UCLA – IPAM

University of California at Los Angeles- Institute for Pure and Applied Mathematics

16 November 2020

Newcastle University

UK | Malaysia | Singapore

Mathematical Challenges and Opportunities for Autonomous Vehicles

Workshop III

Large Scale Autonomy: Connectivity and Mobility Networks

Large scale autonomy on the consumers' side: challenges and opportunities of forecasting the demand for autonomous vehicles

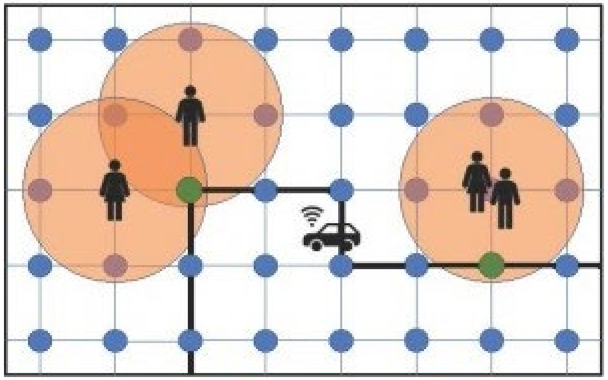
Elisabetta Cherchi

… on the consumers' side

The large scale deployment of autonomous and connected vehicles poses several challenges … as well documented by the various presentations in this workshop …

… on the consumers' side

Forecast the demand for autonomous vehicles



… whether, how fast and under which conditions, consumers will adopt this new technology

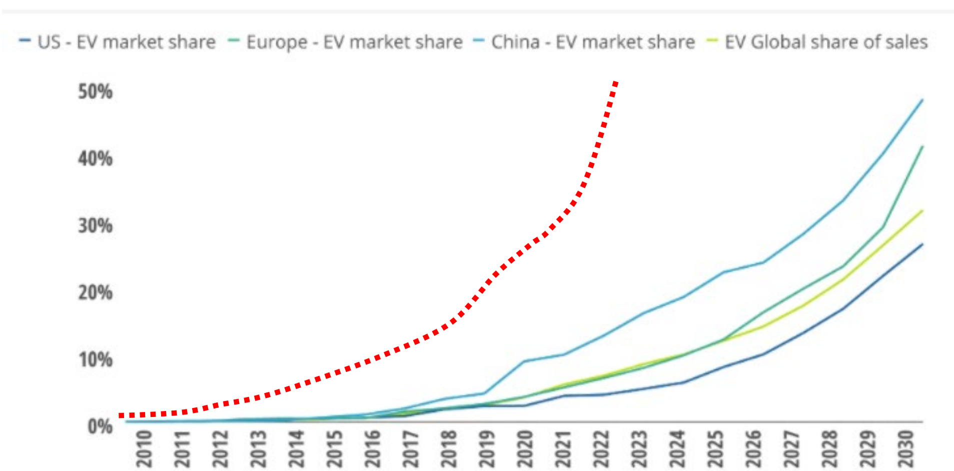
... on the consumers' side

Forecasting the demand for autonomous vehicles

The problem of forecasting the demand for innovative and disrupting technologies is not new. But not solved yet.

A relatively recent and very illustrative example is:

the demand for electric vehicles

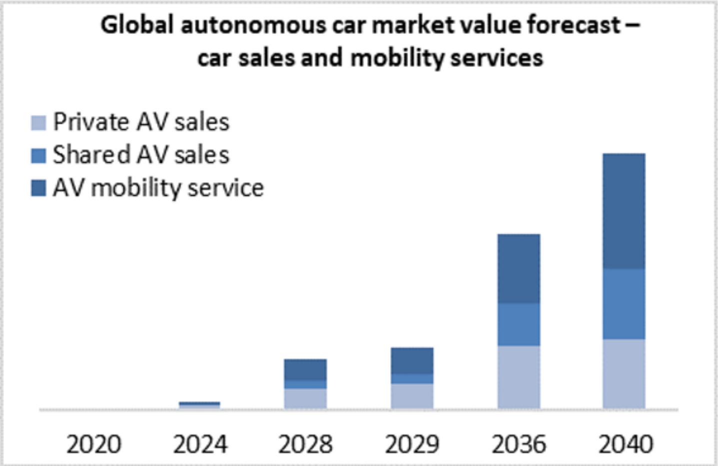


Source: Deloitte analysis (2019),HIS Markit, EV-Volumes.com

10 years ago, the prediction was ...

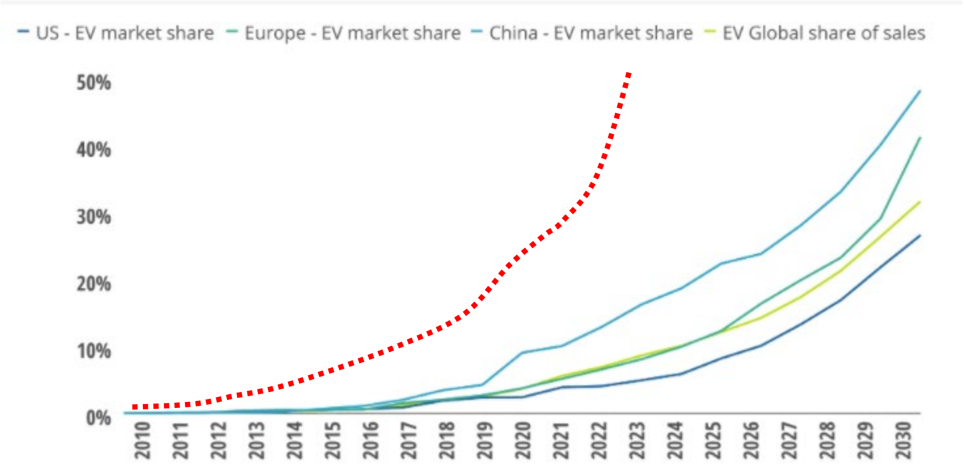
... a much faster market penetration than what instead occurred.

… on the consumers' side



the demand for autonomous vehicles

the demand for electric vehicles



Source: Deloitte analysis (2019),HIS Markit, EV-Volumes.com

10 years ago, the prediction was …

… a much faster market penetration than what instead occurred.

… on the consumers' side

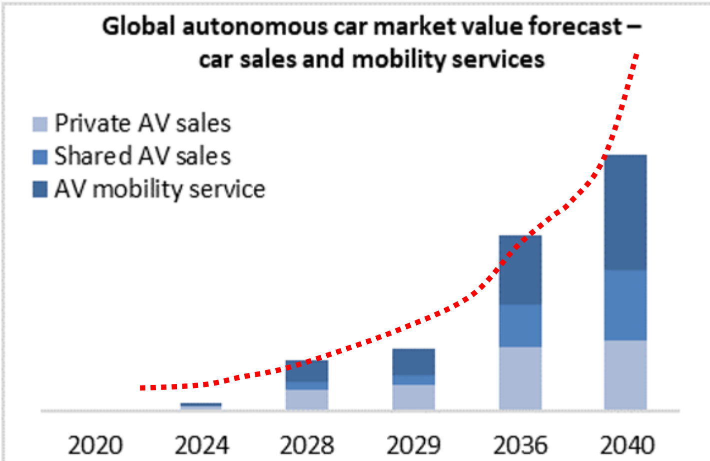
From a researcher point of view, the key question is:

WHY predictions were not correct?

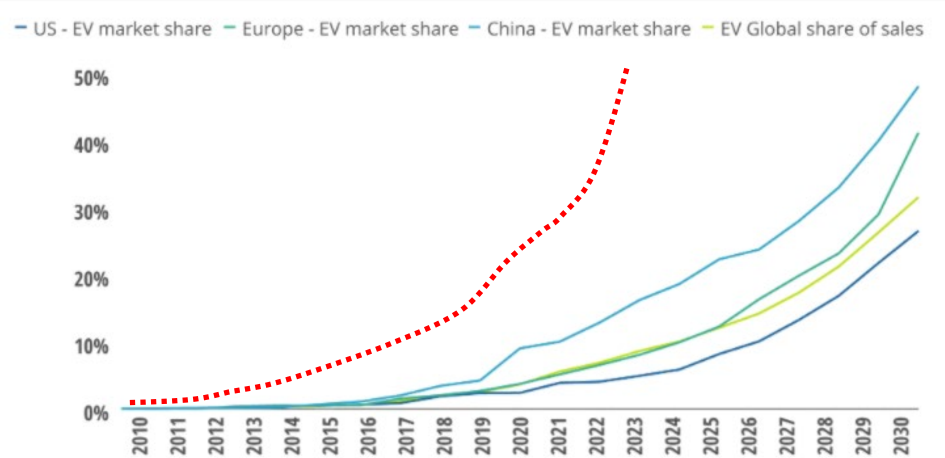
WHY consumers didn't (might not) adopt the new technology as fast as our models predict?

... on the consumers' side

Why predictions were not correct



Source: IDTechEx



Source: Deloitte analysis (2019),HIS Markit, EV-Volumes.com

These predictions are typically based on

Diffusion Models

(several variants - original Bass model, 1969)

$$a_t = \underbrace{p\left(M - S_{t-1}\right)}_{\text{innovators}} + \underbrace{q\,\frac{S_{t-1}}{M}\left(M - S_{t-1}\right)}_{\text{imitators}}$$

a_t ➔ new adopters at time *t*

M ➔ Potential Market

S_{t-1} ➔ Cumulative # of EV sales until time *t-1*

... on the consumers' side

Why predictions were not correct

- Market homogeneous and monopolistic
- Does not consider the impact of competitive alternatives (substitution effect)

- Imitation is due to word-of-mouth or observing the innovation in use
- Does not include "external" input such as advertising
- Does not include other aspects that can either enhance or slow down the diffusion

- Coefficients of innovation and imitation are taken by similar products or based on assumptions.

- Aggregate model
- Social network fully connected

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Diffusion Models

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… on the consumers' side

Why predictions were not correct

- Market homogeneous and monopolistic
- Does not consider the impact of competitive alternatives (substitution effect) → Substitution effect

- Imitation is due to word-of-mouth or observing the innovation in use
- Does not include "external" input such as advertising → Other variables
- Does not include other aspects that can either enhance or diminish the diffusion → Policy variables

- Coefficients of innovation and imitation are taken by similar products or based on assumptions.

Coeff. estimated ←

- Aggregate model → Disaggregate model
- Social network fully connected

Transport demand predictions are typically based on

Substitution Models

(several variants - McFadden, 2000)

$$P^t_{qj} = \frac{\exp(ASC_j + \beta_j X^t_{qj})}{\sum_j \exp(ASC_j + \beta_j X^t_{qj})}$$

P_{qj} → probability that individual *q* choose alternative *j* in time *t*

X_{qj} → vector of exogenous variables

β_j → "preference"

... on the consumers' side

Why predictions were not correct

Transport demand predictions are typically based on

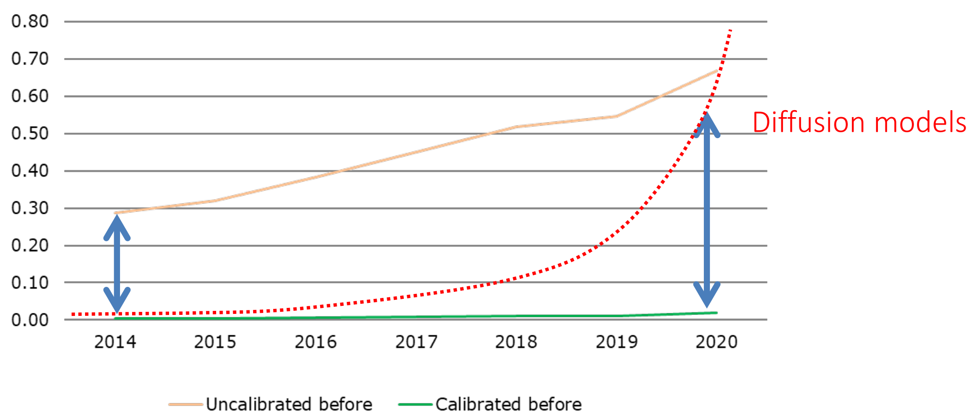
Substitution Models

(several variants - McFadden, 2000)

suitable to forecast demand in relatively **stable markets**

- without major variations in the characteristics of the transport systems
- No impact of social network (few exceptions)
- Preference stability

$$P_{qj}^{t}=\frac{\exp(ASC_j+\beta_j X_{qj}^{t})}{\sum_j \exp(ASC_j+\beta_j X_{qj}^{t})}$$



P_{qj} ➔ probability that individual *q* choose alternative *j* in time *t*

X_{qj} ➔ vector of exogenous variables

β_j ➔ "preference"

… on the consumers' side

Why predictions were not correct

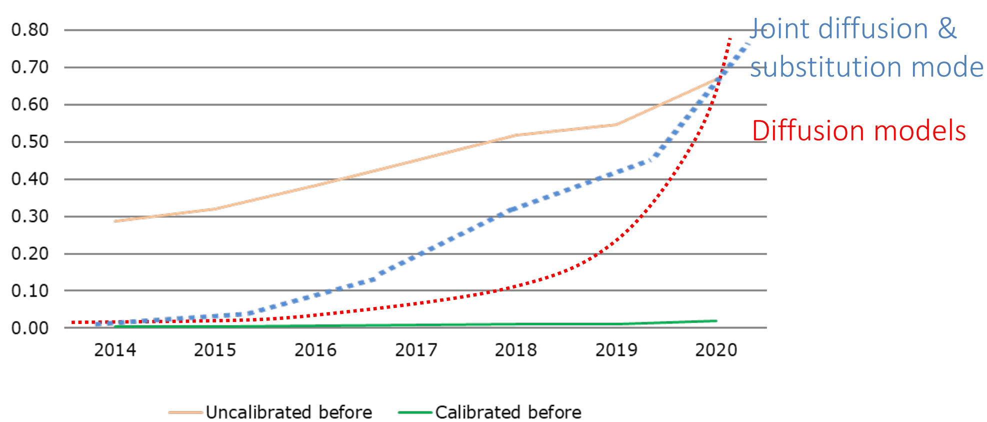
- Aggregate model
- Does not account for social interaction at the individual level

- Preference stability

Recent developments

Joint diffusion and substitution Models

(several variants)



… on the consumers' side

Why predictions were not correct

- Aggregate model ← disaggregate
- Does not account for social interaction at the individual level ← social interaction
- Preference stability
- Mostly focus on instrumental attributes and highly simplified models of social interaction
- Few develop the social interaction but do not include instrumental attributes
- Mostly based on very simple decision rules
- Few include very simple substitution models
- Coefficients from other studies

Recent developments

Agent Based Models

(several variants)

Simplified virtual representations of the social system

Simulate the actions and interactions of autonomous agents

To assess the effects of the agents on the system as a whole

... on the consumers' side

Preference stability

Common to all these methods ➔ Preference exist and can be estimated
Preferences do not vary over time

In case of innovations, it is likely that individuals have:

- few/no knowledge about the product
- few/no experience with the product

The problem in forecasting demand for innovations is that:

- consumers **do not have preferences** for products that they have not experienced first hand, they have not been able to construct adequate preferences (Kurani et al., 1996)

Moreover individual preferences change:

- over time (not only in case of innovation)
- with the characteristics of the product (instrumental variables)
- with the with knowledge (word of mouth / advertisement)
- observing the innovation in use
- with own experience

… on the consumers' side

How to measure these preference …

Substitution Models

$$P_{qj}^{t} = \frac{\exp(ASC_j + \beta_j X_{qj}^{t})}{\sum_j \exp(ASC_j + \beta_j X_{qj}^{t})}$$

Revealed preferences cannot be used
(for real behaviours in current market)

- If the product does not exist …
- There is not yet a market

Stated preferences are typically used
(for alternatives that do not currently exist or are revamped)

- People revisit and alter their preferences when encountering a new domain.
- SP experiments force respondents to rethink their preferences.

... on the consumers' side

SP experiments are used for ...

Alternatives that do not exist ≠ the innovation

less — Degree of innovation ... — more

New Metro line

The alternative is new but individuals know it and have experience with it

Electric vehicles

The alternative is new, individuals know it (there can be some misconception) but have no experience with it

Automated vehicles

The alternative is new, few individuals know something about it and none have experience with it

Flying vehicles

??

Jetsons

Demo projects — VR experiments

more — Realism/adequacy SP — less

Elisabetta Cherchi

... on the consumers' side

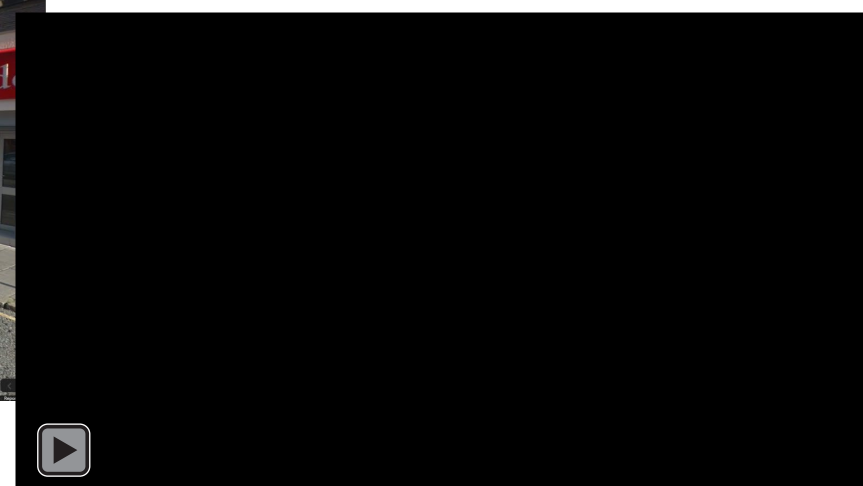
Some evidence: Using Virtual Reality to measure preferences for AV

Methodology:

- a stated choice experiment embedded into a VR environment.
- choice between a traditional taxi and a fully automated taxi.

Context:

An urban environment, a street in Newcastle city centre where there is currently located a taxi rank used by more than 1,000 people a week



VERONICA project, funded by ESRC - UK

Elisabetta Cherchi

... on the consumers' side

Some evidence: Using Virtual Reality to measure preferences for AV

Participants can move around, cross the street, join the queue ...

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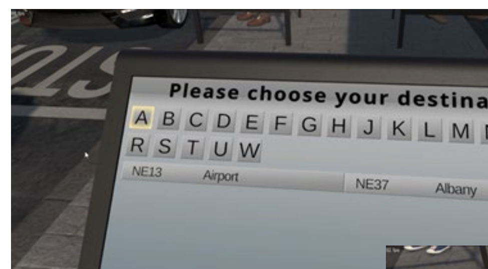
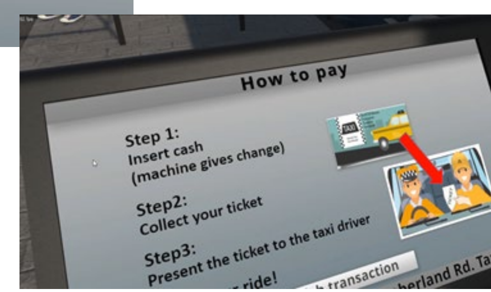
Some evidence: Using Virtual Reality to measure preferences for AV

Info board

SC Experiment

Ticket board





VERONICA project, funded by ESRC - UK

Elisabetta Cherchi

… on the consumers' side

Some evidence: Using Virtual Reality to measure preferences for AV

Hao Y. and Cherchi, E. (2020) Conducting Stated Choice Experiments within a Virtual Reality environment: an application to the choice of automated taxi. *12th International Conference on Transport Survey Methods. Travel Survey and Big Data: how to make the best of both worlds*, Portugal.

Overall results

Knowledge (*several pilots approx. 150 respondents*)

- 87% of the respondents have heard about AVs
- but approx. 40% is not familiar at all with AV (46% among the female) and 32% is slightly familiar. All male are at least slightly familiar.
- only 1% tried a level 3 automation (max level)

A post-experiment questionnaire indicated that:

- almost 100% of the respondents found the content of the experiment very clear and extremely easy to make the choice in it
- 90% of the respondents felt the VR experiment was realistic
- 50% did feel as if to some extent they were making a choice in reality
- none of the respondents experienced locomotion issues or dizziness

... on the consumers' side

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Results from the SC experiment indicated that:

- Probability to use automated taxi is higher for respondents who are familiar with AVs, lower among respondents over 60.

The most striking result … though still in the pilot phase:

- results from the VR experiment are way better than with a standard SC. All have the expected sign, all significant at least around 90%
- the impact of social influence is positive and significant only in the VR experiment.

Regarding VR environment:

- It seems that the realism of the VR experiment might play an important role in particular in studying the impact of social influence.

Regarding AVs:

- There seems to be a “human” need to interact with other humans. In the automated taxi, respondents valued positively the possibility to chat with an operator, but ONLY if they are travelling alone.

... on the consumers' side

Some evidence: Impact of experience with EV on individuals' preferences

Jensen, A., Cherchi, E. and Mabit, S. (2013) On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research* D 25, 24-32.

- long panel survey: individuals were interviewed before and after they had experienced (i.e. used in real life) an EV for 3 months.
- estimate preferences and attitudes before and after

Key results:

- For half of the attributes in the DCM, individual preferences were significantly different before and after the direct experience with an EV.

- Individuals' concern about driving range doubled after the direct experience.
- The effect of top speed double after the direct experience.

- less scepticism about having to remember to charge the EV
- less scepticism about the power of EV to make a safe take over
- more scepticism about being able to maintain current mobility (cancel some activities).

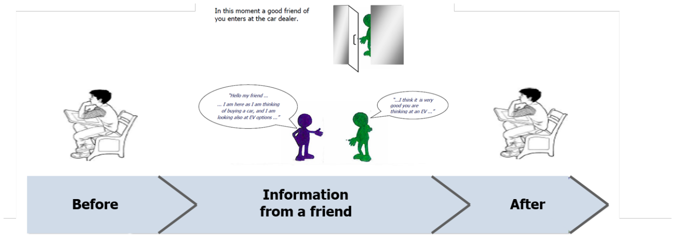
The more people used the cars (during the three months) the more marked were the above effects.

… on the consumers' side

Some evidence: Impact of information about EV on individuals' preferences

Cherchi, E. (2017) A stated choice experiment to measure the effect of social conformity in the preference for electric vehicles. Transportation Research A 100, 88-104.

- Stated preference with treatment: information from a friend who had experience with EV
- estimate preferences before and after receiving information



Key results:

- Negative information (i.e. experience) affects individual's preferences much more than positive information (negativity bias).
- What people care more about is the fact that with an EV they have to change activity schedule.
- Women are more likely to conform to norms when they receive accurate information about reality (they know less about car!)

Policy implications:

The impact of social conformity can be high enough to compensate also significant differences in purchase price (e.g. 1/3 higher for EV than ICV, around € 5000) or a quite low driving range for EV (e.g. around 130 km).

… on the consumers' side

Conclusion

Technology is transforming the way we interact among us and with the surrounding environment and the way we move.

Results indicate that:

- People have no experience and little/no knowledge about recent innovations in transport.
- VR seems to be able to give respondents the "feeling" of a real experience.
- Preferences and attitudes are affected by direct and indirect experience.
- Policy forecast for innovation are very different if we account for experience, knowledge, diffusion via social channels.
- Modelling and forecasting the travel demand for innovation is very challenging.

Will the "innovation" become reality before we are able to predict its effect?

Many thanks

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References

Hao Y. and Cherchi, E. (2020) Conducting Stated Choice Experiments within a Virtual Reality environment: an application to the choice of automated taxi. *12th International Conference on Transport Survey Methods. Travel Survey and Big Data: how to make the best of both worlds*, Portugal. (Accepted).

Farooq, B., Cherchi, E. and Sobhani, A. (2018) Virtual Immersive Reality for Stated Preference Travel Behaviour Experiments: A Case study of Autonomous Vehicles on Urban Roads. Transportation Research Record 2672 (50), 35-45

Bas, J., Cherchi, E., Cirillo, C. and Jensen, A. (2018) Predicting the diffusion of EV: A dynamic approach to model the impact of imitation and experience. *Operation Research Conference: Stream: Traffic, Mobility and Passenger Transportation.* Brussels, Belgium.

Cherchi, E. (2017) A stated choice experiment to measure the effect of social conformity in the preference for electric vehicles. *Transportation Research* A 100, 88-104.

Jensen, A., Cherchi, E., Mabit, S. and Ortúzar, J. de D. (2017) Predicting the potential market of electric vehicles. *Transportation Science* 51, 427-440..

Jensen, A., Cherchi, E., and Ortúzar, J. de D. (2014) A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. *Transportation* 41(5), 973-993.

Jensen, A., Cherchi, E. and Mabit, S. (2013) On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research* D 25, 24-32.