

ACCEPTED MANUSCRIPT • OPEN ACCESS

Interactions between social learning and technological learning in electric vehicle futures

To cite this article before publication: Oreane Edelenbosch *et al* 2018 *Environ. Res. Lett.* in press <https://doi.org/10.1088/1748-9326/aae948>

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2018 The Author(s). Published by IOP Publishing Ltd.

As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 3.0 licence, this Accepted Manuscript is available for reuse under a CC BY 3.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by/3.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

Interactions between social learning and technological learning in electric vehicle futures

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

O.Y. Edelenbosch^{a,b}, David L. McCollum^{c,d}, Hazel Pettifor^e, Charlie Wilson^{c,e}, Detlef P. van Vuuren^{a,f}

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

^a PBL Netherlands Environmental Assessment Agency, Bezuidenhoutseweg 30, 2594 AV Den Haag, The Netherlands (E: Oreane.Edelenbosch@pbl.nl, Detlef.vanvuuren@pbl.nl);

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

^b Department of Management and Economics, Politecnico di Milan, Via Lambruschini 4/B, Milan

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

^c International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, 2361 Laxenburg, Austria

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

^d University of Tennessee, 1640 Cumberland Avenue, Knoxville, TN 37996, USA

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

^e Tyndall Centre for Climate Change Research, University of East Anglia (UEA), Norwich NR4 7TJ, UK

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

^f Copernicus Institute of Sustainable Development, Utrecht University, Heidelberglaan 2, 3584 CS Utrecht, The Netherlands;

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

Acknowledgements:

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

The research leading to these results received funding from the European Union's Seventh Framework Programme FP7/2007-2013, under grant agreement 308329 (ADVANCE). Part of the research was developed in the Young Scientists Summer Program at the International Institute for Applied Systems Analysis, Laxenburg (Austria).

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

Abstract:

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

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

1

2

The transition to electric vehicles is an important strategy for reducing greenhouse gas emissions from passenger cars. Modelling transition 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 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 only for early adopters an attractive choice. 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 (GHG) emissions (IPCC 2014). Integrated assessment models (IAMs) have been used extensively to identify global mitigation strategies to meet stringent climate targets (Kriegler, Weyant 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, McCollum 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 (L. Mundaca 2010, Tran, Banister et al. 2012, Stephens 2013, McCollum, Wilson 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, Sovacool et al. 2016). Behavioural factors also tend to be highly heterogeneous across different consumer groups (John, De Canio et al. 2000). The IAMs used for analyzing 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 behavioral 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 behavioral aspects of consumer decision making has been criticized (Rosen 2015, Mercure, Pollitt 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 behavioral 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, Wilson 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, Evely 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, Bradlow et al. 2012). Adopters' preferences are therefore dynamic and respond reflexively to changes in the adoption environment. Pettifor, Wilson et al. (2017) recently developed

1 a modelling approach for including social learning effects. They compiled and synthesized empirical
2 data on risk aversion to new vehicle technologies among different consumer groups. Following
3 diffusion of innovations theory (Rogers 2003), they then translated differing adoption propensities in
4 to a single aggregated 'risk premium' which declined as a result of social influence effects between
5 the heterogeneous adopter groups. By including these effects in two global IAMs, they could identify
6 the potential accelerating effect of social influence on low-carbon vehicle transitions.

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

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

25 **Methods**

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

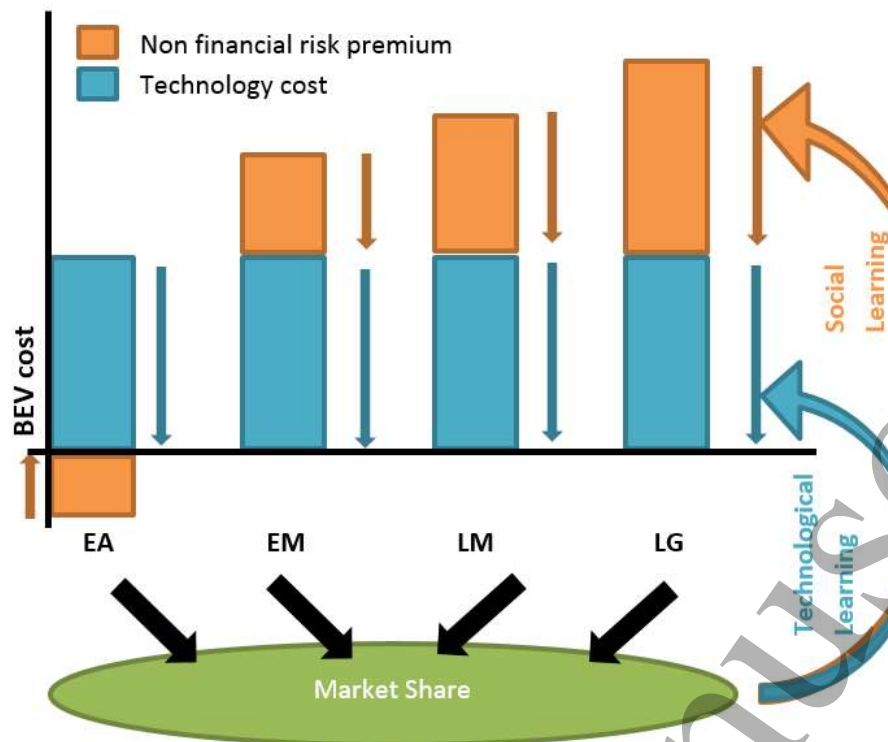


Figure 1: Schematic overview of the dynamic relationship between technological learning, social learning and market deployment of new technologies. Four adopter groups are distinguished: early adopters (EA), early majority (EM), late majority (LM) and laggards (LG). At a given time point, all four groups 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.

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, Vuuren 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, van Vuuren 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.

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
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

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

$$VehicleShare_{i,t} = \frac{e^{\lambda \cdot Cost_{i,t}}}{\sum_i e^{\lambda \cdot Cost_{i,t}}}$$

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

9 *Technological learning*

10 Technology costs are often found to decrease with increasing experience of production and use, a
11 phenomenon referred to as learning-by-doing and represented by a learning or progress curve
12 (McDonald and Schrattenholzer 2001). Technological learning is commonly formulated as a learning
13 rate (LR) which is the percentage reduction in unit cost for each doubling of experience represented
14 by cumulative installed capacity or production. IAMs tend to include technological learning either by
15 prescribing exogenous assumptions on cost declines as a function of time (representing a number of
16 processes that lead to cost reduction) or by including learning curves directly in the model. There are
17 different views on the best representation. Endogenous learning curves better emphasize better the
18 importance of experience, but exogenous assumptions can also represent the role of other factors
19 driving cost reductions (McDonald and Schrattenholzer 2001, Anandarajah and McDowall 2015). The
20 two representations also lead to different model outcomes as they could lead to a preference bias
21 either towards delaying action or towards promoting early learning to reduce future costs (Van Vuuren
22 et al., 2002).

23 *Vehicle cost assumptions in IMAGE*

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

28 Battery costs are by far the most important difference between the cost of BEVs and conventional
29 internal combustion engines (ICEs). Electrification of the transport sector is strongly affected by the
30 future development of battery costs (Edelenbosch, Hof et al. 2018). As a result, we focus on
31 technological learning of battery costs, and distinguish between exogenous and endogenous learning
32 scenarios. As battery costs in EVs have declined rapidly over recent years (Nykvist and Nilsson 2015),
33 we have updated battery costs in IMAGE to reflect recent developments, starting from a cost estimate
34 of 300 US\$/kWh in 2014 in line with the sector's market leader (Nykvist and Nilsson 2015). In the
35 exogenous cost scenario we assume that battery costs could reach 125 \$/kWh by 2025 (Faguy 2015),
36 and decline further to 100 US\$/kWh over the course of the century. In the endogenous cost scenario
37 we use a learning rate of 7.5%¹ (uncertainty range from 6 to 9%) in line with estimates from the

¹ Learning rate equals the cost reduction for doubling in cumulative production

literature (Nykqvist and Nilsson 2015). We also assume a floor price of 50 \$/kWh, affecting the purchase cost of plug-in electric vehicles (PHEVs), battery electric vehicles (BEVs) and fuel cell vehicles (FCVs). As technological learning occurs as a function of cumulative battery production, deploying BEVs has a larger learning effect than 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 (2003:342) has been repeatedly confirmed both in general terms (e.g.(Peres, Muller et al. 2010, McShane, Bradlow et al. 2012)) and in studies specific to vehicle choice (e.g.,(Grinblatt, Keloharju 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, Wilson 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, Wilson 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 adopters² 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, Wilson 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

² Our Early Adopter (EA) group contains the both the early adopters and innovators described by Rogers, E. M. (2003). "Elements of diffusion." *Diffusion of innovations* 5: 1-38.

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
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1 increase in market share, risk premiums (RPs) decrease by 0.241 standard deviations which increases
2 vehicle adoption propensities (95% CI [0. 157, 0. 322], Z= 5. 505, |p|< 0. 000). In other words RPs
3 decline as market share grows, using market share as a proxy for social influence. In the vehicle choice
4 model of IMAGE the risk premiums (in \$/passenger-km) for each consumer group have been added to
5 the travel cost. More details on the empirical analysis and the implementation in IMAGE are provided
6 in Supplementary Materials C, D and E.

7 *Scenario framework*

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

16 The three learning scenarios (in Table 1, no. 2-4) are tested with and without climate policy. The latter
17 is implemented in the form of an economy-wide carbon price. This is a standard approach for
18 representing climate policy in IAMs (and should be interpreted as a generic placeholder for other
19 forms of policy inducing emission reductions). Three carbon tax scenarios are compared: 1) a global
20 carbon tax of 40 \$/tCO₂³ in 2020, increasing gradually at 3% per year (labelled 'Ctax exp'); 2) a constant
21 global carbon tax of 130 \$/tCO₂, i.e. the value that tax path 1 reaches in 2060 (labelled 'Ctax cons'); 3)
22 a global carbon tax peak from 2020 to 2040 of 273 \$/tCO₂ returning to a constant of 72 \$/tCO₂ in 2040,
23 the same value that tax path 1 reaches in 2040 (labelled 'Ctax peak'). These carbon tax scenarios are
24 selected to be comparable with an important diagnostic study of how IAMs behave in response to
25 future carbon taxes of different stringencies (Kriegler, Petermann et al. 2015). A visualisation of the
26 carbon tax scenarios is provided in Supplementary Materials F.

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

NR	SCENARIO	TECHNOLOGICAL LEARNING	SOCIAL LEARNING	HETERO- GENEITY	POLICY
1	Ref	Exogenous	RPs remain at 2010 level	Explicit	None
2	TL	Endogenous	RPs remain at 2010 level	Explicit	None

³ 40\$/tCO₂ is the value proposed recently by the Climate Leadership Council. Baker, J. A., et al. (2017). The conservative case for carbon dividends. Washington, Climate Leadership Council.

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

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

Results

Technological learning scenarios

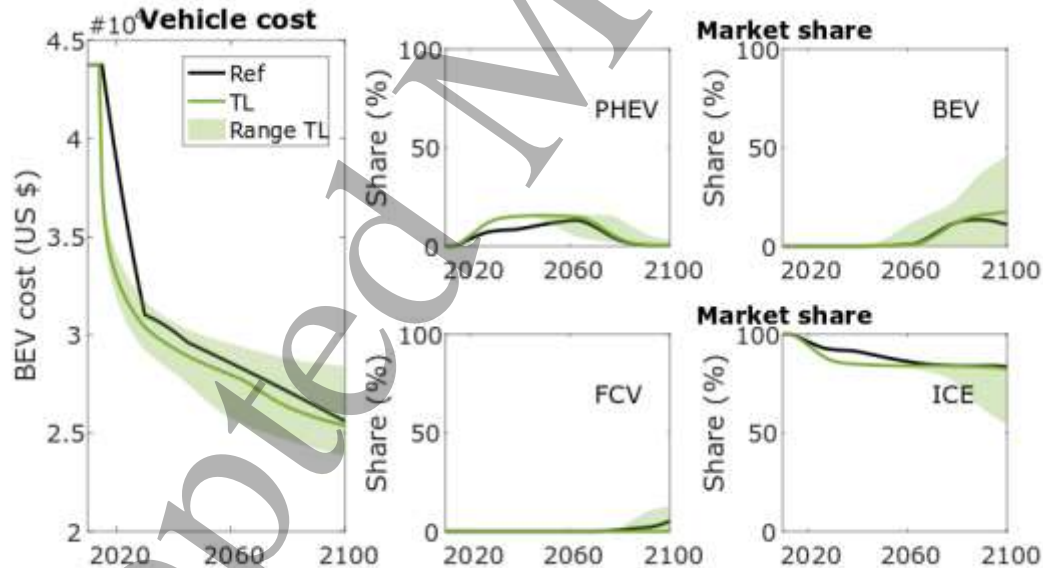


Figure 2: Battery electric vehicle (BEV) cost over time in the Ref and TL scenarios (left panel), with resulting BEV, plug-in electric vehicle (PHEV), fuel cell vehicle (FCV), and internal combustion engine (ICE) market shares of the global vehicle fleet (middle and right panels). Shaded colors indicate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

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)

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
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

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 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

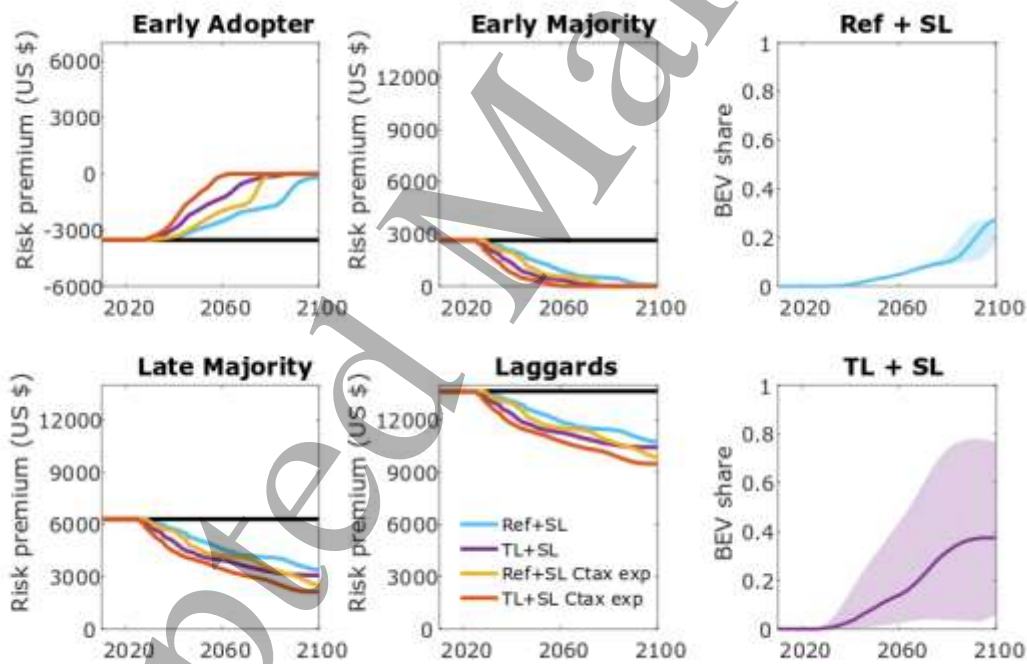


Figure 3: Risk premiums towards BEVs for the early adopter, early majority, late majority and laggards in scenarios with social learning (SL) including those with an exponential carbon tax (Ctax exp) (left and middle panels), and resulting market shares of the global vehicle fleet for BEVs. Shaded colors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

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

1 makes them less attractive as risk premiums become less negative. Figure 3 shows how the BEV risk
2 premiums change over time for all four adopter groups in the Ref + SL and TL + SL scenarios.

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

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

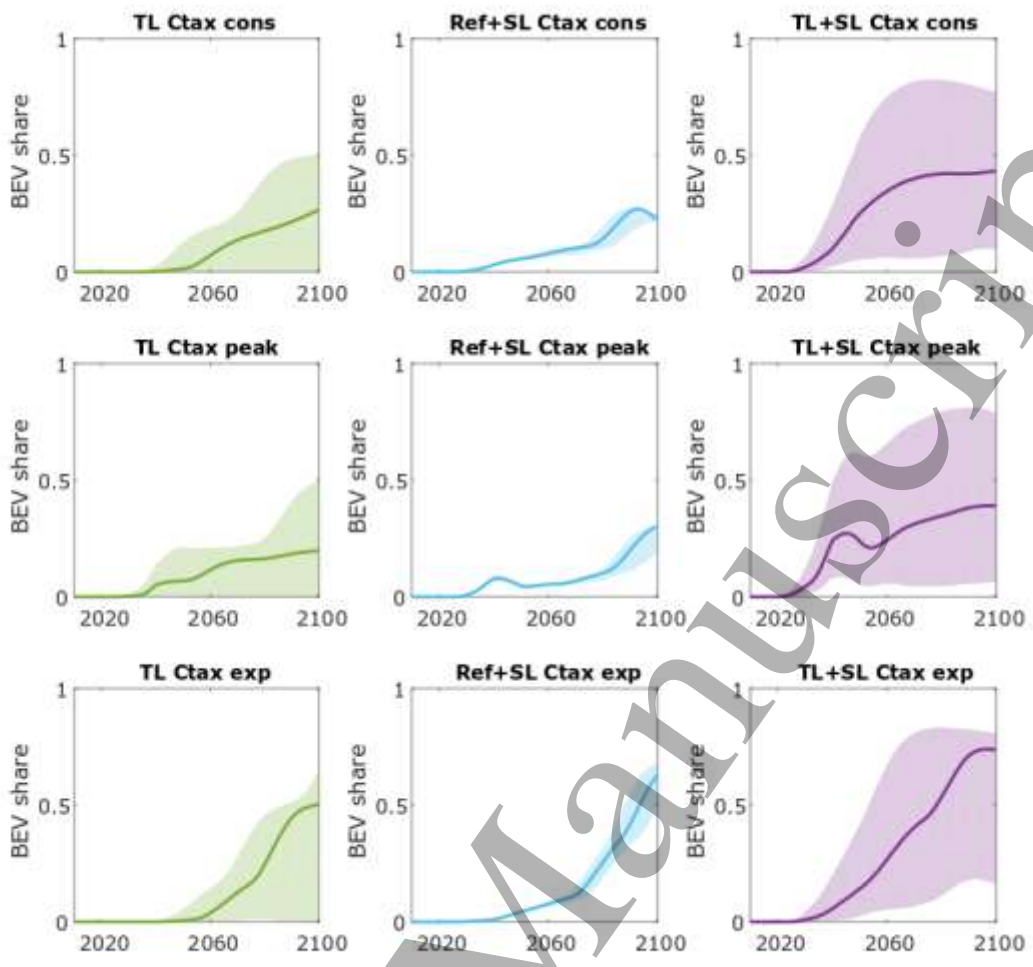


Figure 4: Market shares of BEVs in the global vehicle fleet for the constant (top row), peak (middle row) and exponential carbon tax (bottom row) scenarios. Shaded colors indicate the scenario range depending on technology learning rates and social influence effect size.

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 effective (in terms of market share increase) than in the TL or Ref + SL scenario. In the TL + SL scenario, market share jumps 30 to 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 risk premium declines 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, 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.

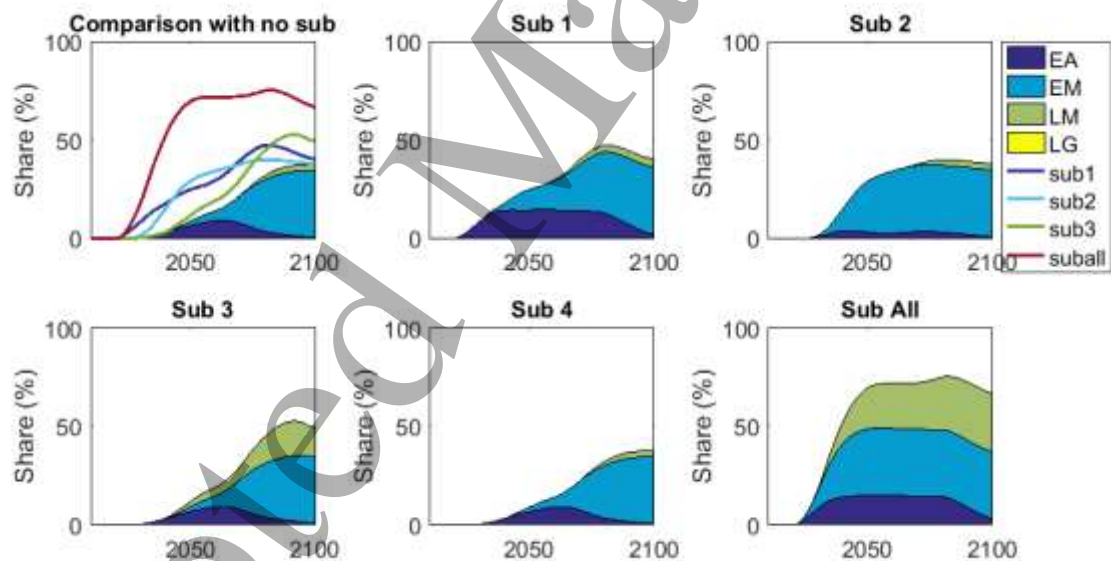


Figure 5: Market shares of the global BEV vehicle fleet in the TL+SL scenario without any form of policy (top left panel) compared to scenarios with subsidies for PHEVs and EVs targeted specifically at the early adopter (EA), early majority (EM), late majority (LM) and laggards (LG) adopter groups shown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

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

1 equals the reduction in risk premium after an increase in market share, whereas the technological
2 learning rate equals the cost reduction per doubling of cumulative battery production in EV
3 application. Given the exponential form of the learning rate equation with its floor price to limit ever-
4 falling costs, the fastest learning happens in the initial deployment phase. In contrast, social influence
5 has a linear relationship with deployment⁴.

6 **Conclusions and discussion**

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

22 **Technological learning and social learning can be successfully represented in a LDV choice model**
23 **within an IAM framework.** While both processes impact vehicle choice in expected ways, their
24 interaction is interesting and revealing. Our new modelling approach demonstrates the different
25 phases of a technology transition and its relevant dynamics. It shows how niche or early adopter
26 groups can drive technology innovation by stimulating market demand. The adoption of alternative
27 technologies that are still relatively expensive by these groups plays an important role in further
28 technology development during the learning phase. Recent sales of luxury BEVs that are in higher
29 vehicle price ranges and contemporaneous rapid reductions of battery costs is an example of this
30 dynamic (Nykqvist and Nilsson 2015, EV-volumes 2018). Moreover, the deployment of alternative
31 technologies by early adopters could also reduce behavioral barriers perceived by other consumer
32 groups.

33 **BEVs can reach a larger market share if technological learning and social learning processes work to**
34 **mutually reinforce each other.** Through social learning and technological learning new technologies
35 can become more attractive to consumers. Generally speaking, technological learning affects the
36 timing of adoption by early adopters whereas social learning affects diffusion to other adopter groups.
37 The two learning processes can stimulate each other in a positive feedback loop. Policy incentives
38 stimulating EV deployment, such as a carbon tax or dedicated transport sector policies, can spark

⁴ 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.

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 to 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.

References

- Anandarajah, G. and W. McDowall (2015). Multi-cluster technology learning in TIMES: a transport sector case study with TIAM-UCL. Informing Energy and Climate Policies Using Energy Systems Models, Springer: 261-278.
- Axsen, J. and K. S. Kurani (2012). "Interpersonal influence within car buyers' social networks: applying five perspectives to plug-in hybrid vehicle drivers." Environment and Planning A **44**(5): 1047-1065.
- Axsen, J. and K. S. Kurani (2012). "Social influence, consumer behavior, and low-carbon energy transitions." Annual Review of Environment and Resources **37**: 311-340.
- Baker, J. A., et al. (2017). The conservative case for carbon dividends. Washington, Climate Leadership Council.
- Bosetti, V., et al. (2015). "Sensitivity to energy technology costs: A multi-model comparison analysis." Energy policy **80**: 244-263.
- Edelenbosch, O., et al. (2018). "Transport electrification: the effect of recent battery cost reduction on future emission scenarios." Climatic change: 1-14.
- Edelenbosch, O., et al. (2016). "Decomposing passenger transport futures: Comparing results of global integrated assessment models." Transportation Research Part D: Transport and Environment.
- EV-volumes (2018). "The electric vehicle world sales database." Retrieved 20-feb-2017, 2018.
- Faguy (2015). "Overview of the DOE Advanced Battery R&D Program." Retrieved 28-1-2017, 2017.
- Girod, B., et al. (2012). "Global travel within the 2 C climate target." Energy policy **45**: 152-166.

- Grinblatt, M., et al. (2008). "Social influence and consumption: Evidence from the automobile purchases of neighbors." The review of Economics and Statistics **90**(4): 735-753.
- IPCC (2014). Assessing Transformation Pathways. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change K. J. Clarke L., K. Akimoto, M. Babiker, G. Blanford, K. Fisher-Vanden, J.-C. Hourcade, V. Krey, E. Kriegler, A. Löschel, D. McCollum, S. Paltsev, S. Rose, P.R. Shukla, M. Tavoni, B.C.C. van der Zwaan, and D.P. van Vuuren Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- IPCC (2014). Transport. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change R. Sims, R. Schaeffer, F. Creutzig et al. Cambridge, United Kingdom and New York, NY, USA.
- John, A., et al. (2000). Incorporating behavioural, social, and organizational phenomena in the assessment of climate change mitigation options. Society, Behaviour, and Climate Change Mitigation, Springer: 1-64.
- Krey, V. (2014). "Global energy-climate scenarios and models: a review." Wiley Interdisciplinary Reviews: Energy and Environment **3**(4): 363-383.
- Krey, V., et al. (2014). "Getting from here to there—energy technology transformation pathways in the EMF27 scenarios." Climatic change **123**(3-4): 369-382.
- Kriegler, E., et al. (2015). "Diagnostic indicators for integrated assessment models of climate policy." Technological Forecasting and Social Change **90**: 45-61.
- Kriegler, E., et al. (2014). "The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies." Climatic change **123**(3-4): 353-367.
- L. Mundaca, L. N., E. Worrell, M. McNeil (2010). "Annual Review of Environment and Resources, Evaluating Energy Efficiency Policies with Energy-Economy Models." **35**: 305 -344
- McCollum, D. L., et al. (2018). "Interaction of consumer preferences and climate policies in the global transition to low-carbon vehicles." Nature Energy **3**(8): 664.
- McCollum, D. L., et al. (2017). "Improving the behavioral realism of global integrated assessment models: an application to consumers' vehicle choices." Transportation Research Part D: Transport and Environment(This special issue).
- McDonald, A. and L. Schrattenholzer (2001). "Learning rates for energy technologies." Energy policy **29**(4): 255-261.

- McShane, B. B., et al. (2012). "Visual influence and social groups." Journal of Marketing Research **49**(6): 854-871.
- Mercure, J.-F., et al. (2016). "Modelling complex systems of heterogeneous agents to better design sustainability transitions policy." Global Environmental Change **37**: 102-115.
- Nykqvist, B. and M. Nilsson (2015). "Rapidly falling costs of battery packs for electric vehicles." Nature Clim. Change **5**(4): 329-332.
- Peres, R., et al. (2010). "Innovation diffusion and new product growth models: A critical review and research directions." International Journal of Research in Marketing **27**(2): 91-106.
- Pettifor, H., et al. (2017). "Modelling social influence and cultural variation in global low-carbon vehicle transitions." Global Environmental Change **47**: 76-87.
- Plotkin, S. and M. Singh (2009). Multi-path transportation futures study: vehicle characterization and scenario analyses., Argonne National Laboratory (ANL).
- Reed, M. S., et al. (2010). "What is social learning?" Ecology and society **15**(4).
- Rogers, E. M. (2003). "Elements of diffusion." Diffusion of innovations **5**: 1-38.
- Rosen, R. A. (2015). "Critical review of: "Making or breaking climate targets—the AMPERE study on staged accession scenarios for climate policy". " Technological Forecasting and Social Change **96**: 322-326.
- Stehfest, E., et al. (2014). Integrated Assessment of Global Environmental Change with IMAGE 3.0: model description and policy application. Bilthoven, The Netherlands, PBL Netherlands Environmental Assessment Agency Institute.
- Stephens, T. (2013). Non-Cost Barriers to Consumer Adoption of New Light-Duty Vehicle Technologies. Transportation Energy Futures Series. P. f. t. U. S. D. o. E. b. A. N. Laboratory. Argonne: 47.
- Stern, P. C., et al. (2016). "Towards a science of climate and energy choices." Nature climate change.
- Tran, M., et al. (2012). "Realizing the electric-vehicle revolution." Nature climate change **2**(5): 328-333.
- Young, H. P. (2009). "Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning." The American economic review **99**(5): 1899-1924.

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
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1

2