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

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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

10 years ago, the prediction was ...

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

Source: Deloitte analysis (2019), HIS Markit, EV-Volumes.com
... on the consumers' side

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the demand for autonomous vehicles

the demand for electric vehicles

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

These predictions are typically based on

**Diffusion Models**

(several variants - original Bass model, 1969)

\[
a_t = p \left( M - S_{t-1} \right) + q \frac{S_{t-1}}{M} \left( M - S_{t-1} \right)
\]

- **innovators**
- **imitators**

\( a_t \rightarrow \) new adopters at time \( t \)

\( M \rightarrow \) Potential Market

\( S_{t-1} \rightarrow \) Cumulative # of EV sales until time \( t-1 \)

Source: Deloitte analysis (2019), HIS Markit, EV-Volumes.com
... 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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- Aggregate model  ➞ Disaggregate model
- Social network fully connected

Transport demand predictions are typically based on

Substitution Models
(several variants - McFadden, 2000)

\[ P_{tq}^j = \frac{\exp(ASC_j + \beta_j X_{qj}^t)}{\sum_j \exp(ASC_j + \beta_j X_{qj}^t)} \]

- \( P_{tq} \) ➞ probability that individual \( q \) choose alternative \( j \) in time \( t \)
- \( X_{qj} \) ➞ vector of exogenous variables
- \( \beta_j \) ➞ "preference"
- \( \text{Coeff. estimated} \) ➞ Other variables
- \( \text{Policy variables} \) ➞ Aggregate model
- \( \text{Aggregate model} \) ➞ Disaggregate model
- \( \text{Social network fully connected} \) ➞ Aggregate model

**Disaggregate model**

- \( q \) ➞ individual
- \( t \) ➞ time
- \( j \) ➞ alternative
- \( ASC \) ➞ attributes
- \( \beta \) ➞ coefficients
- \( X \) ➞ variables
- \( P \) ➞ probability
- \( \exp \) ➞ exponential function
... on the consumers' side

Why predictions were not correct

- 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

Transport demand predictions are typically based on

Substitution Models
(several variants - McFadden, 2000)

$$p_{t}^{q} = \frac{\exp(ASC_{j} + \beta_{j}X_{qj}^{t})}{\sum_{j} \exp(ASC_{j} + \beta_{j}X_{qj}^{t})}$$

- $p_{qj}$ $\rightarrow$ probability that individual $q$ choose alternative $j$ in time $t$
- $X_{qj}$ $\rightarrow$ vector of exogenous variables
- $\beta_{j}$ $\rightarrow$ "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

- 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 preferences ...

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

People revisit and alter their preferences when encountering a new domain.

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

SP experiments force respondents to rethink their preferences.
... on the consumers' side

SP experiments are used for ...

Alternatives that do not exist ≠ the innovation

Degree of innovation ...

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

Realism/adequacy SP

less

more
... 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
... on the consumers' side

Some evidence: Using Virtual Reality to measure preferences for AV

Participants can move around, cross the street, join the queue ...
... on the consumers' side

Some evidence: Using Virtual Reality to measure preferences for AV

Info board

Ticket board

VERONICA project, funded by ESRC - UK

Elisabetta Cherchi
... on the consumers' side

Some evidence: Using Virtual Reality to measure preferences for AV


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
Some evidence: Using Virtual Reality to measure preferences for AV


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


- 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


