ensures that the effects of changes in policies are not affected by changes in economic growth or changing oil prices. Table 5 summarizes the effect of shocks to policies on both NRG/CAP and FLEET/CAP shown graphically in Figure 7. For more details, see Doc3.2.

Tab. 5: Summary of Figure 7: Effect of shocks to policies on newly registered cars per capita (NRG/CAP) and fleet per capita (Fleet/CAP).

Impact Variable	Shock Variable	Effect of an Increase in Shock Variable on Impact Variable	Significance	Comment
NRG/CAP	Fuel Tax	Negative effect	Yes	Strongest effect among taxes
	Ins Tax	Negative effect	No	
	SFC Tax	Negative effect	Yes	Effect size about 2/3 of Fuel Tax
	Usage	Negative effect	Yes (up to ~8 years)	Strong effect, but big shock
Fleet/CAP	Fuel Tax	Negative effect	No	
	Ins Tax	Negative effect	Yes	The only significant tax shock
	SFC Tax	Negative effect	No	
	Usage	Negative effect	Yes	Strong effect, but large shock



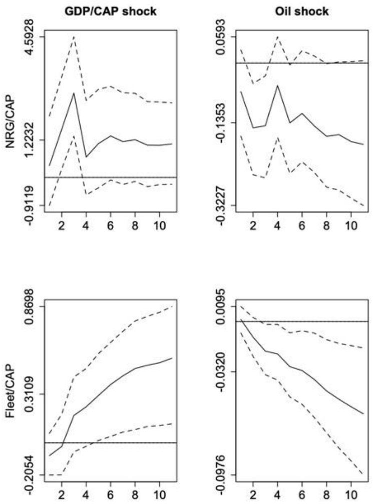
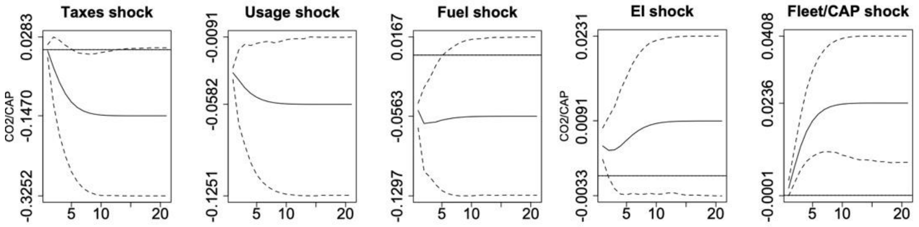


Fig. 7: Econometric analysis of NRG/CAP and Fleet/CAP responses. Upper panel: endogenous policy variables per unit shock and other endogenous variables per 1% shock; lower panel: (socioeconomic) exogenous variables per 1% shock. All variables in log scale. Coverage: 1952-2019.

Step 2: The policy-stringency-index perspective: CO_2 emissions. Here we took a broader view and analyzed the interaction between policies and CO_2 emissions. In NEMO, the emissions are determined through the modules *Emissions* and *Fleet* (see Fig. 1). The *Emissions* module controls overall CO_2 emissions via specific CO_2 emissions ($gCO_2/100km$), which can be interpreted as energy intensity. The *Fleet* module influences CO_2 emissions mainly via the size of the entire fleet. Again, such a system is characterized by system dynamics and interdependencies. We thus employed the same basic methodology as in the foregoing analysis, i.e., a VAR approach. However, this broader analysis came with complications. Reliable data on energy intensity are only available as of 1965. Thus, we were restricted by fewer observations, with the consequence that we could not disentangle the categories of the policy stringency index as previously and could thus not go beyond its main three categories. Here, the VAR system was characterized by the following endogenous variables: Taxes, Usage, Fuel, energy intensity (EI), and CO_2/CAP (to control for population growth). Variables not modelled were as before (GDP/CAP and Oil). The data can be found in Dat3.2.

Tab. 6: Summary of Figure 8: Effect of shocks to policies on emissions of CO_2 per capita (CO_2/CAP).

Impact Variable	Shock Variable	Effect of an Increase in Shock Variable on CO_2 Emissions	Significance	Comment
CO2/CAP	Taxes	Negative effect	Yes	Strongest effect
	Usage	Negative effect	Yes	Effect size 1/3 of Fuel Tax
	Fuel	Negative effect	Yes (up to ~5 years)	Effect size 1/3 of Fuel Tax, but smaller long-run shock



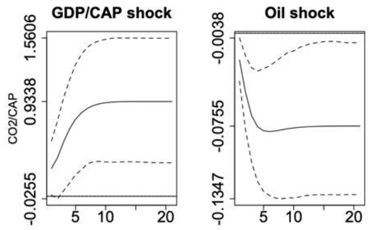


Fig. 8: Econometric Analysis of CO_2/CAP responses: Upper panel: endogenous policy variables per unit shock and other endogenous variables per shock of one standard deviation; lower panel: (socioeconomic) exogenous variables per unit shock. Exogenous variables in log scale. Coverage: 1965–2019.

The effect of shocks in each variable is shown in Figure 8. The figure shows the response of CO_2/CAP to a shock in a specific variable as a function of time: endogenous policy variables per unit shock, other endogenous variables per shock of one standard deviation, and exogenous variables (log-scaled) per unit shock. The response is given by the solid curve, the dashed lines show the upper and lower bounds of the confidence interval (95%), and the straight line shows the zero line. Table 6 summarizes the effect of shocks to policies on CO_2/CAP shown graphically in Figure 8. For more details, see Doc3.1.

Part 3: The NEMO perspective. From the perspective of NEMO, uncertainty is the common thread running through WP5. Being aware of this uncertainty, which is in the order of **about six years** (see below), is of prime importance in using NEMO for policy analyses. It can be understood as a measure of inaccuracy which underlies the assessment of structural breaks allowing a plausible cause-effect relationship to be established ranging from a policy stringency index to the response of passenger cars to these policies in terms memory and persistence.

As stated, Austria's passenger-car data for 1950–2019 exhibit a linear behavior versus time over wide intervals. Both total fleet and newly registered passenger cars can be divided into two piecewise linear intervals, before and after 2002 (see Fig. 5). Going from Interval 1 (1958–2002) to Interval 2 (2002–2019), a structural break can be observed in both memory and persistence.

Interestingly, the policy stringency index is also conducive to a linear, two-interval approach (see Fig. 4), but with the structural break now at about 1996 (see Dat 3.1). In this context, we recall Figure 3 to remind us that the detectability of this structural change, although still obvious, must be expected to be weaker than that of the structural break in the passenger car data.

In consequence, we interpret the time between 1996 and 2002 as uncertainty; nonetheless, however, as an indication that policy changes facilitate changes in memory and persistence.

For the sake of completeness, it is mentioned that we can also detect a structural break at 1999 in the CO_2 emissions from passenger cars (see Fig. 9), when searching for it (applying the concept of minimizing the sums of squared residuals and the Chow test) in the interval 1990-2003. This finding, too, appears to confirm our concept of detectability of structural changes as indicated qualitatively in Figure 3.

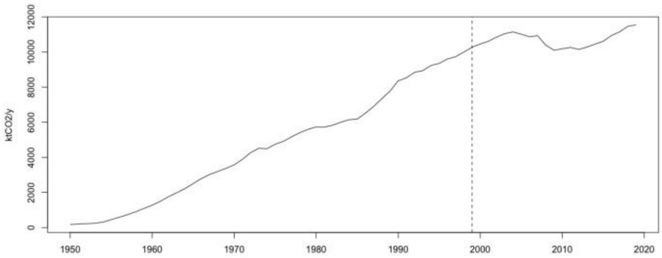


Fig. 9: Passenger cars (fleet in use): CO_2 emissions (in $ktCO_2$) for 1950–2019 with a structural break in 1999. For details see Dat2.1.

WP6: Sensitivity and policy conclusions

In WP6 we explore, on the basis of an agreed set of six prospective scenarios for 2021–2050, how sensitive NEMO responds to changes in crucial parameters (stock, new registrations, and drop-out rates of passenger cars) and to compare future changes in emissions from passenger cars with the structural breaks experienced historically, notably in CO_2 emissions from passenger cars.

Sensitivity experiments: Prospective view. The six scenarios (Scen) 1–6 simulate changes above and beyond Austria’s current, with-existing-measures (WEM19) scenario in terms of CO_2 emissions. The six scenarios are described in Doc1.1 (see Tab. 6 therein). They range from a linear decrease (Scen1: -20%; Scen2: -40%) in the stock of passenger cars between 2021–2050 to a prescribed increase in the number of newly registered electric passenger cars as of 2021 (Scen3: doubling; Scen4: quadrupling) to a prescribed dropout rate of passenger cars over a certain period of time (Scen5: 4% over 20y; Scen6: 6% for 10y). The scenarios are not meant to assess how to achieve climate neutrality before or until 2050. Table 7 provides a summary of the scenarios and their projected 2021–2050 reductions in CO_2 emissions (also with respect to WEM19). A linear, start/end-point perspective is sufficient for the purposes here, although not all reductions are linear.

Tab. 7: Characterization of 2021–2050 NEMO CO_2 emission reduction scenarios (linear, start/end-point perspective): WEM19 serves as reference scenario for scenarios (Scen) 1–6 which respond to measures going beyond those realized in the WEM19 scenario (see text).

	WEM19	Scen1	Scen2	Scen3	Scen4	Scen5	Scen6
	2021 – 2050 (30 y)						
From ktCO₂ y^{-1}	11047 – 11698						
To ktCO₂ y^{-1}	6478	5262	4046	3041	666	5967	4009
Change ktCO₂ y^{-1}	5031	6435	7434	8514	10782	5403	7038
Factor of Change	0.56	0.45	0.35	0.26	0.06	0.52	0.36
Percent of Change	-43%	-55%	-65%	-74%	-94%	-48%	-64%
Change per year ktCO₂ y^{-1}/y	-168	-215	-248	-284	-360	-180	-235
Change per year beyond WEM19 ktCO₂ y^{-1}/y	---	-47	-80	-116	-192	-12	-67

Policy Conclusions: Prospective versus retrospective view. Table 8 provides a summary of the structural breaks which allowed, based on a linear two-interval analysis, a plausible cause-effect relationship to be established (see WP5), ranging from the stringency index aggregating relevant policies affecting Austria’s passenger cars (Otto and Diesel) to CO_2 emissions from the use of these cars (fleet in use) to their overall medium-term dynamical behavior in terms memory and persistence. The two-interval view suggests an uncertainty in the structural break of about 6 y (here between 1996 and 2002).

Table 8 shows that an increase in the policy stringency index by a factor of 3 – 8 led to a reduction in the annual increase in passenger cars of about 30% – equivalent to a reduction in the annual increase in emissions of about 92% (from decreased overall 216 to 18, or 198, ktCO$_2$ y^{-1} annually). Concomitantly, memory and persistence of the Austrian passenger-car system decreased but only little, reflecting the difficulty in overcoming the inertia of the passenger-car sector. Memory by about 10% (the extent of memory even increased by about 13%), while persistence, equivalent to the system's path dependency, decreased by about 15%.

Tab. 8: Retrospective, linear two-interval analysis of Austria's PCs in terms of stringency of policy measures, CO$_2$ emissions, and memory and persistence: Summary of insights. The two-interval view suggests a plausible cause-effect relationship with an uncertainty in the structural break of about 6 y (here between 1996 and 2002). The structural change in CO$_2$ emissions (from 216 to 18, or 198, ktCO$_2$ y^{-1} annually) allows quantitative comparisons with Table 7 (see *Change per year* entries therein).

	Stringency Index	**CO$_2$ Emissions**	**Fleet**	**Memory**	**Persistence**
Interval 1	**1950 – 1996**	**1950 – 1999**	**1958 – 2002**	**1958 – 2002**	**1958 – 2002**
Interval 2	**1996 – 2019**	**1999 – 2019**	**2002 – 2019**	**2002 – 2019**	**2002 – 2019**
From (Interval 1)	0.023 SP/y	216 ktCO$_2$ y^{-1}/y	84852 PC/y	11.7 yeu	0.15 yeu^{-1}
To (Interval 2)	0.067–0.185 SP/y	18 ktCO$_2$ y^{-1}/y	60597 PC/y	10.5 yeu	0.13 yeu^{-1}
Change	0,043–0,161 SP/y	-198 ktCO$_2$ y^{-1}/y	-24255 PC/y	-1.2 yeu	-0.02 yeu^{-1}
Factor of Change	2.9-7.8	0.08	0.7	0.9	0.8
Percent of Change	290–680%	-92%	-30%	-10%	-15%

Units: SP = stringency points; ktCO$_2$ = 1000 tCO$_2$; PC = passenger cars; yeu = year-equivalent units (dimensionless time).

The order of magnitude of these structural changes may appear impressive but they are more than insufficient when compared to the changes needed in the near future. Table 7 shows that Austria's WEM19 scenario alone foresees a reduction in emissions between 2021–2050 of about 43% (or 168 ktCO$_2$ y^{-1} annually; or 186 ktCO$_2$ y^{-1} annually if the increase of 18 ktCO$_2$ y^{-1} annually prior to 2021 is also considered), implying a total change comparable to the reduction Austria had experienced in the past (198 ktCO$_2$ y^{-1} annually) before versus after 1996–2002. By way of comparison, the most stringent scenario (Scen4) of the six scenarios we investigated – this scenario prescribes a quadrupling of newly registered electric passenger cars until 2031 from when on only electric vehicles are allowed to be registered – foresees a reduction in emissions of about 94% (or 360 ktCO$_2$ y^{-1} annually; or 378 ktCO$_2$ y^{-1} annually if the increase of 18 ktCO$_2$ y^{-1} annually prior to 2021 is also considered), implying a total change greater (than 198 ktCO$_2$ y^{-1}/y) by a factor of about 2. We, therefore, conclude that our retrospective analysis can serve as a valuable reference but not as a blueprint for the future in terms of measures, or combination of measures, which need to be taken. These must be exceedingly more progressive.

Nonetheless, our retrospective analysis indicates that some policies can cause memory and persistence to change more than others. This may serve as a guide for decision-makers which measures to focus on, in particular, to impact longevity in the transport sector.

These measures include taxes on emissions and policies influencing the usage of vehicles (see Fig. 8). The Excise Duty on Mineral Oils exhibits the greatest impact on both new registrations and fleet. The Engine Related Insurance Tax significantly affects the fleet (but not new registrations), whereas the Standard Fuel Consumption Tax significantly affects new registrations (but not the fleet). Limiting the usage of vehicles has a limited effect on both. Aside from policies influencing fleet and new registrations (i.e., emissions indirectly), we saw that more efficient fuels can also influence emissions directly (see Fig. 9). The effect on CO_2 emissions of more efficient fuels and limiting the usage of vehicles is comparable; it is about one third of the effect resulting from more stringent taxes on CO_2 emissions.

In our analysis for the EU (see Doc 3.3), we found that a switch from road to rail for both passenger and freight transport can reduce emissions further. The same holds for a switch from road to water for freight transport. A switch from oil to electricity and renewables (biofuels) also helps to decrease emissions significantly for both passenger and freight transport.

5 Conclusions and Recommendations

PETRA provides a retrospective, qualitative-quantitative analysis of processes which come with a lag-time (here in the focus: the development of Austria's passenger-car system) to provide a reference for models (here in the focus: NEMO) which are used to provide prospective scenarios of these processes. PETRA seeks to better understand the interaction between policy measures and systemic delays (here in the focus: the reduction of CO_2 emissions from Austria's passenger-car system), **not** to assess scenarios designed to achieve climate neutrality before or until 2050.

Our conclusions and recommendations, in particular:

- Memory and persistence are hidden characteristics of Austria's passenger-car system, which could be quantified (see Table 4). It is important to note that these characteristics come with a (medium-term) temporal resolution which is lower than the annual resolution applied by NEMO in 25odelling the Austrian passenger-car system.
- The weighting of memory inherent in Austria's passenger car data decays Gaussian, not exponentially, backward in time. The theoretical basis allowing Gaussian memory (and persistence) to be dealt with analytically did not exist but could be established (see Doc2.1 – Doc2.3). This basis satisfies current requirements, but further research is needed to broaden that basis and to elaborate it in greater depth.
- The difference between memory decaying Gaussian and memory decaying exponentially backward in time appears small (see Figures 7a,b) but could not be greater. Exponential memory as, e.g., exhibited by Earth under pressure of GHGs emitted into the atmosphere is limited, while Gaussian memory is not. That is, the "rheological" behavior of Earth eventually faces constraints, while the "anthropogenic" car sector goes unconstrained. Ultimately, this means that not only the emissions resulting from the use of cars must be reduced to zero, but their entire cradle-to-grave emissions.
- To analyze the connection between pertinent policies and changes in memory and persistence, these policies must be quantified. To this end, we created a policy stringency index for the Austrian transport sector for the period 1950–2019. This was a novel step because such an index in that detail and with that temporal coverage did not exist. The index combined individual policies grouped into three main categories by way of expert judgement from EAA. They include taxes on emissions, policies influencing the usage of vehicles, and regulations on biofuel usage. Remarkably, we also found a structural break in the index but at around 1996, while the structural break in memory and persistence appeared around 2002.
- By applying a linear two-interval analysis to assess structural breaks between 1950–2019, we could establish a plausible cause-effect relationship ranging from the stringency index aggregating relevant policies affecting Austria's

passenger cars (Otto and Diesel) to CO_2 emissions from the use of these cars (fleet in use) to their overall medium-term dynamical behavior in terms memory and persistence (see Table 8). The structural breaks come with an uncertainty of about six years – they took place between 1996 and 2002 – and exhibit the following cascade of effects: An increase in the policy stringency index by a factor of 3 – 8 led to a reduction in the annual increase in passenger cars of about 30% – equivalent to a reduction in the annual increase in emissions of about 92% (from 216 to 18, or 198, $ktCO_2\ y^{-1}$ annually). Concomitantly, memory and persistence of the Austrian passenger-car system decreased but only little, reflecting the difficulty in overcoming the inertia of the passenger-car sector. Memory decreased overall by about 10% (the extent of memory even increased by about 13%), while persistence, equivalent to the system's path dependency, decreased by about 15%.

- The order of magnitude of these structural changes may appear impressive but they are more than insufficient when compared to the changes needed in the near future. We explored, on the basis of an agreed set of six prospective scenarios for 2021–2050, how sensitive NEMO responds to changes in crucial parameters (stock, new registrations, and drop-out rates of passenger cars). These scenarios simulate changes above and beyond Austria's current, with-existing-measures (WEM19) scenario in terms of CO_2 emissions. However, the scenarios are not meant to assess how to achieve climate neutrality before or until 2050. Nonetheless, by comparing the annual reduction in emissions between 2021–2050 with the reduction in the annual increase achieved historically between 1950–2019, we find that the first outnumbers the latter by a factor of up to 2, resulting in a prospective range in the order of/greater than [3;16] (= [3;8] * [1;2]) for the stringency index. We, therefore, conclude that our retrospective analysis can serve as a valuable reference but not as a blueprint for the future in terms of measures, or combination of measures, which need to be taken. These must be exceedingly more progressive.
- At the outset of summarizing our policy-related findings and recommendations, it needs to be clearly stated that avoiding motorized traffic in the first place (by way of digitalization, urban planning, increased awareness, etc.) and/or shifting from motorized to active mobility (bicycling and walking) are most effective in reducing emissions. In the PETRA project, we focused on accompanying measures that affect transport-related stocks and their emissions.

  Increasing the share of newly registered emission-free vehicles should receive high priority. In addition, the longevity of the transport sector (reflected by its memory and persistence) needs to be tackled, e.g., by

  - increasing the excise duty on mineral oils (strongest impact on new registrations)
  - increasing the standard fuel consumption tax (affects new registrations)

  - increasing the engine related insurance tax (affects fleet)
  - influencing the usage of cars through, e.g., speed limits, car-free days, hefty tolls, etc. (affects both fleet and new registration)

  Additional measures are:

  - more efficient fuels (biofuels)
  - switch from road to rail for both passenger and freight transport
  - switch from road to water for freight transport.

  Last but not least, it needs to be mentioned that GDP per capita has a strong (positive) effect on CO_2 emissions (see Fig. 9). To recall, the impacts of policy shocks are analyzed and interpreted at constant levels of GDP per capita. Decision-makers need to be aware that an increase in GDP per capital can significantly increase emissions, and thus work against the effect of increased policy stringencies.

- As stated above, by assessing structural breaks between 1950–2019, we could establish a plausible cause-effect relationship ranging from the stringency index aggregating relevant policies affecting Austria's passenger cars (Otto and Diesel) to CO_2 emissions from the use of these cars (fleet in use) to their overall medium-term dynamical behavior in terms memory and persistence. The structural breaks come with an uncertainty of about six years – they took place between 1996 and 2002. A repetition of our research for other countries (ideally also with the focus on the passenger-car transport sector) could help to reduce this uncertainty and thus lead to increased robustness.

- We see a need for more basic research to advance science on memory and persistence. In PETRA we deal with a system which includes processes exhibiting a temporal offset (or delay time). PETRA demonstrates the limits as well as how far one can go in elaborating such systems. Mathematics knows how to deal with systems which come with a temporal offset; but mathematics does not know how to deal with such systems in terms of memory (and persistence), an obvious reason being that a given delay time can be satisfied by memories with different extents and weightings backward in time. It is here where we make the step from classical (Newton's) mechanics to a "non-Newton" mechanics. Metaphorically speaking, we make the step from describing a kite without a tail which, under the impact of a force, can change directions instantaneously to a kite with a tail which reacts gradually, and which needs time to transition into a new direction. It is the length and the weight of the tail which we are usually interested in and which we need to extract from observations.

C) Project Details

6 Methods

Below we distinguish between methods applied to derive and quantify memory and persistence and methods applied to establish and quantify the policy stringency index.

Methods to derive and quantify memory and persistence:

In brief, a generally applicable methodology to derive and quantify memory and persistence as (potentially) contained in the dynamics of a series of observations or statistically surveyed data does not (yet) exist. However, we are aware of special cases, i.e. special mathematical-physical settings, which allow memory and persistence to be derived and quantified successfully. It is important to understand why and in which way these cases are special (limited) and how they can be generalized. Here we provide this understanding primarily by way of philosophical insight and where helpful we refer to the mathematical-physical formulas which we had derived and applied. We do so by following WP1 where we had argued that ...

When inspecting Austria's passenger car data for 1950–2019 (see Dat1.3 and Dat2.1, respectively), it can be observed that the data exhibit a linear behavior versus time piecewise over wide intervals. This points strongly at a weighting of memory inherent in the passenger-car system which decays Gaussian (or sufficiently close to Gaussian), not exponentially, backward in time (see WP5). But knowledge of how to extract these memory characteristics from data did/does ***not*** *exist. This explains why we produced the following series of three documents (Doc2.1 – Doc2.3):*

Document Doc2.1 (Learning Phase): This document focuses on a pertinent (here the atmosphere–land and ocean carbon) system exhibiting memory with a weighting which decays exponentially backward in time. There are several good reasons why this type of memory should be studied initially. Generating this document may appear as a detour but can be considered an extremely useful exercise. It allowed a deep understanding of memory and persistence to be achieved which, to the best of our knowledge, goes beyond of what was known about memory and persistence so far (see Tab. 2). The detour also allowed memory and persistence to be defined analytically. In addition, we attained a valuable guide of how to approach memory with a weighting decaying Gaussian backward in time.

Our methodological insights of this phase, pertinent to treating the atmosphere–land and ocean carbon system, a system with memory decaying exponentially backward in time, are:

- In Doc2.1 we had applied a rheological (stress–strain) approach to understand the planetary burden (and its dynamics) caused by the effect of the continued increase in GHG emissions and by global warming. Rheology is principally concerned with extending continuum mechanics to characterize the flow of materials that exhibit a combination of elastic, viscous, and plastic behaviour (that is, including hereditary behaviour) by properly combining elasticity and (Newtonian) fluid mechanics. Guided by observations, we followed the concept of a Maxwell body. An unbeatable advantage of rheology is that it allows working under controlled (consistency) conditions because it allows a stress-strain process to be described in a stress and a strain-explicit form (see Doc2.1: Eq. 1a and 1b).

- The stress-explicit form comes with a (variable) temporal offset which allows the past to be screened and, once integrated, historical events to be summed up; here with reference to strain. The integral is generic and can be shown to be a convolution integral. It is valid for any strain which can be described as a (continuous) function in time.
- For a (human-disturbed) natural system (in the case of our example also supported by observational evidence), it is obvious to expect that the system's overall strain is exponential or close to exponential. It is this assumption which allows three system characteristics – delay time (reflecting the temporal offset mentioned above), memory, and persistence – to be distilled from the stress-explicit equation and to be defined analytically (see Doc2.1: Eq. 3 to 5). These three system characteristics behave asymptotically, which is a consequence of assuming strain to be exponential.

In brief, the example studied, the atmosphere–land and ocean carbon system, provided access to studying analytically systems with memory decaying backward in time other than exponential.

Document Doc2.2 (Expansion Phase): This document provides a 1:1 comparison of memories with weightings which decay exponentially and Gaussian backward in time – in terms of definitions, characteristics, behaviors, etc. It thus provides the theoretical basis for the Gaussian memory concept (not yet, though, how it can be applied). Without this comparison (i.e., Document Doc2.1), we wouldn't have been able to gain an equally thorough understanding of Gaussian memory.

Our methodological insights of this phase, pertinent to treating a system with memory decaying Gaussian backward in time such as the Austrian passenger-car system, are:

- The beginning of Doc2.2 (see Sections 2.1 and 2.2) – the parallel treatment of time-dependent functions the argument of which comes with a delay time – was incentivized by a figure which is not shown in Doc2.2 but in Doc2.3 (see Fig. 2). Nonetheless, that comparison of memory decaying exponentially and Gaussian backward in time can, in the end, be described as curiosity-driven. Additionally, it is noted that using Figure 2 in Doc2.3 as reference is equivalent to replacing the rheological model underlying Doc2.1 by a mass balance model (here for passenger cars); meaning that the manifestation of memory (and persistence) is not model dependent.

- We understood the full meaning of Gaussian memory only later, after succeeding in the derivation of analytical expressions for delay time and memory (see Doc2.2: Eq. 2.3-1 and 2.3-2) and persistence (not mentioned in Doc2.2 but in Doc2.3: Eq. 18). The analytical derivation of delay time also shows that exponential and Gaussian memory lead to partial differential equations (PDEs) that are mirrored to each other (see Doc2.2: Tab. 3 and 4).
- However, we also saw that, in contrast to exponential memory, Gaussian memory comes with an additional unknown. Its delay time is defined by two unknowns (see also Doc2.2: Eq. 2.2-10). This is not the case for exponential memory (see Doc2.2: Eq. 2.1-4), the reason being that it behaves asymptotically. Its extent and the decrease of weights backward in time are interlinked unambiguously. One could say that asymtosy in the case of exponential memory replaces an unknown.

In brief, the 1:1 comparison of exponential and Gaussian memory provided access to studying the Austrian passenger-car system analytically. However, to be able to do so, the problem of the additional unknown still needed to be overcome, which explains the emergence of Doc2.3.

Document Doc2.3 (Applicational Phase): Document Doc2.3 goes beyond Document Doc2.2. It describes how the Gaussian memory concept can be applied to the Austrian passenger-car system and tangible results relevant to modelers and practitioners be achieved. In contrast to applying the exponential memory concept, the application of the Gaussian memory concept requires additional knowledge. Weighting and extent of memory are not linked unambiguously (see Doc.2.2).

Our methodological insights of this phase, pertinent to applying the Gaussian memory concept to the Austrian passenger-car system with the support of additional knowledge, are:

- As already mentioned, Austria’s passenger car data for 1950–2019 exhibit a linear behavior versus time piecewise over wide intervals. It is this behavior which readily allows a mass balance model (as shown in Doc2.3: Fig. 2) to be applied and data of both annual (net) fleet and newly registered cars to be combined. Collating these data, in turn, is equivalent to making up for one of the two unknowns defining delay time. In practice, this happens by bringing together the slopes of both fleet and newly registered cars in one equation (see Doc2.3: Eq. 17).
- This equation contains an additional parameter, which can be linked (here) to the extent of memory, one of the two unknowns. That is, reading the slopes of both fleet and newly registered cars graphically allows the extent of memory to be deduced.

- In turn, knowledge of this unknown and being able to read delay time graphically allows its second unknown (which indicates how fine we must resolve delay time for a given extent of memory) to be deduced (see Doc2.3: Eq. 7).

Finally, and in conclusion, being able to decompose delay time into its two parts and to quantify these enables us to also derive memory and persistence in the case of Gaussian memory (see Doc2.3: Eq. 11 and 18).

Methods to establish and quantify the policy stringency index:

The environmental policy stringency index captures the evolution of the stringency of various policies related to the transport sector for the period 1950–2019. The policies considered for the index are summarized in Table 3, and the index is shown in Figure 4. The methodology that we applied to compute individual policies in terms of policy stringency is described below (see also Dat 3.1). The approach is closely linked to the environmental policy stringency index applied by the OECD (Botta and Koźluk, 2014).

Individual policies across and within categories are weighted equally. The fuel tax, for example, can contribute a maximum of 6 * 1/3 * 1/3 = 2/3 to the overall index. A one-step increase of, e.g., the fuel tax then contributes 6 * 1/3 * 1/3 * 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 = ABS(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.

These calculations are 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. 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 CO_2 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 of these policies, one could 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.

Therefore, we applied the policies to constant attributes of cars over the period 1970–2019 (We chose this time period mainly due to data availability reasons).

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). Here, we assume that data referring to German cars serve as a good proxy for characteristics of Austrian cars. 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 (EAA, 2021). The bonus-malus system affects the tax in absolute terms (in EURs instead of percentages). To convert these to percentages, we calculated the average net price of new cars with the price index for new vehicles for Germany. The relevant attributes for the fleet are: 1660 ccm, 69 kW; and for new registrations: 7.1 l/100km, 173 gCO_2/100km, and 18,650 EUR net for a new car.

The Excise Duty on Mineral Oil (fuel tax) allows the calculation of the index to be exemplified. The minimum value of the tax over the entire sample period for diesel was EUR 0.0061, for petrol 0.01471. 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 9. The lowest threshold for an existing policy is calculated as the sum of its minimal numeric realization plus k (in this example: 0.0114+0.0735=0.0849). 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.

Tab. 9: The excise duty on mineral oils as part of the environmental policy stringency index.

	Range	Score	Contribution to Index
=	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

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.

7 Work and Time Plan

	PETRA – Project Month																										
WPs and tasks	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
WP 1: Preparing the basis: Developing the conceptual data set-up and structure to capture the memory-persistence effect for the transport sector																											
Conceptual data set-up and structure	▨	▨	▨	▨	▨	M1.1																					
Making Austrian data available	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M1.1															
Ensuring consistency: Data needs vs availability						▨	▨	▨	▨	▨	▨	M1.2															
WP 2: Identification of drivers: Trends and policies																											
Drivers identified in empirical studies for Austria	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M2.1															
Socioeconomic development emission drivers						▨	▨	▨	▨	▨	▨	M2.2															
Policy emission drivers						▨	▨	▨	▨	▨	▨	M2.3															
WP 3: Parameter analysis and uncertainty ranges																											
Transport sector emissions: Assessming socioeconomic drivers						▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M3.1										
Econometric analysis: Policy measures influencing composition and effectiveness of newly introduced vehiles						▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M3.1										
Transport sector emissions: Quantifying memory and persistence						▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M3.1									
Uncertainty analysis in consideration of persistence									▨	▨	▨	▨	▨	▨	▨	▨	▨	M3.2									
WP 4: Scenario simulation: Base case																											
PETRA: Specification of base case											▨	▨	▨	▨	▨	▨	▨	▨	▨	M4.1							
NEMO: Specification of base case (emissions)											▨	▨	▨	▨	▨	▨	▨	▨	▨	M4.2							
Comparison and analysis															▨	▨	▨	▨	▨	▨	M4.3						
WP 5: Scenario simulation: Policies																											
PETRA: Specification of new policies and their integration													▨	▨	▨	▨	▨	▨	▨	▨	M5.1						
Modelling policy scenarios															▨	▨	▨	▨	▨	▨	▨	▨	▨	M5.2			
Analysis of scenario model runs																	▨	▨	▨	▨	▨	▨	▨	M5.3			
WP 6: Sensitivity and policy conclusions																											
Sensitivity analysis														▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M6.1			
Integrated evaluation: Long-term GHG emission reduction potential																▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M6.2
Gap analysis and preparation of communication																▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	M6.2
WP 7: Project management																											
Project coordination, internal project meetings etc.	M7.1: continuously																								▨	▨	▨
Stakeholder integration and disseminations						M7.2: continuously (EAA serving representative and knowledgeable stakeholder; dissemination as described)																			▨	▨	▨
Project controlling, legal management~~, and publications~~	M7.3: continuously																								▨	▨	▨
Activity/project reports and publications	M7.4: continuously																								▨	▨	▨

8 Publications and Other Dissemination Activities

Publications	
	Jonas, M., R. Bun, I. Ryzha, and P. Żebrowski, P. (2022a). Quantifying memory and persistence in the atmosphere–land and ocean carbon system. *Earth System Dynamics* 13, 439–455. DOI: 10.5194/esd-13-439-2022 [pure.iiasa.ac.at/17844].
	Eibinger, T., and H. Manner (2022). Policy Stringency and Drivers of CO_2 Emission from Passenger Cars in Austria from 1965–2019. Manuscript, Graz University, Austria (to appear as PhD journal publication).
	Eibinger, T., B. Deixelberger, and H. Manner (2022). Drivers of GHG Emissions in the EU Transport Sector: A Nonstationary Macropanel Analysis. Manuscript, Graz University, Austria (to appear as PhD journal publication).
	Jonas, M., R. Bun, I. Ryzha, and P. Żebrowski (2022b). Delay Time, Memory and Persistence: Current Insights. Working Paper WP-22-XXX, International Institute for Applied Systems Analysis, Laxenburg, Austria (forthcoming and to become part of a journal publication).
	Jonas, M., and P. Żebrowski (2022). PETRA: Determining Memory ... when the temporal extent of memory is limited and the weighting of memory decreases Gaussian backward in time. Manuscript, International Institute for Applied Systems Analysis, Laxenburg, Austria (to become part of a journal publication).
	Eibinger, T. (2022). Policy Stringency and Passenger Cars in Austria from 1952–2019. Manuscript, Graz University, Austria (to become part of a dissertation).
Workshops and presentations on conferences	
	Jonas, M., P. Żebrowski, G. Bachner, K. Steininger, T. Eibinger, H. Manner, A. Angelini, H. Heinfellner, and S. Lambert (2020): The role of persistence in tackling Austria's climate target: Policies for the transport sector. Poster, 22. Österreichischer Klimatag, 02–04 September, Vienna, Austria, https://ccca.ac.at/fileadmin/00_DokumenteHauptmenue/05_Veranstaltungen/Klimatag/2020/ACRP_03_09_PETRA.pdf.
	Jonas, M., P. Żebrowski, H. Manner, T. Eibinger, K. Steininger, H. Heinfellner, and S. Lambert (2022): PETRA – Persistence in the TRAnsport Sector. Presentation V18, 22. Österreichischer Klimatag, 20–22 April, Vienna, Austria, https://ccca.ac.at/fileadmin/00_DokumenteHauptmenue/03_Aktivitaeten/Klimatag/Klimatag2022/V18_Eibinger.pdf.
	Eibinger, T., and H. Manner (2022): Determinants of greenhouse gas emissions in the transport sector. Invited presentation, Workshop "Statistics and its role in societal challenges", 12–13 May, Louvain-la-neuve, Belgium, https://uclouvain.be/en/research-institutes/lidam/isba/30th-anniversary-of-isba-may-12-13-2022.html.
	18 internal all-collaborator working meetings / workshops

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Jonas, M., and P. Żebrowski (2022). PETRA: Determining Memory ... when the temporal extent of memory is limited and the weighting of memory decreases Gaussian backward in time. Manuscript, International Institute for Applied Systems Analysis, Laxenburg, Austria (to become part of a journal publication).

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Supplementary documents (Doc) and data (Dat) files generated over the course of the PETRA project are available at https://iiasa.ac.at/petrafar22. However, this website is password-protected. For access, please contact Matthias Jonas (jonas@iiasa.ac.at) or Piotr Żebrowski (zebrowsk@iiasa.ac.at).