Trigger or time fuse? An empirical framework for detecting change points and pace in the diffusion of low carbon technologies

Paper presented at 20th Global Conference on Environmental Taxation, Cyprus

Veronika Kulmer, Dominik Kortschak, Sebastian Seebauer

JOANNEUM RESEARCH Forschungsgesellschaft mbh,

LIFE Centre for Climate, Energy and Society, Austria

1 Introduction

The necessity to transform the Austrian transport and energy sector towards less carbon emissions is well understood. Energy efficient technologies to support this transformation are equally well known (APCC 2014, UBA 2015, WBGU 2011). Eventually, in some decades, market forces and pressure from limited resources alone will lead to a replacement of conventional, fossil-fuel based technologies by their innovative, low carbon substitutes. However, relying just on slow self-regulatory market turnover will incur substantial social and ecological costs (Stern 2006, Steininger et al. 2014). Time is of the essence in setting out for transformative pathways, as each year of delay further depletes the carbon budget available to remain within the guardrails of +1.5°C or +2°C global warming, and restricts the room for maneuver in the coming years. This calls for an in-depth understanding of the dynamics in the market uptake of low carbon technologies, in particular its discontinuities and acceleration/deceleration phases, in order to identify potential avenues for targeted policy intervention.

Rogers' (1989) diffusion of innovations theory is the backbone of numerous technology forecast studies. This theory characterizes market uptake as a s-shaped diffusion curve with initial slow onset, followed by a longer phase of fast diffusion and eventual levelling off as soon as the market becomes saturated (van der Kam et al. 2018, Gnaan et al. 2018). Various modelling approaches root in the widely established s-shape (e.g. Bass model (Adner 2002, Bass 1969); Fisher-Pry model (Gnann et al. 2018)). Rogers' s-shaped pattern includes two turning points at which the diffusion dynamic changes direction: the take-off point, when a niche product enters the market mainstream, and the saturation point, when the growth rate fades out as full market penetration draws near.

However, it is empirically evident that technology diffusion happens in a socio-political context and that real-world diffusion processes do not strictly adhere to the idealized s-shape. Sood and Tellis (2005) identify for several technologies multiple consecutive s-shapes, suggesting refreshing and pause phases. They also find linear instead of exponential growth during the take-off phase. Technology diffusion is influenced by a variety of factors such as investment costs, operating costs, attributes and characteristics, popularity, policy measures, social aspects, infrastructure, etc. (Lee et al. 2012, van der Kam et al 2018, Simpson and Clifton 2016, Changgui et al. 2018). Policies and protocols initiated by governments and international organizations are a major influence. A prominent example is the UK Climate Change Act 2008, which underpinned the market diffusion of low carbon innovations in order to meet the ambitious emission targets (Carter and Jacobs 2013). Thus, linking the observed market diffusion of low carbon technologies with political, technological and societal interventions requires to explicitly identify when turning points occur that boost or hinder the diffusion of innovations and how the shape of the diffusion curve changes after these turning points.

Therefore the aim of the paper is to demonstrate a methodology for identifying change points in market diffusion in order to pinpoint when the empirically observed market diffusion of low carbon technologies deviates from Rogers' baseline s-shape pattern and to show how the pace of technology diffusion changes. The empirical framework presented here enables to identify critical moments during the diffusion process – such as triggers that spark rapid market take-off, or time fuses that set off gradual but accelerating growth.

For the case of Austria four low-carbon technologies are analyzed in the timespan from 1970 to 2018 using the mathematical technique of change point analysis: (1) privately owned electric vehicles (EV), (2) privately owned hybrid electric vehicles (HEV), (3) photovoltaics panels (PV), and (4) heat pumps for space heating (HP). All four technologies are large-purchase technologies with mature products available on the private consumer market, but they differ in their current levels of market penetration and in the length of their investment cycles. Following Rogers' classification, EV are in the innovator stage, HEV and PV are in the early adoption, and HP are in the early majority stage of diffusion in Austria. Consequently, our discussion of the Austrian low carbon market development addresses the early stages of market take-off long before consolidation to a satiated, stabilized market share. While our results only reflect the context of Austria as a typical western industrialized country, we expect that our proposed methodology may be replicated in other countries in order to enable cross-country comparisons.

1.1 *Rogers' diffusion of innovations theory*

By means of case studies Roger (1983) found that the adoption of an innovation over time follows a bell shaped normal distribution and consequently the cumulative number of units adopted shows an s-shaped curve of diffusion. During slow initial development mainly innovators and early adopters are attracted, followed by a rapid upscaling, where the early and later majority adopts the technology and finally a plateau is reached, describing market satiation as laggards eventually adopt the technology. Figure 1 illustrates Rogers (1983) theory and assigns the low carbon technologies analyzed in this study to the respective stages of market diffusion.

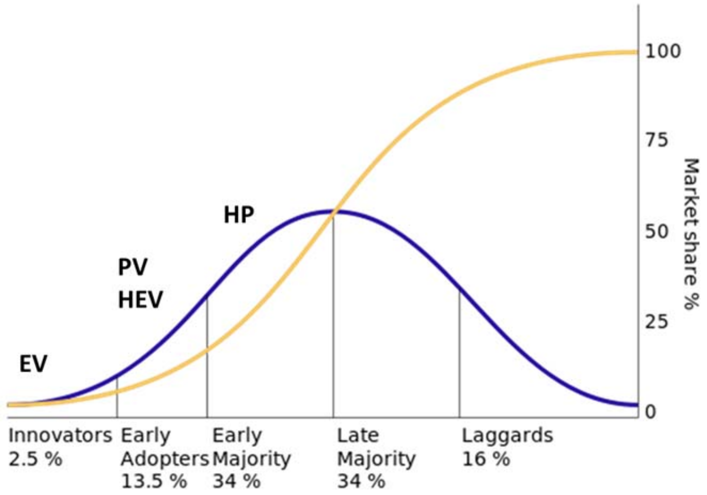

Figure 1: Roger's S-shaped curve describing the diffusion of innovations (edited, source: Rogers 2012)

Within energy and climate research a vast number of models for forecasting innovative, emerging technologies build on Rogers' s-shaped diffusion theory. A famous example is the Bass diffusion model (Bass 1969), which is the most commonly used model to predict technology adoption. It is frequently applied to the cases of PV and e-car use (Dong et al. 2016, Kurdgelashvili et al. 2019, van der Kam et al. 2018, Guidolin et al. 2010). Other examples of s-shaped diffusion models are the Fisher–Pry model (Fisher & Pry, 1971), applied in the areas of digital innovation (Michalakelis et al. 2018, Oughton et al. 2018), renewable energy scenarios (Devezas et al. 2008) as well as low carbon mobility (Björn et al. 2011) and logistic models in general (Bewley & Fiebig, 1988) used for forecasting diffusion of renewable electricity (Lee and Huh 2017, Xu et al. 2016) as well as energy generation (Harris et al. 2018).

The s-shaped diffusion curve provides the null hypothesis of this study, reflecting the theoretically assumed baseline model of technology diffusion. The idealized s-shape consists of three phases of technology diffusion: slow onset, rapid growth, saturation. A range of alternative diffusion models are tested that represent these three phases as sequences of exponential, linear and logistic functions, with the aim of providing a more realistic and accurate picture of real-world market dynamics.

2 Data

This study uses time series data on technology performance over the last three to five decades, drawing on national vehicle statistics and annual market reports of technology development (Table 1). Data on the motor vehicle stock compiles information of the monthly released registration of new and used vehicles in Austria and documents the stock of e-cars and hybrid electric cars for the time-span of 1990 to 2018. The annual report on innovative energy technologies in Austria (Biermayer et al. 2019) shows the market development of installed PV capacities and number of heat pumps and aggregates annual reports of industry associations, annual accounts of major firms, market research and surveys among distributors, retailers as well as operators. As of now, the timeline of technology performance published in the annual report on innovative energy technologies provides the best market coverage on PV and heat pump evolution in Austria and is widely accepted in the Austrian technical and scientific community.

Table 1: Description of data

Technology	Indicator	Timespan	Source
Electric cars	Number of privately owned e-cars	1990-2018	Statistics Austria, Stock of motor vehicles
Hybrid electric cars	Number of privately owned hybrid electric cars	1990-2018	Statistics Austria, Stock of motor vehicles
Photovoltaics	Installed PV capacity in kWp	1990-2018	BMVIT (Biermayr et al. 2019, Innovative Energy Technologies in Austria - Market Development 2019
Heat Pumps	Number of heat pumps for space heating [a]	1970-2018	BMVIT (Biermayr et al. 2019), Innovative Energy Technologies in Austria - Market Development 2019

[a] excluding all heat pumps that are only used for water heating.

3 Method

A stepwise methodological approach is adopted to compare the observed market diffusion of low carbon technologies to Rogers' s-shape pattern; first to show <u>when</u> (change points), second to show <u>how</u> (parametric functions) the observed diffusion curve deviates from the baseline s-shape.

<u>Step 1: Baseline model</u>

The s-shaped diffusion curve is the baseline model and null hypothesis of our analysis. Mathematically speaking, the s- curve corresponds to a logistic function. As at the starting year of our time series data a small number of units had already been adopted, the observed technology diffusion curve does not originate at zero; therefore an intercept term D is added to the logistic function.

$$F(t|a,b,C,D) = \frac{C}{1+\exp(-(a+bt))} + D \qquad Eq.1$$

F describes the technology diffusion in year t. Four parameters are to be estimated: b denotes the logistic growth rate and controls the slope of the curve, i.e. the pace of technology diffusion. The term $-\frac{a}{b}$ is the midpoint of the logistic curve, i.e. the point in time when the annual growth rate levels off. C denotes the maximal, satiated value of the logistic function, while D is the minimal, starting value of the curve.

Step 2: Alternative change point models

The mathematical technique of change point analysis fits alternative models to the observed technology diffusion data. Three alternative models (discrete CP, smooth CP, two CP) with one or two change points are tested against the baseline logistic-model.

- Smooth CP: Model with one or two change points, where after each change point a new parametric function may follow and with the condition that the whole function is smooth.
- Discrete CP: Model with one or two change points, where after each change point a new parametric function may follow. In contrast to above, this specification allows for discrete functions in order to cater to fluctuations and volatility in real-world market environments.
- Two CP: Model with two change points, with the same parametric function applied before the first change point and after the second change point, and another parametric function between the two change points. This specific model allows to detect pull-forward effects, a special case of market dynamics. One prominent example is the German accelerated vehicle retirement program, which led to a sharp increase in demand for new cars as long as the policy was active, but shortly after the policy was discontinued, the car registration numbers returned to the pre-policy trend (Böckers et al. 2012).

Due to the number of parameters to be estimated and the short timespan of available data, we restrict the number of change points to maximal two. Otherwise, overfitting would be an issue.

Each alternative change point model consists of a set of parametric functions before and after each change point. These functions can be understood as building blocks, which are pieced together to approximate the course of market diffusion over time. For instance the logistic S-curve initially behaves similar to an exponential function and turns approximately linear in the intermediate stage of rapid diffusion. Due to the fact that the analyzed technologies are in the early stages of market uptake, the following three building blocks are used:

(i) Logistic: $logit(t|a,b,C,D) = \frac{C}{1+\exp(-(a+bt))} + D$ *Eq.2*

(ii) Exponential: $exp(t|a,b,D) = e^{a+bt} + D$ *Eq.3*

(iii) Linear: $lin(t|a,b) = a + bt$ *Eq.4*

The parameterization of the logistic function (i) is identical to the baseline model in Eq.1. In the exponential function (ii) D denotes the intercept starting level of the curve, while b describes the exponential growth rate. Note that in case of small values of t, the growth rate corresponds to logistic growth. The term a, more precisely e^{a} is a multiplicative factor. If we approximate the logistic function (with parameters a_l, b_l, C_l, D_l) near a point t_0, we would estimate the parameters as follows $b = b_l$, $D = D_l$ and $a = \log(C_l e^{a_l}) - \log\left(1 + e^{a_l + b_l t_0}\right)$. In the linear function (iii) b is a linear growth factor and a denotes the intercept. If we approximate the logistic function (with parameters a_l, b_l, C_l, D_l) near a point t_0 with a linear function then we would estimate the parameters as follows $b = b_l * C_l \frac{e^{-(a_l + b_l t_0)}}{1+e^{-(a_l+b_l t_0)}}$ and $a = \frac{C_l}{1+e^{-(a_l+b_l t_0)}} + D_l - t_0 * b$.

Step 3: Parameter estimation for each alternative model variation

Every possible combination of number of change points and building blocks in the alternative models is estimated. The advantage of this additive approach is that we are able to detect the point in time when the shape of the diffusion curve changes as well as to identify how the curve changes in terms of dynamic and pace (e.g. exponential or linear acceleration in diffusion). The drawback however is the large number of variations of functions to be estimated. For each alternative model 33 functional variations are possible from all permutations of three building blocks and one or two change points: 3^2 variations of one change point models plus 3^3 variations of two change point models. Consequently, model selection is crucial.

Step 4: Model selection

The model selection relies on the corrected Akaike Information Criterion (AICc) (Akaike 1973) which is a second order correction for the approximation of the Kullback-Leibler distance between the distribution of the data and the estimated model (Snipes and Taylor 2014). The AICc is preferable to the standard AIC if the number of observations is small. AICc is a powerful method for comparing models and frequently used in model selection (Andrews and Currim 2003, Ingdal et al. 2019, Wagenmakers and Farrel 2004, Jakubczy 2019). Note that the AICc scores are ordinal and dimensionless; they are simply a tool for model ranking (Snipes and Taylor 2014).

Additionally, the AICc is used to derive posterior model weights in a Bayesian setting with special prior distribution (Eq.A1 in the appendix gives the details). Basically the probability weights are formulated as difference between the AICc of a particular model and the AICc of the model with the minimal AICc. These weights then show the probability that one model fits better than the other models. Thus, the weights can be interpreted similar to p-values in classical hypothesis testing. These probabilities are helpful in case of small differences between AICc scores.

Due to the large number of 33 variations in each alternative model a stepwise selection process is adopted: First, within each alternative model (i.e., smooth CP, discrete CP, two CP) the AICc for all 33 functional variations is compared and the variation with the lowest AICc is selected. Next, this best fitting functional variation within each alternative model is compared to the AICc of the baseline model. If the baseline model has a higher AICc, the null hypothesis is rejected and the alternative model variation with the lowest AICc is selected as it describes the observed data best. This model then provides the change point(s) when and how the model shape changes. If the baseline model has the lowest AICc, the null hypothesis is retained as the observed data adhere to the idealized s-shape.

4 Results

4.1 *Comparison of baseline versus alternative models*

The null hypothesis of this study states that technology diffusion follows an s-shaped logistic function (baseline model), as posited by diffusion of innovations theory. Table 2 reports the AICc and the Bayesian weights for the baseline and the best fitting alternative models. Figure 2 compares the observed market diffusion with the best fitting variation of alternative models and the s-shape baseline. None of the four investigated technologies evolves logistically as presumed by theory and hence the null hypothesis is rejected throughout.

Table 2: Comparison of models: AICc and bayesian probability weights (w) for the baseline and best fitting variation of alternative models for all technologies

	EV		HEV		PV		HP	
	AICc	*w*	AICc	*w*	AICc	*w*	AICc	*w*
Baseline	384	0%	453	0%	686	0%	893	0%
Discrete CP	353	0%	383	33%	**545**	**97%**	**739**	**100%**
Smooth CP	354	0%	394	0%	552	3%	754	0%
Two CP	**322**	**100%**	**382**	**67%**	604	0%	778	0%

According to the AICc values, for EV and HEV the two CP model and for PV and HP the discrete CP model shows the best fit. In contrast to theory, the empirically observed diffusion does not follow a smooth function. Among all alternative models in all technologies, the smooth CP model performs worst.

In HEV the AICc values differ only marginally between the discrete CP and the two CP alternative model. The Bayesian probability weights however suggest to select the two CP model: with a probability of 67% the two CP model is more likely to outdo the discrete CP model with a probability of 33%. For all other technologies the differences in AICc are more pronounced, resulting in probabilities of 97% or more for the best model.

Although two change points and a discrete functional form are detected in all technologies, market diffusion unfolds quite differently over time. Taking a closer look at our results reveals that the location of as well the timespan between change points vary and that the building blocks of functions as well as their specific parameters differ strongly between the technologies.

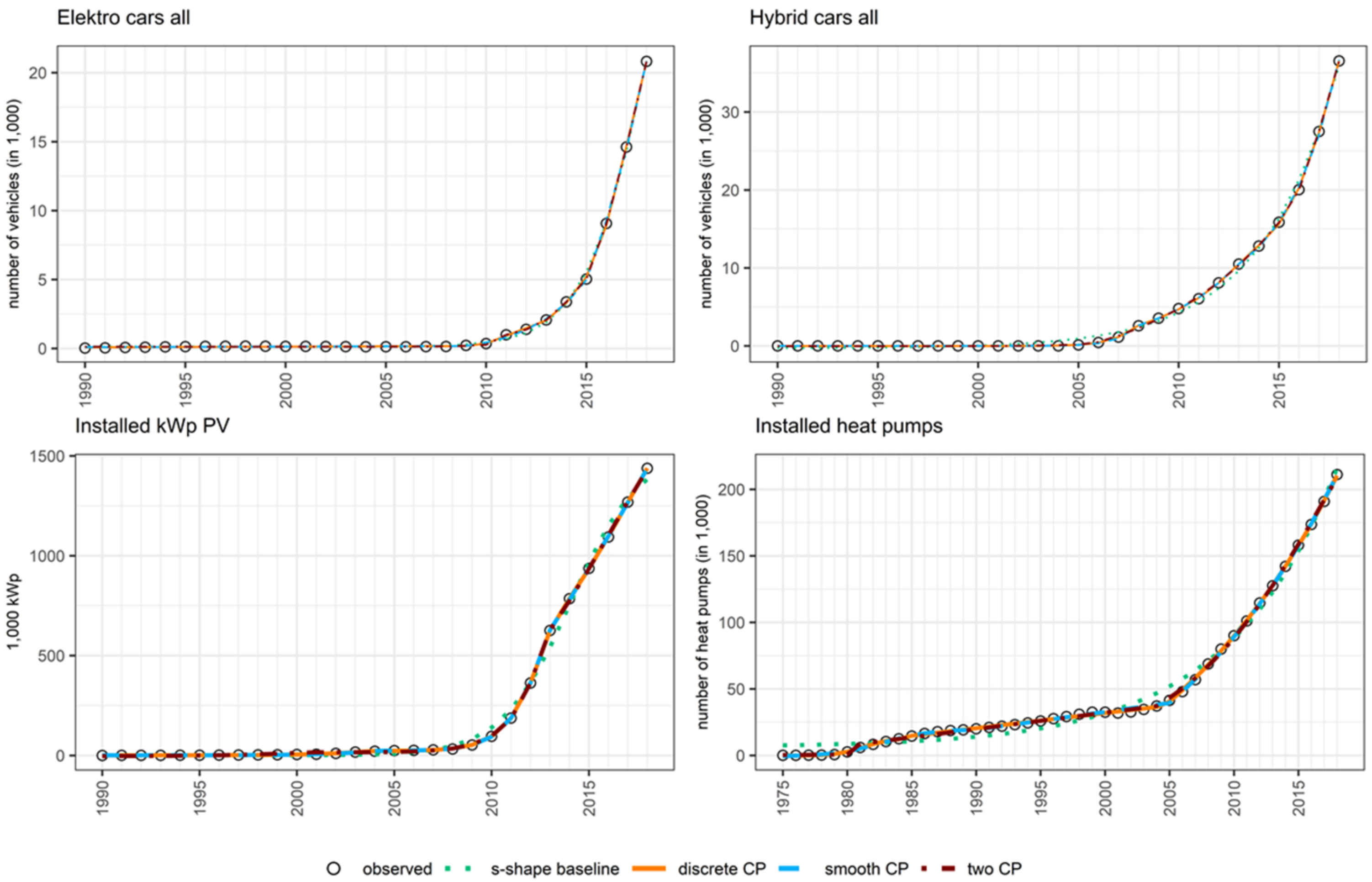

Figure 2: Comparison of estimated models with empirical observations: Black circles illustrate observed market diffusion. Dotted and solid lines show the diffusion of the best fitting alternative model (discrete CP, smooth CP, two CP) and of the s-shape Baseline.

4.2 *Change points and shapes of technology diffusion*

The technique of change point analysis offers the double advantage of identifying (1) change points when the diffusion dynamic changes and (2) functions how the shape of the diffusion curve, implying pace and dynamic, changes. Comparing the alternative models between the technologies reveals some contrasting and striking differences. Figure 3 illustrates the functions of each building block of the selected best-fit model for each technology in order to emphasize the sharp transitions in pace from one building block to the next. It also illustrates how observed market diffusion fluctuates and does not follow a smooth trajectory. The year of the change point and the ensuring reorientation in the shape of the curve informs on the occurrence of accelerate and brake effects. Table A1 summarizes the main attributes of the selected models (functional form of building blocks, parameterization and year of change points) for each technology. Going back in history from the change points and their characteristics provides the starting point for searching various events in the past which may have lead up to these change points.

For a long period of time EV were hardly visible in the total vehicle stock. They started to take hold in the vehicle market in 2011, when market performance changed to a phase of rapid growth (modelled as an exponential function). This stark growth phase was quite short and lasted until 2015, when the pace of growth decreased and returned to the logistic function of the first building block. The period between 2011 and 2015 seems to represent a pull forward effect, where the market development deviates only for a limited period from the underlying trend (as illustrated in Figure 3 the logistic function of the first and third building block). Still, post-2015 the number of vehicles continues to grow fast, but seems to level off.

Previous studies on EV diffusion, in particular referring to the Austrian context (Biermayr et al 2019; Yu et al. 2018) suggest crucial developments in technological and policy-related factors as explanations for the 2011-2015 growth period. After the introduction of the Tesla Roadster in Austria in 2009, the range of battery EV increased dramatically. Austrian policy makers made great efforts from 2007 onwards to boost adoption (e.g. purchase subsidies in all federal states, implementation of e-mobility test regions, support of charging infrastructure). In parallel, EU legislation limiting emissions of new passenger cars was passed in 2009 (Regulation (EC) No 443/2009). The continuing, but less rapid growth since 2015 is likely to be linked to ongoing efforts of the Austrian government to support EV purchase and operation. For instance, from 2016 onwards EV are exempt from sales tax and car registration tax.

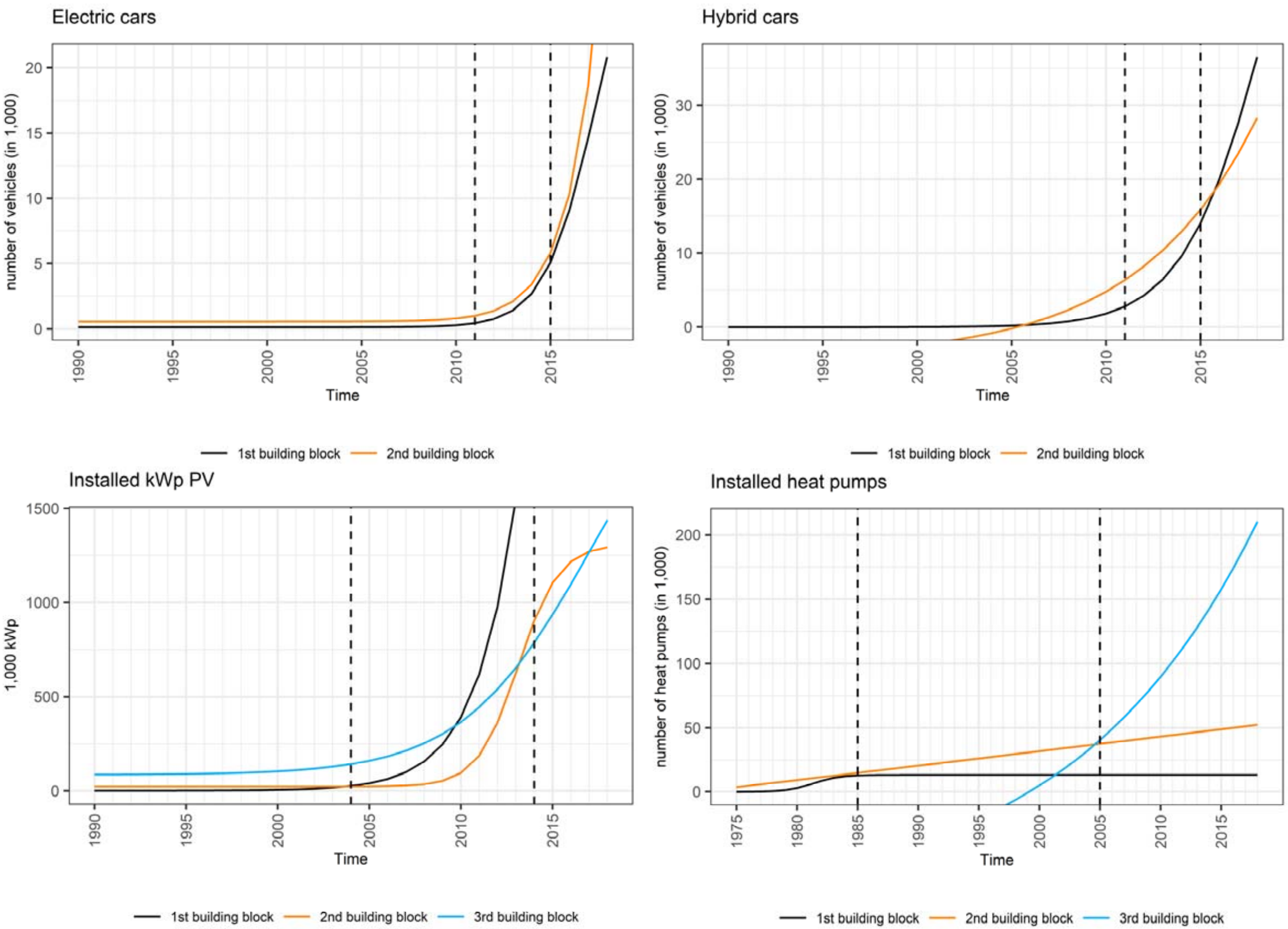

Figure3: Functional parameterization of each building block of the selected best-fit model for each technology: Black, orange and blue lines denote the function of each building block of the selected best-fit model (exact parameterization is reported in Table A1). Black dotted vertical lines denote the year of the change point, where shape of diffusion switches from one building block to the other. For comparison, observed empirical market diffusion is illustrated in Figure 2.

HEV appeared on the market in the early 1990s but remained on an indiscernible level for a long period of time. The year 2006 marks the first change point, when modest logistic growth changed to rapid exponential growth. In the following decade HEV diffusion was characterized by exponentially increasing annual growth rates. The second change point is detected in 2016, when the pace of diffusion returned to modest logistic growth. Similar to EV diffusion, the 2006-2016 period indicates a pull-forward effect.

The market diffusion of HEV mirrors the EV dynamics, only with the growth period being twice as long. This similarity is not surprising since both technologies are linked in terms of technology development, policy incentives and infrastructural conditions. Various political efforts favoring EV also applied to HEV, such as purchase subsidies initiated around 2005 and vehicle emission standards passed in 2009 (Regulation (EC) No 443/2009). Range extended batteries were also a highly relevant technological breakthrough for HEV. However, in contrast to EV, the second change point in 2016 which terminated the HEV pull forward phase, most likely can be traced back to changes in political agendas. Although EV still receive extensive governmental support, initiatives and support schemes for HEV are being phased out. Consequently, as illustrated in Figure 3 by comparing the 1st (equal to the 3rd) building block functions between EV and HEV, the current pace of HEV diffusion is considerably slower than for EV.

Around the year 2000 PV gained market visibility and started slow yet with exponential growth. In 2004 PV diffusion shifted to a strong logistic growth. In 2014 the curve changed again to less rapid, but still logistic growth. As of now, the pace of technology diffusion is still fast but levelling off.

The first 2004 change point emerged shortly after the technology entered the energy market in 2000 (notwithstanding early fringe applications prior 2000). Both, the market entry and the short initial period of hesitant growth, are likely to trace back to political decisions. At the beginning of 2000 the Austrian green electricity bill was passed (BGBl. I 149/2002). In 2004, PV feed-in tariffs, a central part of the green electric bill, were capped and consequently the pace of diffusion decelerated from an exponential to a logistic function (Biermayer et al. 2019). The subsequent 10 years still featured substantial growth, which presumably rooted in subsidy initiatives and support schemes by national government and federal states. However, extrapolating the function of the second building block suggests that market satiation would have been achieved by ca. 2020. In 2014 the curve shape remained logistic but the pace decreased; this most recent trajectory of the third building block however indicates a much higher level of eventual market saturation. The second change point corresponded with the change in PV subsidy schemes. Since 2012 only installations between 5 and 350 kWp are eligible for feed-in tariffs and investment grants. Installations smaller than 5 kWp however may apply for other support schemes, such as the subsidy package issued by the Austrian climate and energy fund in 2014 budgeted with 30 million Euro for the next 10 years.

HP are the most mature of the four investigated low carbon technologies and entered the market in the early 1980s. Market entry was characterized by a standard logistic function, but in 1985 diffusion changed to a 20-year period of linear growth. In 2005, the diffusion curve changed to rapid exponential growth. In comparison to all other technologies, the market diffusion of HP deviates most from the baseline s-shape.

Previous studies on heat pump diffusion in Europe (Nyborg and Ropke 2019, Baardsen et al. 2008, Biermayer et al. 2019) discuss underlying developments that may help to understand the detected change points and curve shapes. The dramatic increase in fuel prices during the second oil crisis in the 1980s initiated a political debate on energy independency that later manifested in support schemes for alternative, domestic and renewable energy sources. Presumably, these policy actions enabled the constant growth in HP after the first change point. In the beginning of the 2000s more efficient air-to-air heat pumps became publicly available (Hartl et al. 2018), and stricter energy efficiency regulations in Austrian building standards favored HP installation. Furthermore the installation of renewable energy systems in private households was subsidized. This combination of technology development, building standards and subsidies was likely to trigger exponential growth.

5 Discussion and conclusions

We used mathematical change point analysis to analyze (i) whether the empirically observed market diffusion of low carbon technologies conforms with Rogers' (1983) baseline s-shape pattern and, if the s-shape is not confirmed, (ii) how the pace of technology diffusion changes after certain turning points in the diffusion curve. This analysis allows to link past political and technological developments with accelerate and brake effects on market diffusion.

This mathematical framework is applied to four low carbon technologies in Austria: electric vehicles (EV), hybrid electric vehicles (HEV), photovoltaics panels (PV), and heat pumps for space heating (HP). Market diffusion of these technologies does not follow the idealized s-shape used in various diffusion models. Moreover, none of the studied technologies follows a continuous, smooth function, hence implying that real-world market diffusion fluctuates and can be highly volatile. In order to represent these fluctuations mathematically, we use building blocks of functions to gain the best fit of the estimated models to the observed market data.

Comparing the alternative models of the four low carbon technologies underscores the high heterogeneity in the location and timespan between change points as well as in the combination and parameterization of functions. EV and HEV feature pull-forward effects from intermittent promotion by policy initiatives; HPs were locked in constant linear growth for 20 years until accelerated by product innovation and stricter building standards; PV show subsequent logistic functions pointing to shifting levels of potential market saturation. This heterogeneity strongly questions the presumption of uniform, idealized diffusion processes, such as the s-shape. Yet, this heterogeneity calls for replication of our mathematical framework in other countries and extension to other technologies, in particular in course of digitalization (e.g. telecommunication and health services).

The mathematical framework developed in this study looks back on historical market diffusion and should be used as a forward-looking forecasting tool only with caution, particularly because unexpected technological or political breakthroughs can evoke a change point and a functional variation in the model's most recent building block. In a similar vein, extending the time series data by additional data points could yield different estimates of model parameters or may even shift change points or suggest other functions within selected building blocks. Thus, the change point analysis method crucially depends on reliable time series spanning 15+ years of observed market development, and model results should be continuously revisited for robustness checks as additional data points become available. This applies especially to low carbon technologies which are in the early stage of market diffusion, where the take-off point from niche product to market mainstream has yet not been reached.

The main purpose of our framework is to provide an entry point for an in-depth understanding of the social-technical-economic processes leading to a certain pattern of market diffusion. Mathematically identifying change points and curve shapes raises the subsequent (and more interesting in terms of enabling and managing the low carbon transformation) question which events induced these discontinuities in market uptake. We propose battery development or subsidy schemes as potential reasons for the identified discontinuities in the Results section. Heuristics such as the Multiple Streams Approach (Kingdon 1989) could guide a more systematic historical analysis when parallel developments in policy, public opinion and technology converged to turning points; these turning points would appear as change points in our framework, and the dynamics in these parallel developments would be reflected in the function after the change point. However, it should be kept in mind that any search for post-hoc explanations holds the risk of hindsight bias and an over-deterministic worldview and may underrate the effect of random serendipitous events.

Acknowledgments

This research received financial support from the Austrian Climate and Energy Fund and was carried out within the ACRP program (project number: B670150).

References

Adner R (2002) When are technologies disruptive: A demand-based view of the emergence of competition. Strategic Management J. 23(8):667–688

Andrews, R., Currim, I., 2003. Retention of latent segments in regression based marketing models. Int. J. Res. Mark. 20 (4), 315–321.

APCC, Kromp-Kolb H.,Nakicenovic N., Steininger K., Gobiet A., Formayer H., Köppl A., Prettenthaler F., Stötter J., Schneider J. (Hg.). Österreichischer Sachstandsbericht Klimawandel 2014 (AAR14). Austrian Panel on Climate Change (APCC), Verlag der Österreichischen Akademie der Wissenschaften, Wien, Österreich.

Bass FM (1969) A new product growth for model consumer durables. Management Sci. 15(5):215–227

Bewley, R., & Fiebig, D. (1988). A flexible logistic growth model with applications in telecommunications. International Journal of Forecasting, 4(2), 177–192

BGBl. 149/2002, Bundesgesetz, mit dem Neuregelungen auf dem Gebiet der Elektrizitätserzeugung aus erneuerbaren Energieträgern und auf dem Gebiet der Kraft-Wärme-Kopplung erlassen werden (Ökostromgesetz)

Biermayr, Peter, Christa Dißauer, Manuela Eberl, Monika Enigl, Hubert Fechner, Kurt Leonhartsberger, Florian Maringer, Stefan Moidl, Christoph Schmidl, Christoph Strasser, Werner Weiss, Patrik Wonisch, Elisabeth Wopienka, 2019, Innovative Energy Technologies in Austria - Market Development 2018, BMVIT - Austrian Ministry for Transport, Innovation and Technology, Vienna, Austria

Brunner S. 2008. Understanding policy change: multiple streams and emissions trading in Germany.Global Environmental Change 18(3): 501–507. https://doi.org/10.1016/j.gloenvcha.2008.05.003.

Changgui Dong, Benjamin Sigrin, Gregory Brinkman, Forecasting residential solar photovoltaic deployment in California, Technological Forecasting and Social Change, Volume 117, 2017, Pages 251-265, ISSN 0040-1625, https://doi.org/10.1016/j.techfore.2016.11.021.

Cherp, Aleh, Vadim Vinichenko, Jessica Jewell, Elina Brutschin, Benjamin Sovacool, Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework, Energy Research & Social Science, Volume 37, 2018, Pages 175-190, ISSN 2214-6296, https://doi.org/10.1016/j.erss.2017.09.015.

Chul-Yong Lee, Sung-Yoon Huh, Forecasting the diffusion of renewable electricity considering the impact of policy and oil prices: The case of South Korea, Applied Energy, Volume 197, 2017, Pages 29-39, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2017.03.124.

Collantes Gustavo, Daniel Sperling, The origin of California’s zero emission vehicle mandate, Transportation Research Part A: Policy and Practice, Volume 42, Issue 10, 2008, Pages 1302-1313, https://doi.org/10.1016/j.tra.2008.05.007.

Cooper-Searle , Simone, Finbarr Livesey Julian M. Allwood, Why are Material Efficiency Solutions a Limited Part of the Climate Policy Agenda? An application of the Multiple Streams Framework to UK policy on CO2 emissions from cars, Environmental Policy and Governance, 28,51–64 (2018)

Duk Hee Lee, Sang Yong Park, Jong Chul Hong, Sang Jin Choi, Jong Wook Kim, Analysis of the energy and environmental effects of green car deployment by an integrating energy system model with a forecasting model, Applied Energy, Volume 103, 2013, Pages 306-316, https://doi.org/10.1016/j.apenergy.2012.09.046.

Fisher, J. C., & Pry, R. H. (1971). A simple substitution model of technological change. Technology Forecasting and Social Change, 3(1), 75–88.

Guidolin M. C. Mortarino, Cross-country diffusion of photovoltaic systems: modelling choices and forecasts for national adoption patterns, Technol. Forecast. Soc. Change 77 (2) (2010) 279–296

Harris, Tyler M., Jay P. Devkota, Vikas Khanna, Pragnya L. Eranki, Amy E. Landis, Logistic growth curve modeling of US energy production and consumption, Renewable and Sustainable Energy Reviews, Volume 96, 2018, Pages 46-57, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2018.07.049.

Ingdal, Mats , Roy Johnsen, David A. Harrington, The Akaike information criterion in weighted regression of immittance data, Electrochimica Acta, Volume 317, 2019, Pages 648-653,https://doi.org/10.1016/j.electacta.2019.06.030.

Jakubczyk, T. 2019, Analysis of distribution of precipitation duration and amounts in Legnica in the period of 1966-2015 , Journal of Water and Land Development, 2019, No. 41 (IV–VI): 69–76, DOI: 10.2478/jwld-2019-0029

Kurdgelashvili, L., Shih, C.-H., Yang, F., Garg, M., 2019, An empirical analysis of county-level residential PV adoption in California , Technological Forecasting and Social Change

Oughton, E., Frias, Z., Russell, T., Sicker, D., Cleevely, D.D. , 2018, Towards 5G: Scenario-based assessment of the future supply and demand for mobile telecommunications infrastructure , Technological Forecasting and Social Change

Regulation (EC) No 443/2009 of the European Parliament and of the Council of 23 April 2009 setting emission performance standards for new passenger cars as part of the Community's integrated approach to reduce CO 2 emissions from light-duty vehicles. https://eur-lex.europa.eu/eli/reg/2009/443/oj

Rogers E. M., 2012 https://commons.wikimedia.org/wiki/File:Diffusion_of_ideas

Rogers, E. M. 1983. Diffusion of innovations (3rd ed.). New York: Free Press

Simpson, G., Clifton, J., 2017, Testing Diffusion of Innovations Theory with data: Financial incentives, early adopters, and distributed solar energy in Australia, Energy Research & Social Science, Volume 29, July 2017, Pages 12-22,

Snipes, Michael , D. Christopher Taylor, Model selection and Akaike Information Criteria: An example from wine ratings and prices, Wine Economics and Policy, Volume 3, Issue 1, 2014, Pages 3-9, https://doi.org/10.1016/j.wep.2014.03.001.

Sood A., Tellis G., Technological Evolution and Radical Innovation, Journal of Marketing, Vol. 69, pp. 152-168, July 2005

Statistics Austria, Stock of motor vehicle as of 1937, Statistical Database, 2019

Steininger, K., König, M., Bednar-Friedl, B., Kranzl, L., Loibl, W., Prettenthaler, F. (2014). Economic Evaluation of Climate Change Impacts: Development of a Cross-Sectoral Framework and Results for Austria. Springer, Berlin.

Stern, N. (2006). Stern Review Report on the Economics of Climate Change. HM Treasury, London.

Till Gnann, Thomas S. Stephens, Zhenhong Lin, Patrick Plötz, Changzheng Liu, Jens Brokate, What drives the market for plug-in electric vehicles? - A review of international PEV market diffusion models, Renewable and Sustainable Energy Reviews, Volume 93, 2018, Pages 158-164, https://doi.org/10.1016/j.rser.2018.03.055.
UBA (2015). Energiewirtschaftliche Szenarien im Hinblick auf die Klimaziele 2030 und 2050. Szenario WAM plus, Synthesebericht 2015, Umweltbundesamt REP-0535, Wien.
van der Kam, M.J. , A.A.H. Meelen, W.G.J.H.M. van Sark, F. Alkemade, Diffusion of solar photovoltaic systems and electric vehicles among Dutch consumers: Implications for the energy transition, Energy Research & Social Science, Volume 46, 2018, Pages 68-85, ISSN 2214-6296, https://doi.org/10.1016/j.erss.2018.06.003.
Wagenmakers E-J, Farrel, S. 2004. AIC model selection using Akaike weights. Psychonomic Bulletin and Review. Vol. 11. Iss. 1 p. 192–196
WBGU German Advisory Council on Global Change (2011). World in Transition. A Social Contract for Sustainability. Flagship Report, Berlin. ISBN 978-3-936191-37-0.
Yu, J., P Yang, K Zhang, F Wang, L Miao , 2018, Evaluating the effect of policies and the development of charging infrastructure on electric vehicle diffusion in China Sustainability, 2018

Appendix

By means of the AICc posterior model, weights (w) in a Bayesian setting are derived. These probability weights are calculated as follows:

$$w_i = \frac{\exp\left(-\frac{\Delta_i}{2}\right)}{\sum_n \exp(-\frac{\Delta_j}{2})} \quad Eq.A1$$

The difference between the AICc of a mean function model i ($i, j = 1 \ldots n$) and the AICc of the model with the minimal AICc is denoted by Δ_i. The weight w_i shows the probability that model i is the best out of the considered number of models (n). *Eq.A1* hence ensures that the sum of all weights equals one ($\sum_n w_j = 1$). Thus, w_i can be interpreted similar to p-values in classical hypotheses testing when more than one hypotheses is tested.

Table A 1 Change point and building block of the selected model for each technology

	EV	**HEV**	**PV**	**HP**
Selected model	Two CP	Two CP	Discrete CP	Discrete CP
	Parameterization of the building block functions			
1st Building Block	Log (-a/b=2017.4, b= 0.74, C= 34,033, D = 128)	Log(-a/b=2018.8, b= 0.44, C= 88,977, D = -27)	Exp (a=-909, b=0.45, D= 711)	Log(-a/b=1981.4, b= 0.95, C=13.371, D = -183)
2nd Building Block	Exp(a = -1236, b=0.62,D = 551)	Exp(a = -333, b=0.16, D = -4250)	Log (-a/b=2013.1, b= 0.9, C= 1,287,123, D = 21,989)	Lin(a = -2,240,939 B = 1136.4
3rd Building Block	Log (-a/b=2017.4, b= 0.74, C= 34,033, D = 128)	Log(-a/b=2018.8, b= 0.44, C= 88,977, D = -27)	Log(-a/b=2017.2, b= 0.28, C= 2,427,863, D = -85,236)	Exp (a=-118, b=0.064, D= -88468)
	Year of change points			
1st Change point	2011	2006	2004	1985
2nd Change point	2015	2016	2014	2005