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The Role of Persistence in Tackling Austria's Climate Target:

Policies for the Transport Sector (PETRA)

Status Report for 01 Dec 2019 – 30 Jun 2020

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About the PETRA project

Problem:

With the **Paris Agreement** in late 2015 the international community signalled both its commitment to long-term carbon-free societies and its adherence to a voluntary, bottom-up climate policy. Austria was one of the first countries to ratify the Paris Agreement.

From an Austrian perspective, its **transport sector** is of particular concern. Its emissions have grown significantly, in 2018 amounting to more than 47% (without emission trading) of Austria's greenhouse gas (**GHG**) emissions.[1] The transport sector is governed by **delays**, e.g. caused by long-lasting vehicle stocks in operation.

Policies typically influence **current** investments, but current emissions are also governed by **earlier** measures and investments – what we call the **memory** of the system (retrospective view). That is, former decisions come with a **temporal, or explainable, outreach** into the (near-term) future – what we call the **persistence** of the system (prospective view).

For a reliable policy analysis into the future, the quantification of the system's memory and persistence is important.

PETRA is novel:

(i) allows for establishing a robust relationship between relevant (national and international) policies and the diffusion of their impact (e.g. the phase-in of new vehicles in the market); and

(ii) allows for quantifying the memory-persistence effect caused by the share of the old, still existing (remaining) vehicles in the market.

To our knowledge, such a data-based, retrospective, qualitative-quantitative policy-response analysis has not yet been carried out, neither in Austria nor elsewhere.

This analysis will offer two important benefits. It will help:

1) to model-generate more robust **prospective** emission scenarios (or to test existing ones in terms of plausibility); and

2) decision-makers to better understand the effectiveness of their emission reduction policies over time and vis-à-vis uncertainty.

The objective of the poster is to report on both **I)** the **theoretical advance** and **II)** the **data processing progress** we have achieved so far (**01 December 2019 – 30 June 2020**).

I) Theoretical advance:

We use a simple, insightful example to define **memory** and **persistence**. To this end, we break down our system into two parts: a **socio-economic part** and a **systemic (physical) part** (see **Fig. 1**). **Approaching memory and persistence systemically first will come as a great advantage before getting to grips with memory and persistence socio-economically**.

II) Data Processing:

Data processing took place concomitantly, with the main focus on the socio-economic part of our system.

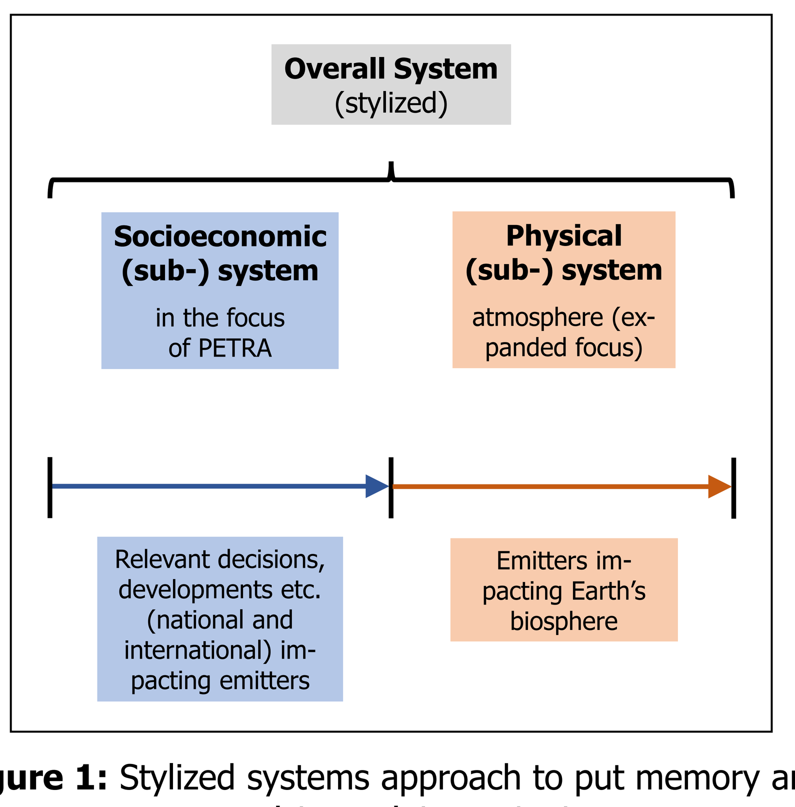
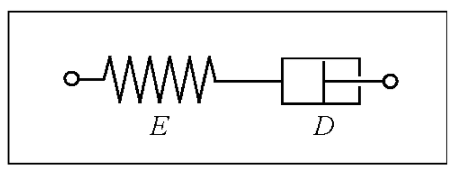


Figure 1: Stylized systems approach to put memory and persistence into context

I. The physical perspective on memory and persistence

We observe during the increase of GHG emissions: The atmosphere expands (**rather quickly**)[2,3] while part of the (carbon) emissions are locked away (**rather slowly**) in land and oceans.[4–7] It is widely debated how reversible and how much out of sync the latter process is compared to the first.

Our current knowledge suggests that using a **Maxwell body (MB)**, consisting of an elastic element (**E**) and damping (viscous) element (**D**), as a useful analogy to describe the relationship between atmospheric expansion and terrestrial and oceanic carbon uptake.



We take atmospheric CO_2 concentrations for 1959–2018 (in Pa) as **observable (strain ε)** and CO_2 emissions for 1959–2018 (converted to Pa) as **deliverable (stress σ)** and use the stress-explicit form of the stress-strain relation for the MB:

$$\sigma(t) = \sigma(0)\exp\left(-\frac{E}{D}t\right) + E\int_0^t \dot{\varepsilon}(t)\exp\left(\frac{E}{D}(\tau - t)\right)d\tau$$

For clarity of demonstration, let $\sigma(0) = 0$, $\varepsilon(0) = 0$ and $\varepsilon(t) = m_\varepsilon t$ (we can deal with polynomial and exponential $\varepsilon(t)$). Then

$$\sigma(t) = Dm_\varepsilon\left(1 - \exp\left(-\frac{E}{D}t\right)\right) = \sigma(q,n) = Dm_\varepsilon(1 - q^n)$$
$$= Dm_\varepsilon(1 - q)S_n$$

where $\frac{D}{E}$ is the characteristic **relaxation time** of the MB, $n = \frac{t}{\Delta t_n}$ is a dimensionless time (here $\Delta t_n = 1$ year), $q = \exp\left(-\frac{E}{D}\Delta t_n\right)$ and

$$S_n = \frac{1 - q^n}{1 - q} = \sum_{i=1}^{n-1} q^i \leftarrow Past$$

We call S_n **memory**. To explore the dependence of σ on q we take

$$\frac{\partial\sigma(q,n)}{\partial q} = Dm_\varepsilon\frac{\partial}{\partial q}\big((1-q)S_n\big) = Dm_\varepsilon\big((1-q)T - q\big)$$

where

$$T = -\frac{q^n}{1-q^n}\left(\frac{t}{\Delta t_n}\right) + \frac{q}{1-q} \xrightarrow[n\to\infty]{} \frac{q}{1-q} = T_\infty$$

We call T the characteristic **delay time** and $P = T^{-1}$ the characteristic **persistence**.

Let's assume that we could change q in retrospect at time $t = 0$. Then, if T is small, that is ΔM per Δq (or, likewiese, $\frac{\Delta M}{M}$ per $\frac{\Delta q}{q}$) is small, P is great because the change in the systems characteristics (contained in q) hardly influences the MB's past. As a consequence, the past exhibits a great path dependency.

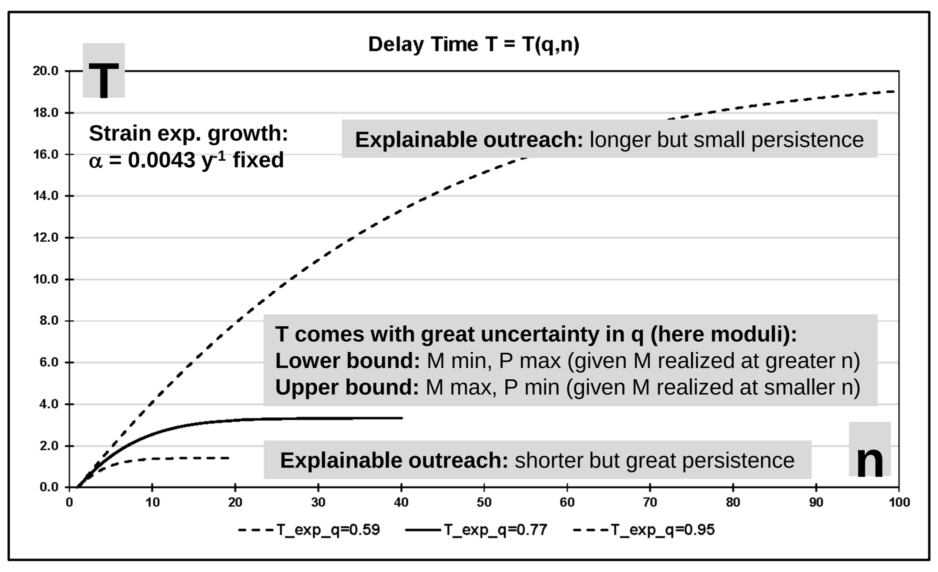


Figure 2: Graphical interpretation of delay time T and explainable outreach (if M-defined)

What we know so far:

- The **memory** of a MB stems from its **damping** element, responsible for the exponential behaviour of the delivarable (stress).
- But memory exists even with **no** damping element around. Old cars, e.g., contribute to today's emissions and may be considered as memory of the transport sector, which one wants to understand better **before influencing emissions socio-economically**.
- On smaller spatio-temporal scales (e.g., **Austria's transport sector**) emissions may exhibit polynomial rather than exponential behavior (potentially with a time-dependent q). But we can deal with that.

This provides the basis for data-processing emissions from Austria's transport sector from a socio-economical perspective, as described in II.

II. The socio-economic perspective on memory and persistence

Literature Review (completed)

- Identification and selection of determinants relevant to the transport sector (by GHG and particular emissions)

  → Literature on GHG determinants is often based on few identities and equations only
- Determinants may be endogenous (interlinked)
- Creation of an extensive list of past transport related policies (mostly with the scope on Austria, a few with the scope on the EU)

Econometric Analysis (commenced)

- **Structural Vector Autoregressive (SVAR) Model**

  → All variables are treated as endogenous; each variable is explained by the past values of all variables
- **Pros**: Captures the dynamics of multiple endogenous variables; dynamic interrelations of variables can be studied; fewer restrictions need to be imposed compared to other econometric models
- **Cons**: A large number of parameters needs to be estimated; due to data-availability, not more than 2–6 variables may be included in the model; some restrictions still have to be imposed on the model
- **Limited data-availability**: Other econometric models may be employed to capture the dynamics of interest

Methodology – Data Provision (advanced)

- EAA made available two suitable energy scenarios which are used to extract data:

  WEM (with existing measures) 2013: contains data from 1950 to 2030

  WEM (with existing measures) 2019: contains data from 1990 to 2050
- WEM scenarios can be seen as business as usual (BAU) scenarios
- Data within the WEM scenarios from 1990 to 2018 come from the Austrian GHG Inventory (OLI)
- Biggest challenge: To satisfy vehicle category needs → categories „PC Otto with catalyst" and „PC Otto without catalyst", e.g., are not distinguished in the WEM scenarios
- Consequence: Data had to be disaggregated and reaggregated to match vehicle category needs
- Second biggest challenge: To merge scenarios
- Finding for the WEM19: Retrospective analysis within WEM19 scenario takes place only back to 1990, not 1950 (for instance, wrt detailed information on exhaust gas after treatment)

  Consequence: This leads to some data leaps in the complete time series 1950 to 2050, which cannot simply be averaged because valuable policy-related information would be lost

Selected Variables and Data Availability

Variables	Metric	Categories	Data Psg.	Data Freight
Emissions	tonnes, g/km	CO2, NOx, PM (total and specific)	1950*	1950*
Activity	Pkm, tkm and km/PC	Passenger: Otto w Cat, Otto wo Cat, HEV, PHEV, Diesel, Diesel HEV, Diesel PHEV, EV; Freight: LDV w Cat, LDV wo Cat, LDV Diesel, LDV EV, HDV Otto, HDV Diesel, HDV Diesel HEV, HDV EV	1950	1950
Population	Avg. Population / year		1950	1950
GDP/Capita	Constant EUR		1954	1954
Fuel Prices	Constant EUR	Normal, Super, Diesel	1950	1950
Energy Intensity	Final Transport Energy Consumption / Activity	Passenger: Otto w Cat, Otto wo Cat, HEV, PHEV, Diesel, Diesel HEV, Diesel PHEV, EV; Freight: LDV w Cat, LDV wo Cat, LDV Diesel, LDV EV, HDV Otto, HDV Diesel, HDV Diesel HEV, HDV EV	1950	1950
Vehicle Stock	total stock	Passenger: Otto w Cat, Otto wo Cat, HEV, PHEV, Diesel, Diesel HEV, Diesel PHEV, EV Freight: LDV w Cat, LDV wo Cat, LDV Diesel, LDV EV, HDV Otto, HDV Diesel, HDV Diesel HEV, HDV EV	1950	1950

Table 1: Turquoise: data for passenger cars disseminated; magenta: data disseminated but still to be checked for inconsistencies; *****: data for PM10 available only from 1990 onward.

References

1. EAA. Austria's National Inventory Report 2020. Environment Agency Austria, Report Rep-0724 (2020). https://www.umweltbundesamt.at/fileadmin/site/publikationen/rep0724.pdf
2. Lackner, B. C., Steiner, A. K., Hegerl. G. C. & Kirchengast, G. Atmospheric climate change detection by radio occultation using a fingerprinting method. *J. Climate* **24**, 5275–5291 (2011). https://doi.org/10.1175/2011JCLI3966.1
3. Steiner, A. K., Lackner, B. C., Ladstädter, F., Scherllin-Pirscher, B., Foelsche, U. & Kirchengast, G. GPS radio occultation for climate monitoring and change detection. *Radio Sci.* **46**, RS0D24 (17pp) (2011). https://doi.org/10.1029/2010RS004614
4. Boucher, O., Halloran, P. R., Burke, E. J., Doutriaux-Boucher, M., Jones, C. D., Lowe, J., Ringer, M.A., Robertson, E. & Wu, P. Reversibility in an Earth system model in response to CO_2 concentration changes. *Environ. Res. Lett.* **7**, 24013 (9pp) (2012). **https://doi.org/10.1088/1748-9326/7/2/024013**
5. Schwinger, J. & Tjiputra, J. Ocean carbon cycle feedbacks under negative emissions. *Geophys. Res. Lett.* **45**, 5062–5070 (2018). https://doi.org/10.1029/2018GL077790
6. Smith, P. Soils and climate change. *Curr. Opin. Enviro. Sust.* **4**, 539–544 (2012). https://doi.org/10.1016/j.cosust.2012.06.005
7. Dusza,Y, Sanchez-Cañete, E. P., Le Galliard, J.-F., Ferrière, R., Chollet, S., Massol, F., Hansart, A., Juarez, S., Dontsova, K., van Haren, J., Troch, P., Pavao-Zuckerman, M. A., Hamerlynck, E. & Barron-Gafford, G. A. Biotic soil-plant interaction processes explain most of hysteric soil CO_2 efflux response to temperature in cross-factorial mesocosm experiment. *Sci. Rep.* 2020; **10**, 905 (2020). https://doi.org/10.1038/s41598-019-55390-6