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Interactions between social learning and technological learning in electric vehicle futures

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Abstract

The transition to electric vehicles is an important strategy for reducing greenhouse gas emissions from passenger cars. Modelling future pathways helps identify critical drivers and uncertainties. Global integrated assessment models (IAMs) have been used extensively to analyse climate mitigation policy. IAMs emphasise technological change processes but are largely silent on important social and behavioural dimensions to future technological transitions. Here, we develop a novel conceptual framing and empirical evidence base on social learning processes relevant for vehicle adoption. We then implement this formulation of social learning in IMAGE, a widely-used global IAM. We apply this new modelling approach to analyse how technological learning and social learning interact to influence electric vehicle transition dynamics. We find that technological learning and social learning processes can be mutually reinforcing. Increased electric vehicle market shares can induce technological learning which reduces technology costs while social learning stimulates diffusion from early adopters to more risk-averse adopter groups. In this way, both types of learning process interact to stimulate each other. In the absence of social learning, however, the perceived risks of electric vehicle adoption among later-adopting groups remains prohibitively high. In the absence of technological learning, electric vehicles remain relatively expensive and therefore is only an attractive choice for early adopters. This first-of-its-kind model formulation of both social and technological learning is a significant contribution to improving the behavioural realism of global IAMs. Applying this new modelling approach emphasises the importance of market heterogeneity, real-world consumer decision-making, and social dynamics as well as technology parameters, to understand climate mitigation potentials.

The transport sector represents one of the fastest growing sources of greenhouse emissions (IPCC 2014). Integrated assessment models (IAMs) have been used extensively to identify global mitigation strategies to meet stringent climate targets (Kriegler *et al* 2014). IAMs show that transitioning to advanced propulsion technologies in the transport sector, and in particular passenger cars, can significantly contribute to reducing sectoral emissions. Relevant technologies include fuel cell vehicles, electric vehicles, or biofuels (depending on feedstocks and conversion processes) (IPCC 2014, Edelenbosch *et al* 2016). Improved technology performance and reduced production costs are essential to make new technologies competitive as alternatives to the internal combustion engine (ICE). In energy system models and IAMs this required progress in 'technological learning' is incorporated through learning rates describing percentage cost reductions per doubling of cumulative production or through exogenous technology improvement assumptions.

Empirical studies show that in addition to costs many other behavioural factors strongly affect vehicle choice. These factors include aesthetics, performance, attitude, lifestyle and social norms, which are not well captured in IAMs (Mundaca *et al* 2010, Tran *et al* 2012, Stephens 2013, McCollum *et al* 2017). Modelling behavioural influences on consumer choice is complex. There are a large number of factors that could be represented and they are not easy to quantify (Stern *et al* (2016)). Behavioural factors also tend to be highly heterogeneous across different consumer groups (Laitner *et al* (2000)). The IAMs used for analysing long-term global response strategies to climate change have relatively aggregated descriptions of subsystems like transport to ensure key relationships are transparent and analytically tractable. Including more detail such as diverse behavioural features across multiple consumer groups increases the number of uncertain assumptions that have to be made. Particularly for long-term projections, detailed representations of sectors could become less meaningful as uncertainties increase (Krey 2014).

The lack of formal treatment in IAMs of the behavioural aspects of consumer decision-making has been criticized (Rosen 2015, Mercure *et al* (2016)). Faced with the same set of observable conditions, clearly not all consumers make the same decision. In a technology transition, this is especially important because market heterogeneity can affect consumer adoption propensities for new vehicle types. Some recent modelling efforts have explored whether the behavioural realism of IAMs can be improved, focusing on consumer choices for light duty vehicles (LDVs). LDVs are of particular interest as they account for approximately half of current energy consumption in the transport sector (IPCC 2014). McCollum *et al* (2018) performed a multi-IAM study which included heterogeneous consumer preferences for certain non-financial attributes of vehicles as exogenous scenario assumptions in one global IAM. They found that sectoral policies explicitly targeting consumer preferences are required to enable widespread adoption of alternative fuel vehicles, particularly among later-adopting consumer groups.

However, this novel approach to modelling consumer heterogeneity in global IAMs omits the dynamic nature of social learning processes. We use 'social learning' in this context to indicate the change in individuals' understanding and preferences towards new technologies as a result of interactions within social networks (Rogers 2003, Young 2009, Reed *et al* (2010)). As an example, early adopters moving to a new technology can impact others' preferences and decision-making processes by changing their perspectives on the status, reliability and safety of a new vehicle (Axsen and Kurani 2012, McShane *et al* (2012)). Adopters' preferences are therefore dynamic and respond reflexively to changes in the adoption environment. Pettifor *et al* (2017) recently developed a modelling approach for including social learning effects. They compiled and synthesized empirical data on risk aversion to new vehicle technologies among different consumer groups. Following diffusion of innovations theory (Rogers 2003), they then translated differing adoption propensities in to a single aggregated 'risk premium' which declined as a result of social influence effects between the heterogeneous adopter groups. By including these effects in two global IAMs, they could identify the potential accelerating effect of social influence on low-carbon vehicle transitions.

In this study we advance on the work of Pettifor *et al* (2017) to explore how a dynamic representation of *both* social learning *and* technological learning influences the long-term transition to battery electric vehicles (BEVs). We use the term 'social learning' to emphasize the analogy with technological learning as a process by which costs or barriers are reduced. Both types of learning effects impact how technologies diffuse, and both are processes that unfold over time. However, for technological learning as well as for social learning it is not time *per se* that decreases perceived risks or costs but rather the experience of others (social learning) and the experience of manufacturing and using technologies (technological learning).

Although technological learning is a well-known process represented in many global IAMs, social learning is not. This study is the first attempt to represent the dynamics of social and technological change in a single IAM, and to systematically analyse the interaction effects between the two interdependent processes. Our main contributions are threefold. First, we demonstrate how heterogeneous consumer preferences and social learning can be represented in a realistic yet tractable model formulation that fits the scope of a global IAM. Second, we shed new light on how social learning processes compare and interact with technological learning to affect long-term transition dynamics and path dependency in the transport sector. Third, we evaluate whether the combined effect of these two dynamics lead to new and specific policy insights for climate change mitigation.

Methods

Consumer heterogeneity, technological learning, social learning, and policy measures, can all influence vehicle choice. Figure 1 demonstrates schematically how these processes are related in the model setup. Increased market share affects social learning and technological learning for different adopter groups: Early Adopter (EA), Early Majority (EM), Late Majority (LM) and Laggards (LG). In this section, we first introduce the IMAGE modelling framework before providing further detail on how social learning, technological learning, and adopter types are accounted for in the new model setup. We then explain the different scenarios used to compare

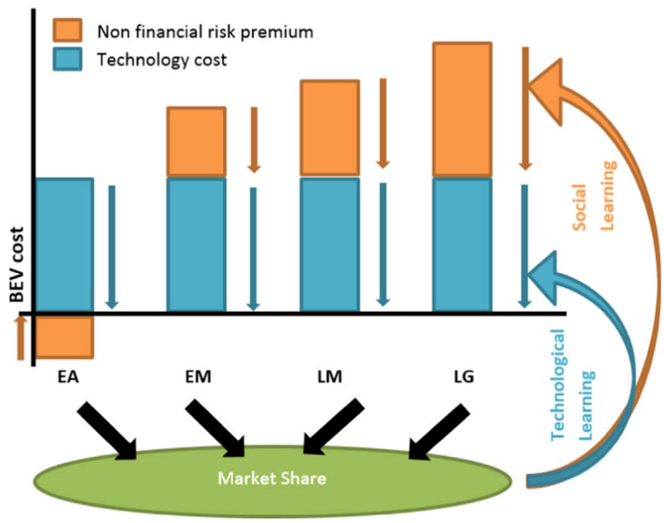

Figure 1. Schematic overview of the dynamic relationship between technological learning, social learning and market deployment of new technologies. Four adopter groups are distinguished: early adopters (EA), early majority (EM), late majority (LM) and laggards (LG). At a given time point, all four groups face the same technology cost but different monetized risk premiums. Net perceived costs therefore differ per group, with the lowest perceived cost vehicle selected by the cost-minimizing decision algorithm, resulting in changes to market share which in turn stimulates further technological and social learning.

how these various influences affect vehicle transition dynamics both in isolation and in combination.

IMAGE vehicle choice model

The IMAGE modelling framework represents interactions between natural and human systems in order to assess global environmental issues related to emissions, energy-use, land-use, climate feedbacks and policy responses. IMAGE is a simulation model with a global scope represented by 26 regions and a time horizon running from 1970 to 2100. Compared to other IAMs it has a rather detailed representation of end-use sectors, including transport, and also of the land-use system (Stehfest *et al* (2014)).

In the original transport module of IMAGE, vehicle choice is made on the basis of travel cost through a multinomial logit (MNL) equation (Girod *et al* (2012)). The MNL distributes market shares among different vehicle types in year by year time steps (t) such that the cheapest vehicle obtains the largest share. Travel costs across vehicles are compared in \$/passenger-km and depend on discounted regional energy costs, technology investment costs, regional load factors, and energy efficiency.

In the new model formulation, developed for this paper, the perceived risk premium for each adopter group is added to the cost equation and market shares are calculated for each adopter group. More detailed descriptions of the IMAGE framework, the transport module, and the general cost calculation, are provided in supplementary materials A available online at stacks.iop.org/ERL/13/124004/mmedia.

The lambda (λ) in the MNL equation determines how sensitive the model is to cost differences between different vehicle types (i). A lower lambda leads to less price sensitivity, which results in a more heterogeneous vehicle fleet.

$$\text{Vehicle Share}_{i,t} = \frac{e^{\lambda \cdot \text{Cost}_{i,t}}}{\sum_i e^{\lambda \cdot \text{Cost}_{i,t}}}.$$

In this study, since market heterogeneity is represented by the different consumer groups, identified by Pettifor *et al* (2017), the lambda is not used to represent market heterogeneity. Instead, the lambda is set to a high value so that each consumer group selects the vehicle with the lowest perceived cost.

Technological learning

Technology costs are often found to decrease with increasing experience of production and use, a phenomenon referred to as learning-by-doing and represented by a learning or progress curve (McDonald and Schrattenholzer 2001). Technological learning is commonly formulated as a learning rate (LR) which is the percentage reduction in unit cost for each doubling of experience represented by cumulative installed capacity or production. IAMs tend to include technological learning either by prescribing exogenous assumptions on cost declines as a function of time (representing a number of processes that lead to cost reduction) or by including learning curves directly in the model. There are different views on the best representation. Endogenous learning curves can better emphasize the importance of experience, but exogenous assumptions can also represent the role of other factors driving cost reductions (McDonald and Schrattenholzer 2001, Anandarajah and McDowall 2015). The two representations also lead to different model outcomes as they could lead to a preference bias either towards delaying action or towards promoting early learning to reduce future costs (Van Vuuren *et al* (2004)).

Vehicle cost assumptions in IMAGE

Base LDV costs and efficiencies in IMAGE are based on the detailed study by the Argonne National Laboratory (Plotkin and Singh 2009). This bottom-up analysis distinguishes between different components of the vehicle that contribute to total cost, such as the engine, battery, motor and controllers, and make projections of cost developments over the coming decades.

Battery costs are by far the most important difference between the cost of BEVs and conventional ICEs. Electrification of the transport sector is strongly affected by the future development of battery costs (Edelenbosch *et al* (2018)). As a result, we focus on technological learning of battery costs, and distinguish between exogenous and endogenous learning scenarios. As battery costs in EVs have declined rapidly over recent years (Nykvist and Nilsson 2015), we have updated battery costs in IMAGE to reflect recent developments, starting from a cost estimate of 300 US$ kWh^{-1} in 2014 in line with the sector's market leader (Nykvist and Nilsson 2015). In the exogenous cost scenario we assume that battery costs could reach 125 $ kWh^{-1} by 2025 (Faguy 2015), and decline further to 100 US$ kWh^{-1} over the course of the century. In the endogenous cost scenario we use a learning rate of 7.5%[8] (uncertainty range from 6% to 9%) in line with estimates from the literature (Nykvist and Nilsson 2015). We also assume a floor price of 50 $ kWh^{-1}, affecting the purchase cost of plug-in electric vehicles (PHEVs), BEVs and fuel cell vehicles (FCVs). As technological learning occurs as a function of cumulative battery production, deploying BEVs has a larger learning effect then PHEVs. This effect aside, there are no further technology cost interactions between vehicles. More widely-used components of cars such as the car frame or engine are not assumed to be influenced by learning after many years of experience and so follow the same path as in the exogenous scenario. More detailed descriptions of the LDV costs and battery cost assumptions are provided in supplementary materials B.

Social learning

Social learning about the benefits and risks of new technologies is central to technology diffusion. In his seminal work on 'diffusion of innovations', Everett Rogers defines diffusion as the process by which an innovation is communicated over time among the members of a social system (Rogers 2003). These members are heterogeneous in their preferences, particularly towards risk and uncertainty. Earlier adopters are risk-tolerant or risk-seeking, preferring new and relatively untested technologies which offer novel attributes. Later adopters are risk-averse, preferring to wait until perceived technology risks are lowered by observing the experiences of early adopters. Heterogeneous adopters are therefore interdependent, connected through social communication processes. Although the specific mechanisms of social learning are diverse—ranging from word of mouth to visible 'neighbourhood effects' and compliance with social norms—the basic insight that heterogeneous consumers exchange information through social networks (Rogers 2003) has been repeatedly confirmed both in general terms (e.g. (Peres *et al* 2010, McShane *et al* 2012)) and in studies specific to vehicle choice (e.g. Grinblatt *et al* (2008), Axsen and Kurani (2012)).

Modelling risk premiums and social influence

Rogers (2003) distinguishes consumer segments along a normal distribution of adoption propensities. Early adopters (EA) have high initial adoption propensities and so high risk tolerance; early majority (EM), late majority (LM) and laggards (LG) are increasingly risk averse and have low initial adoption propensities. Based on this conceptualisation, Pettifor *et al* (2017) calculate initial risk premiums as a measure of adoption propensity for each of the four different adopter groups. Their risk premium estimates are based on discrete choice experiments which provide willingness to pay (WTP) estimates for new technologies, such as BEVs, for which limited market data is available. Pettifor *et al* (2017) use a normal distribution of WTP point estimates from discrete choice studies to calculate a mean risk premium ($\bar{x}$ RP) with associated standard deviation ($\bar{\sigma}$ RP) for different adopter groups. Negative initial RPs indicate attraction to new technologies (risk-seeking) and high positive initial RPs indicate aversion to new technologies (risk-aversion). Following Rogers (2003), the early adopters[9] occupy a 16% market share; the early majority and late majority both account for 34% of the market; and the laggards the final 16%.

Pettifor *et al* (2017) also use a meta-analysis of 21 empirical studies to measure the effect of social influence on vehicle purchase propensities. They find that for every one standard deviation increase in market share, risk premiums (RPs) decrease by 0.241 standard deviations which increases vehicle adoption propensities (95% CI [0. 157, 0. 322], $Z = 5.505$, $|p| < 0.000$). In other words RPs decline as market share grows, using market share as a proxy for social influence. In the vehicle choice model of IMAGE the risk premiums (in $/passenger-km) for each consumer group have been added to the travel cost. More details on the empirical analysis and the implementation in IMAGE are provided in supplementary materials C, D and E.

[8] Learning rate equals the cost reduction for doubling in cumulative production.

[9] Our Early Adopter (EA) group contains the both the early adopters and innovators described by Rogers (2003).

Table 1. Scenario framework with varying assumptions of the four main elements affecting vehicle transitions.

NR	Scenario	Technological learning	Social learning	Heterogeneity	Policy
1	Ref	Exogenous	RPs remain at 2010 level	Explicit	None
2	TL	Endogenous	RPs remain at 2010 level	Explicit	None
3	Ref + SL	Exogenous	Endogenous	Explicit	None
4	TL + SL	Endogenous	Endogenous	Explicit	None
5	TL Ctax exp	Endogenous	RPs remain at 2010 level	Explicit	Tax 1
6	Ref + SL Ctax exp	Exogenous	Endogenous	Explicit	Tax 1
7	TL + SL Ctax exp	Endogenous	Endogenous	Explicit	Tax 1
8	TL Ctax cons	Endogenous	RPs remain at 2010 level	Explicit	Tax 2
9	Ref + SL Ctax cons	Exogenous	Endogenous	Explicit	Tax 2
10	TL + SL Ctax cons	Endogenous	Endogenous	Explicit	Tax 2
11	TL Ctax peak	Endogenous	RPs remain at 2010 level	Explicit	Tax 3
12	Ref + SL Ctax peak	Exogenous	Endogenous	Explicit	Tax 3
13	TL + SL Ctax peak	Endogenous	Endogenous	Explicit	Tax 3
14	Sub 1	Endogenous	Endogenous	Explicit	Subsidy for EA
15	Sub 2	Endogenous	Endogenous	Explicit	Subsidy for EM
16	Sub 3	Endogenous	Endogenous	Explicit	Subsidy for LM
17	Sub 4	Endogenous	Endogenous	Explicit	Subsidy for LG
18	Sub All	Endogenous	Endogenous	Explicit	Subsidy for all groups

Scenario framework

We use a set of 18 scenarios to explore the effects of social and technological learning, and how they dynamically interact (table 1). In the reference scenario (labelled 'Ref'), technology costs decline exogenously over time and risk premiums are frozen for the four adopter groups. In the technological learning scenario (labelled 'TL'), risk premiums are also frozen, but technology cost reductions occur endogenously based on a learning curve. In the reference + social learning scenario (labelled 'Ref + SL'), social learning is included but with exogenous technology cost assumptions. Finally, in the technological and social learning scenario (labelled 'TL + SL'), both technological learning and social learning occur endogenously.

The three learning scenarios (in table 1, no. 2–4) are tested with and without climate policy. The latter is implemented in the form of an economy-wide carbon price. This is a standard approach for representing climate policy in IAMs (and should be interpreted as a generic placeholder for other forms of policy inducing emission reductions). Three carbon tax scenarios are compared: (1) a global carbon tax of 40 $/tCO_2$[10] in 2020, increasing gradually at 3% per year (labelled 'Ctax exp'); (2) a constant global carbon tax of 130 $/tCO_2$, i.e. the value that tax path 1 reaches in 2060 (labelled 'Ctax cons'); (3) a global carbon tax peak from 2020 to 2040 of 273 $/tCO_2$ returning to a constant of 72 $/tCO_2$ in 2040, the same value that tax path 1 reaches in 2040 (labelled 'Ctax peak'). These carbon tax scenarios are selected to be comparable with an important diagnostic study of how IAMs behave in response to future carbon taxes of different stringencies (Kriegler *et al* (2015)). A visualisation of the carbon tax scenarios is provided in supplementary materials F.

In addition to these economy-wide climate policies, we include an additional set of scenarios (labelled 'Sub') with a stylized representation of sectoral policy in the form of purchase subsidies targeted at specific consumer groups. Subsidies of 4000$ for EVs and 2000$ for PHEVs are available between 2020 and 2040. By way of comparison, currently available purchase rebates in Germany are worth approximately 4400$ for BEVs and 3300$ for PHEVs . Other countries such as Japan, France, Norway and the United Kingdom have higher BEV purchase subsidies. Although subsidies may not persist over long timeframes, and targeting subsidies at specific consumer groups may be problematic, our subsidy scenarios are designed to provide useful insights on the role of sectoral policies in the projected vehicle transition dynamics.

Results

Technological learning scenarios

Figure 2 depicts market shares of the global vehicle fleet under endogenous and exogenous technological learning assumptions in the absence of social learning. In the TL (technological learning) scenario, the early adopter group shifts to PHEVs in the first half of the century given their preference for new technologies (represented by a negative risk premium which remains constant as there is no social learning). Although early adopters are also attracted to BEVs, this new technology remains too expensive through the first half of the century (figure 2 right panel). The deployment of PHEVs leads to reduction of both PHEV and BEV costs through technological learning in battery costs (figure 2 left panel). In the Ref (reference) scenario, BEV costs are projected to reduce

[10] 40$/tCO_2$ is the value proposed recently by the Climate Leadership Council. Baker *et al* (2017). The conservative case for carbon dividends. Washington, Climate Leadership Council.

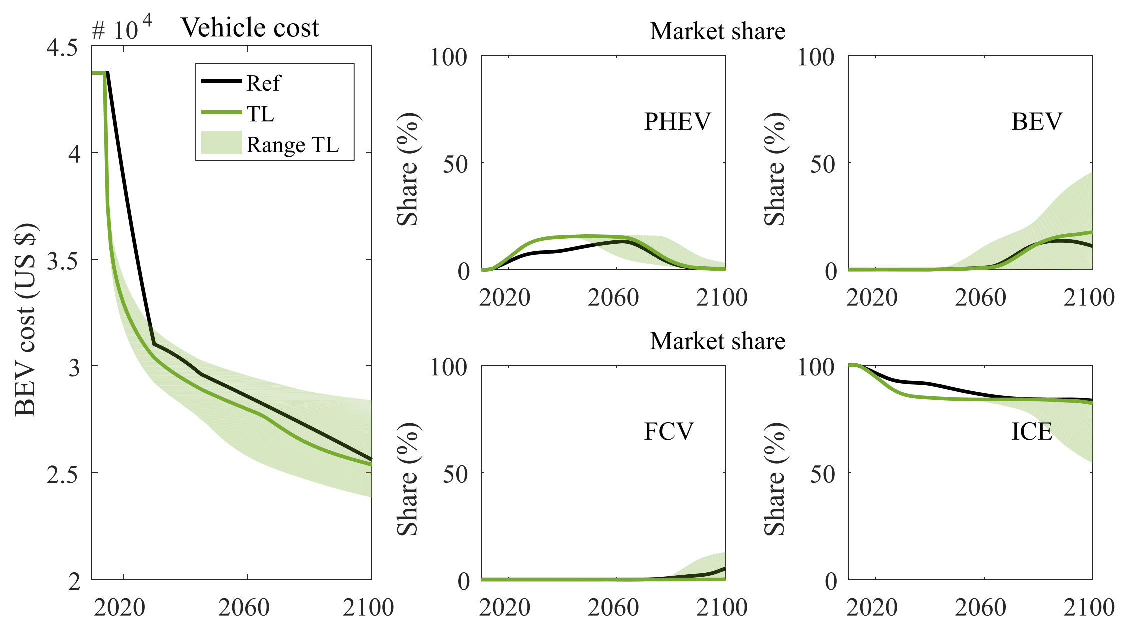

Figure 2. Battery electric vehicle (BEV) cost over time in the Ref and TL scenarios (left panel), with resulting BEV, plug-in electric vehicle (PHEV), fuel cell vehicle (FCV), and internal combustion engine (ICE) market shares of the global vehicle fleet (middle and right panels). Shaded colors indicate the scenario range depending on assumed technological learning rates.

rapidly in this period as well, based on exogenous assumptions. Once a certain BEV cost threshold has been passed, depending heavily on the learning rate (indicated by the TL range), early adopters shift from PHEVs to BEVs. This shift leads to faster BEV cost reductions (figure 2 left panel). Under high learning rate assumptions the early majority group also adopt BEVs by the end of the century, by which point a small group of early adopters move on to FCVs which have become more cost competitive.

The early adopter group and technological learning play an important role in this initial phase of a technology transition. With slower learning rates, BEVs remain relatively expensive and EV adoption might not take place at all. Even though the technology is competitive in terms of costs, if risk premiums remain at current levels purchasing a BEV is not an attractive option for the early majority, late majority and laggards.

Social learning and technological learning scenarios

In the SL (social learning) scenarios, the market deployment of BEVs drives down the risk premiums of the early majority, late majority and laggards whereas for early adopters the reduced novelty of BEVs makes them less attractive as risk premiums become less negative. Figure 3 shows how the BEV risk premiums change over time for all four adopter groups in the Ref + SL and TL + SL scenarios.

The effect of social learning can be seen in the diffusion of BEVs from early adopters to the early majority (figure 3 top right panel, compared to the reference scenario). The risk decline leads to higher BEV deployment which again leads to more risk decline (social learning). As BEVs become mainstream, early adopters become more attracted to distinctive alternatives, such as FCVs (seen previously in figure 2). Similarly, PHEVs become less attractive to early adopters which leads to an increase in the BEV share in the first half of the century compared to those scenarios where social influence is not represented. The Ref + SL scenario range shows that social influence effect size has little impact on the initial phase of the transition, but does significantly affect the speed of diffusion from early adopters to other groups.

The lower right panel of figure 3 shows how the combined effect of technological and social learning leads to a faster technology transition and higher market penetration under assumptions of average learning rates and social influence effects. There are different phases during the technology transition in this scenario. First PHEV use by early adopters leads to battery learning reducing BEV costs. The early adopters then shift to BEVs which results in increased technological learning and risk decline for the other adopter groups. The early majority starts to adopt BEVs enlarging both types of learning effect. Technological learning has occurred faster in the beginning and now starts to level off. Risk premiums continue to decrease for the late majority and laggards. But additional policy is still needed to overcome the risk premium barrier for these groups. Clearly, these results are highly dependent on the social influence effect size and the learning rate, indicated by the colored area. Further details on market shares of the different vehicle technologies for each adopter group in the scenarios without policy assumptions are provided in supplementary materials G.

The different carbon tax scenarios show that once the transition is put in motion, climate policy and learning processes reinforce the transition dynamic. Notably, in the TL + SL scenario a carbon tax is more

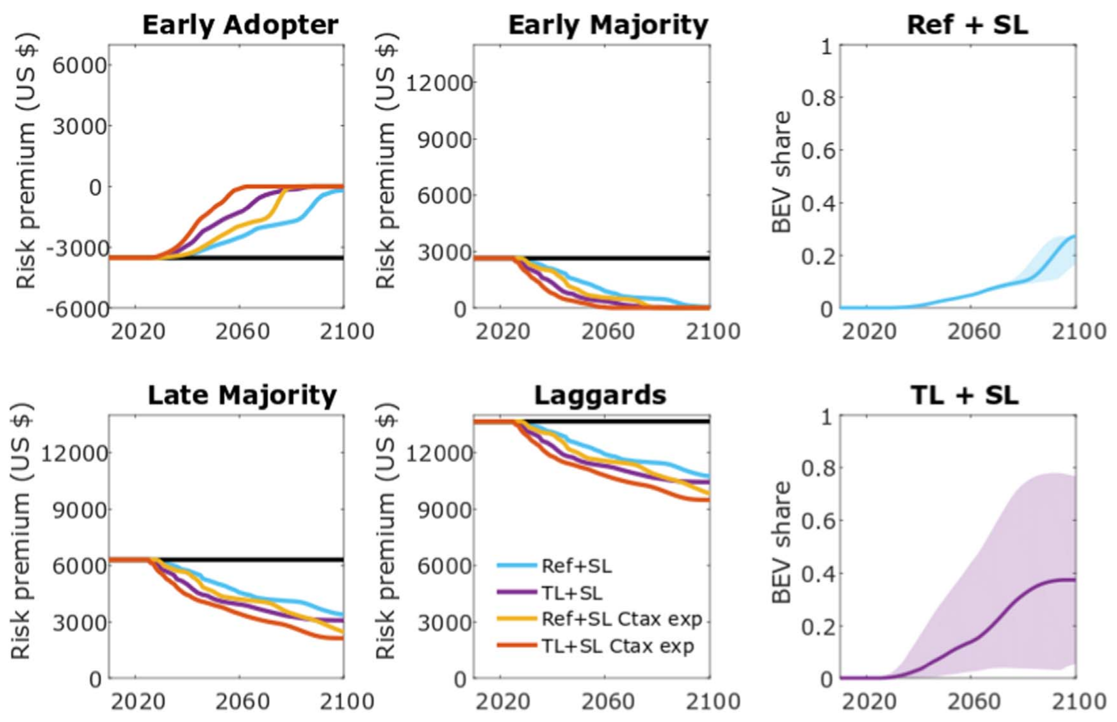

Figure 3. Risk premiums towards BEVs for the early adopter, early majority, late majority and laggards in scenarios with social learning (SL) including those with an exponential carbon tax (Ctax exp) (left and middle panels), and resulting market shares of the global vehicle fleet for BEVs (right panel). Shaded colors indicate the scenario range depending on technology learning rates and social influence effect size.

effective (in terms of market share increase) than in the TL or Ref + SL scenario. In the TL + SL scenario, market share jumps 30%–50% in a period of 10 years in response to the peak carbon tax. The other two carbon tax scenarios, without both technological and social learning, show a much more limited response. However this result strongly depends on learning rates and the social influence effect size, indicated by the colored area.

Only under the stimulus of a very high carbon tax (the exponentially-increasing 'Ctax exp' scenario) does the late majority group also transition to BEVs (see figure 4). In the scenarios, deployment among the earlier adopter and early majority groups does not trigger a full transition (see figure 3). Further details on the adopter groups shares are provided in supplementary materials G.

This is also demonstrated by the sectoral policy scenarios with targeted subsidies (figure 5) which show that although there is some feedback between early adopters and early majority groups, the risk premiums of the late adopter groups are still prohibitively high even if technology costs have become competitive. There are various possible explanations for this. First, other processes than social influence, like for example improved electric vehicle charging infrastructure, might help reduce risk premiums, therefore our approach which only uses social influence to reduce risk premiums is conservative. Second, reduction rates in initial risk premiums are the same across adopter groups whereas the risk premium decline as a result of increased market share could be larger in the later adopter groups which perceive high risks. Third, the social influence effect size is constant, but in reality it may strengthen as social communication around a new technology intensifies. All these explanations could result in quicker transition dynamics, as well as reaching a full transition, and bear further empirical and modelling analysis.

In general, the scenarios in which subsidies are targeted at individual adopter groups lead to increased market penetration of BEVs (figure 5 panel 'Comparison with no sub'), except the scenario where the laggards are targeted, which are unresponsive (figure 5 panel Sub 4). The scenarios also show that targeting specific adopter groups can affect the time profile of adoption. Providing subsidies to the early majority results in the quickest increase in market share in the short term. Compared to the different carbon tax scenario's, providing subsidies to all adopter groups (the Sub All scenario) leads to a faster increase in market share. Although maintaining purchase subsidies throughout the century is not a realistic policy option, our analysis shows that equivalent support might be needed in order to overcome transition barriers for certain adopter groups.

The importance of social learning and technological learning during the different phases of the technology transition—with technological learning affecting the initial phase, and social learning affecting further diffusion—can be traced back to their equational forms. The social influence effect equals the reduction

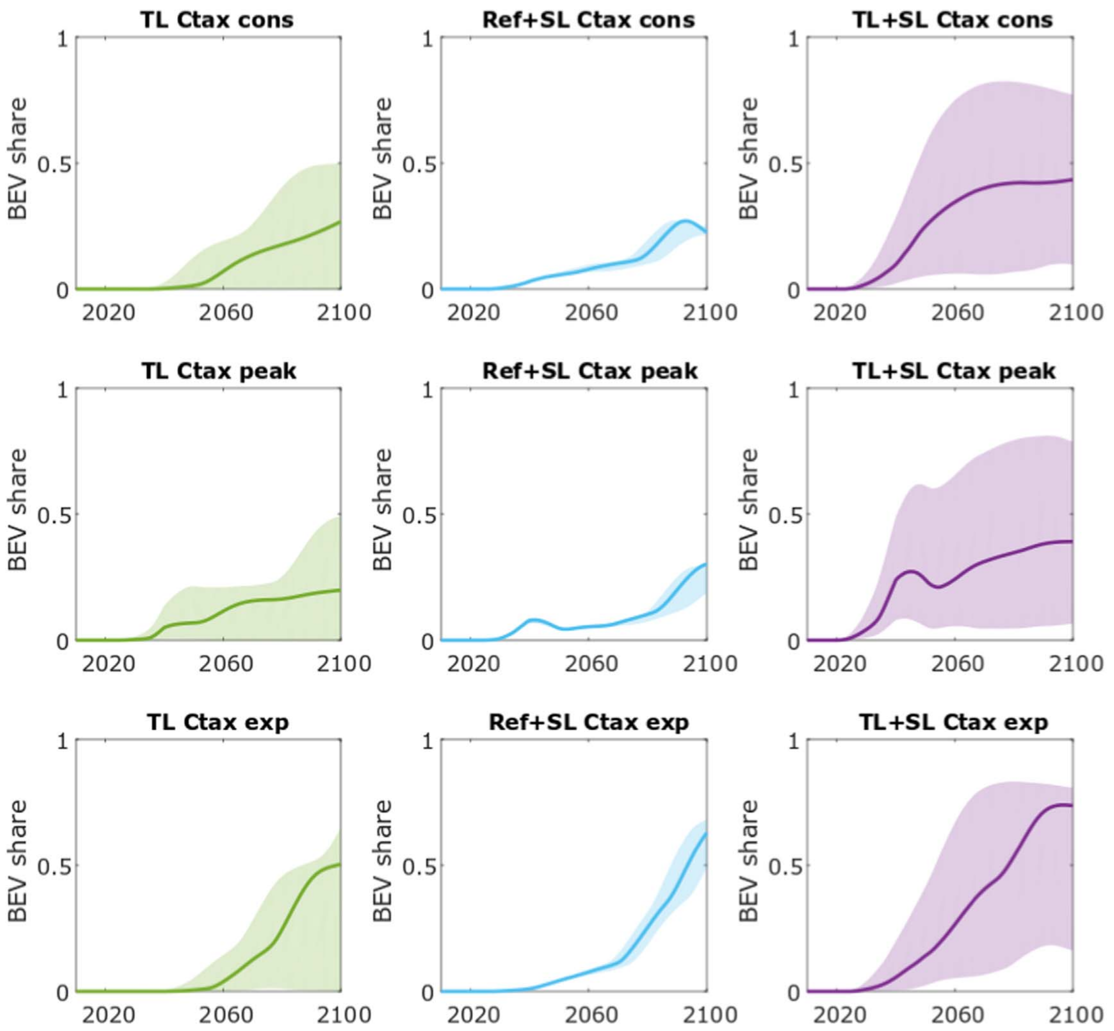

Figure 4. Market shares of BEVs in the global vehicle fleet for the constant (top row), peak (middle row) and exponential carbon tax (bottom row) scenarios. Shaded colors indicate the scenario range depending on technology learning rates and social influence effect size.

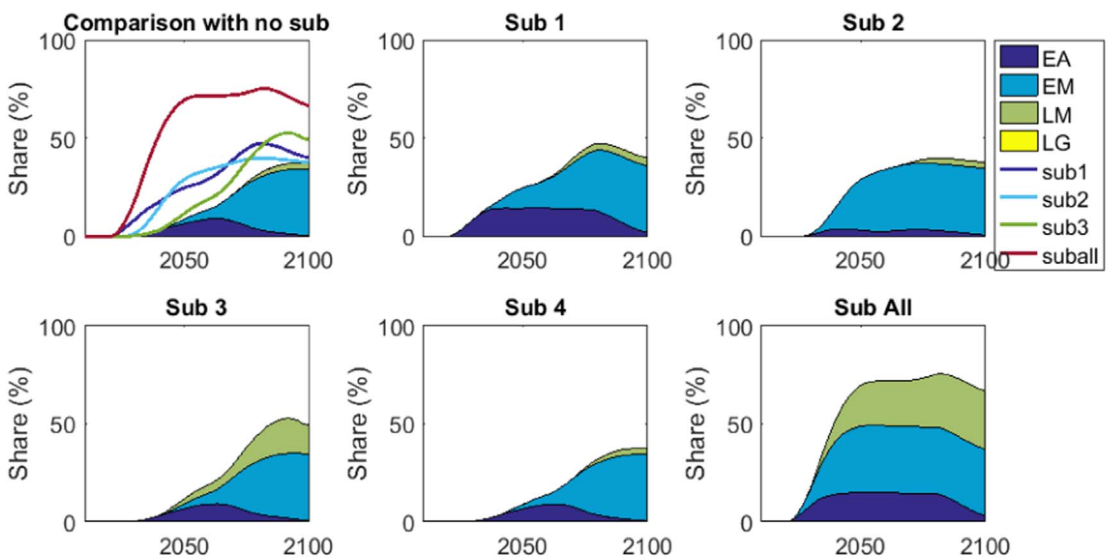

Figure 5. Market shares of the global BEV vehicle fleet in the TL + SL scenario without any form of policy (top left panel) compared to scenarios with subsidies for PHEVs and EVs targeted specifically at the early adopter (EA), early majority (EM), late majority (LM) and laggards (LG) adopter groups shown in panels Sub1, Sub2, Sub3 and Sub4, respectively. In the Sub All scenario (bottom right panel) all adopter groups receive the subsidy.

in risk premium after an increase in market share, whereas the technological learning rate equals the cost reduction per doubling of cumulative battery production in EV application. Given the exponential form of the learning rate equation with its floor price to limit ever-falling costs, the fastest learning happens in the initial deployment phase. In contrast, social influence has a linear relationship with deployment[11].

Conclusions and discussion

IAMs show that technology plays a crucial role in reducing greenhouse gas emissions across regions and sectors (Krey *et al* 2014, Kriegler *et al* 2014) and in determining the cost and feasibility of meeting specified climate targets (Bosetti *et al* 2015). Important aspects of technology transitions such as heterogeneity in consumer preferences and social learning are often omitted from IAM analysis. The aims of this paper were to demonstrate how technological and social learning can be explicitly represented in a global IAM, and to understand how interactions between these two processes influence the dynamics of a technology transition, using LDVs as an example. This research makes a first attempt is made to bridge social science concepts to more technology oriented modelling of technology transition. Similar approaches could be used to model other technology transitions in which heterogeneous preferences and social influence play an important role. Although our paper focusses on consumer heterogeneity there are other important heterogeneous aspects of the vehicle market, such as vehicle size, price and usage that are not explicitly accounted for. Other contextual or cultural factors affecting behaviour might also play important roles, but these too lie beyond the scope of our study. Keeping these limitations in mind, we come to the following conclusions based on our analysis.

Technological learning and social learning can be successfully represented in a LDV choice model within an IAM framework

While both processes impact vehicle choice in expected ways, their interaction is interesting and revealing. Our new modelling approach demonstrates the different phases of a technology transition and its relevant dynamics. It shows how niche or early adopter groups can drive technology innovation by stimulating market demand. The adoption of alternative technologies that are still relatively expensive by these groups plays an important role in further technology development during the learning phase. Recent sales of luxury BEVs that are in higher vehicle price ranges and contemporaneous rapid reductions of battery costs is an example of this dynamic (Nykvist and Nilsson 2015, EV-volumes 2018). Moreover, the deployment of alternative technologies by early adopters could also reduce behavioural barriers perceived by other consumer groups.

BEVs can reach a larger market share if technological learning and social learning processes work to mutually reinforce each other

Through social learning and technological learning new technologies can become more attractive to consumers. Generally speaking, technological learning affects the timing of adoption by early adopters whereas social learning affects diffusion to other adopter groups. The two learning processes can stimulate each other in a positive feedback loop. Policy incentives stimulating EV deployment, such as a carbon tax or dedicated transport sector policies, can spark positive learning feedbacks. However, the size of this effect depends strongly on the assumed technological learning rate and social influence effect size which are key future uncertainties.

Risk premiums of later adopters remain a barrier to a full transition

The targeted policy and carbon tax scenarios show that although there is some feedback between early adopters and early majority groups, the risk premium of the other adopter groups are too high to adopt even if technology costs have become competitive. One key question is whether these risk premiums will reduce further over time either through strengthening social influence effects or alternative policies that help reduce this perceived barrier. Currently available empirical data suggests that even if technology costs come down, adoption barriers could be an important limitation in implementing electric vehicles beyond the first two adopter groups. This is an important area for further research.

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[11] This linear relation has varying slope coefficients in specific periods of adoption due to the varying size of a market share corresponding to a standard deviation.

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