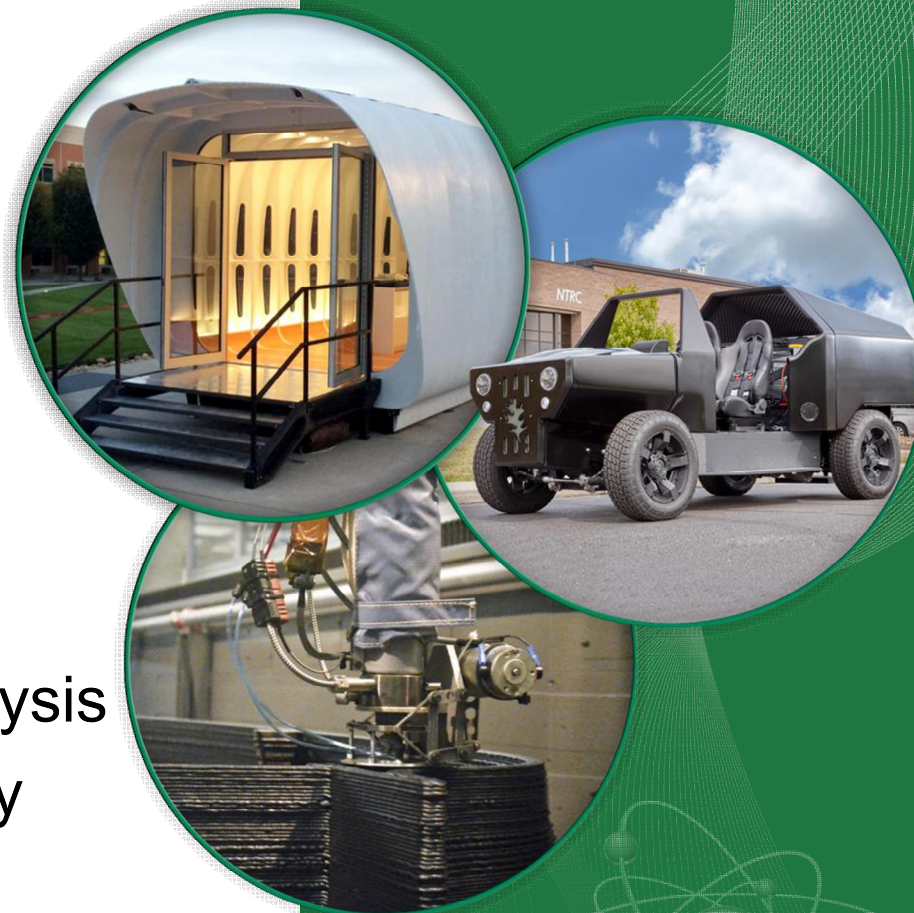
Social Adoption of Plug-In Electric Vehicles: Modeling and Policy Review



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Outline

- Introduction
- Modeling Framework
  - Social Connections
  - Social Adoption Mechanism
  - Decision Context
- Modeling State-of-the-Art
- Summary of General Study Findings
- Conclusion

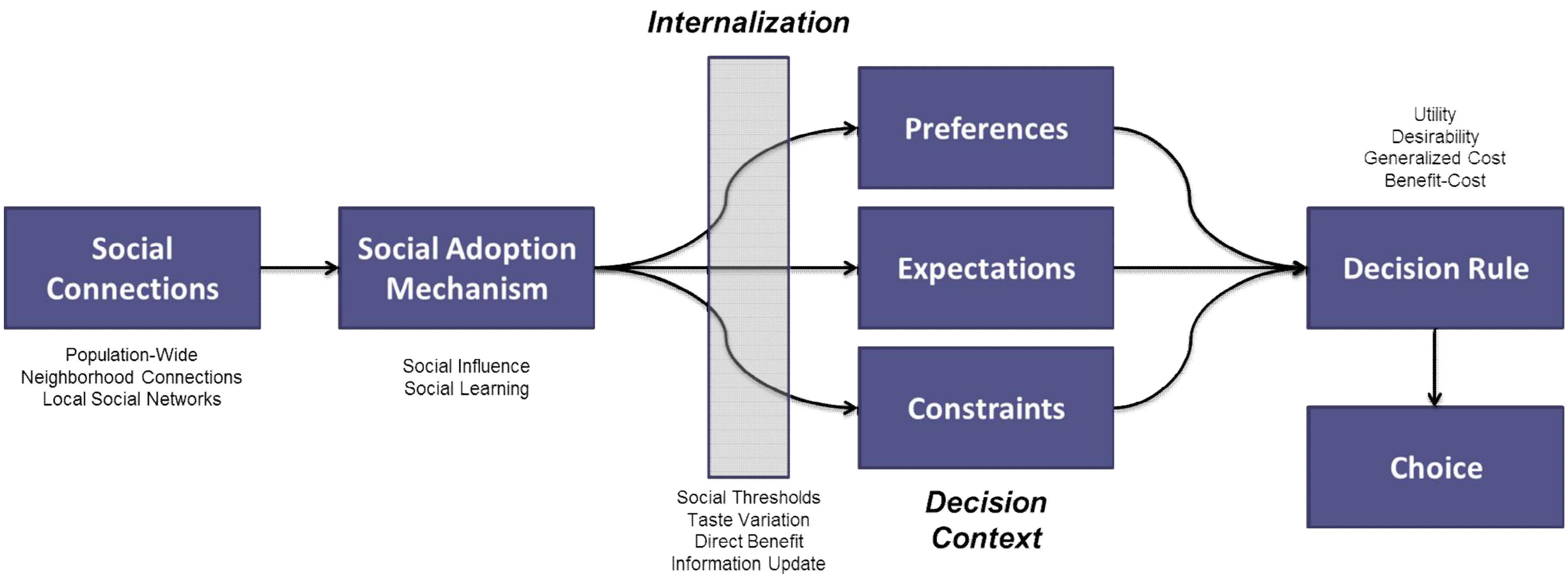
Introduction

- What is Social Adoption of Plug-in Electric Vehicles (PEVs)?
  - Social processes that encourage the adoption of PEVs
- Why would it be important to study?
  - Effectiveness of non-social policies
  - What if there are clustering or local effects?
  - Energy Infrastructure

Papers Reviewed

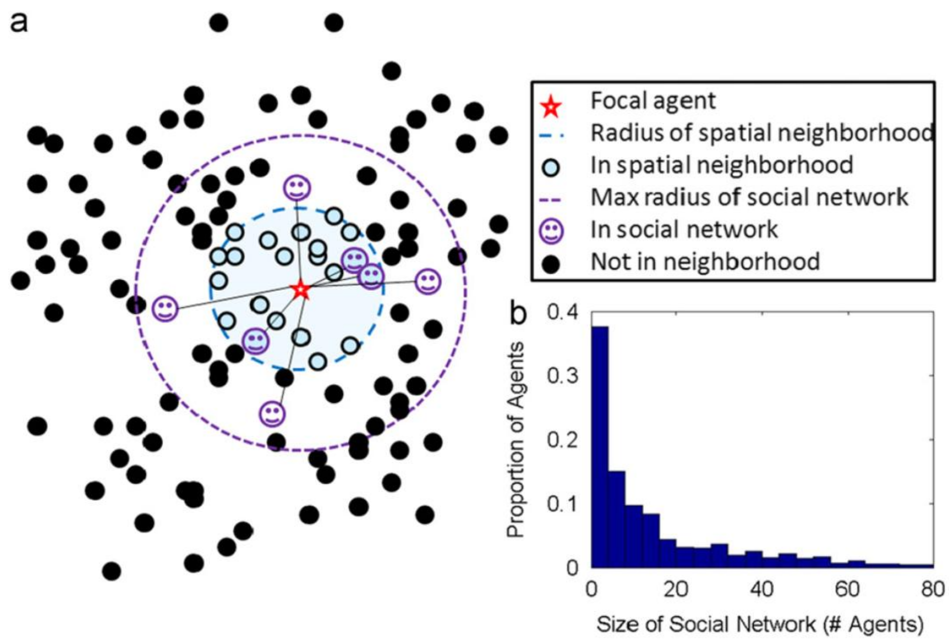
- 12 studies reviewed on social adoption with vehicle choice
  - Paper had to explicitly mention social effects, not just spatial correlation for example
- Most papers involved plug-in electric vehicles
  - Two papers on hybrid papers were included because of unique methodologies that could be applied to PEV sales

A Modeling Framework for Social Adoption



Representing Connections

- Population-Wide
- Neighborhood Connections
- Local (Personal) Social Network



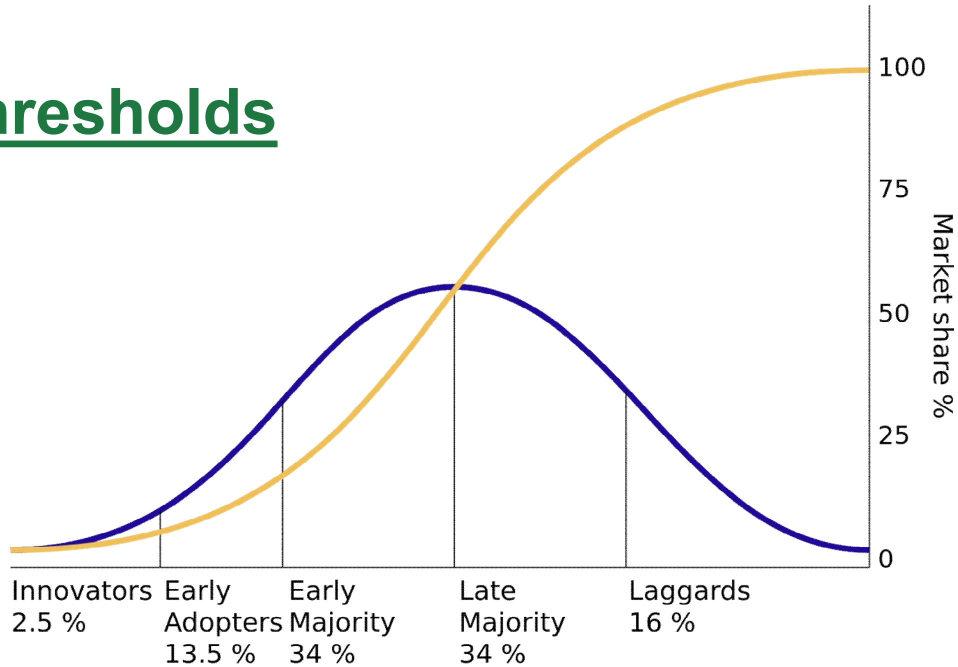
Source: Eppstein et al., 2011

Social Adoption Mechanism

- Social Influence
  - Altering an individual's decision making process through the actions, behaviors, attitudes, and beliefs of others
  - Conformity and social norms
- Social Learning
  - When individuals learn new behavior and beliefs through observations and social experiences
  - Updating an individual's personal information

Modifying the Decision Context

Social Thresholds



Direct-Benefits

- $$Utility(PEV) = \beta_{cost} * Purchase\ Cost$$
$$+ \beta_{range} * Vehicle\ Range$$
$$+ \beta_{social} * Market\ Share\ of\ PEV$$

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Modifying the Decision Context

Taste Variation / Preference Change

$$Utility(PEV) = \begin{cases} \beta_{cost}^{<20\%MC} * Purchase\ Cost + \beta_{range}^{<20\%MC} * Vehicle\ Range, & \text{if } \mathrm{MS_{PEV}}<20\% \\ \beta_{cost}^{\geq 20\%MC} * Purchase\ Cost + \beta_{range}^{\geq 20\%MC} * Vehicle\ Range, & \text{if } \mathrm{MS_{PEV}}\geq 20\% \end{cases}$$

Information Updates

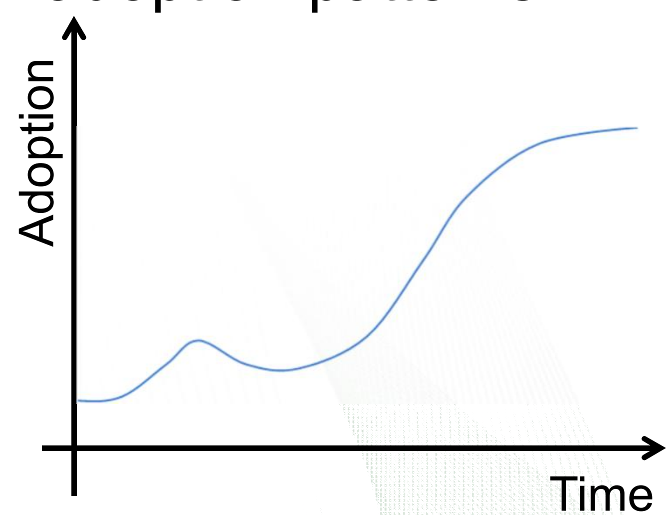
$$Utility(PEV) = \begin{cases} \beta_{price} * Vehicle\ Price + \beta_{fuel} * perceived\ fuel\ cost & \text{if not informed} \\ \beta_{price} * Vehicle\ Price + \beta_{fuel} * accurate\ fuel\ cost & \text{if informed by peers} \end{cases}$$

Modeling State-of-the-Art

- Agent-based Models
  - Enables Agent Heterogeneity and Social Interactions
- Plug-in Electric Vehicle Purchases
  - Some incorporated vehicle usage, charging behavior, supply side, and regulations
- Data Sources
  - Typically questionnaires to calibrate models and obtain distributions of agent characteristics
  - Social network data not typically collected

Adoption Behavior

- Adoption tended to be S-shaped
  - Spatial differences in adoption leads to clustering
  - Policy needs to be targeted and varied locally / regionally
- Some variations on the S-shape were observed
  - Can be high variability in short-term adoption patterns
  - Saddle point adoption pattern: Early dipping before breakout (Tran 2012)
  - Suggests to be careful with aggregate market trends (Tran 2012)



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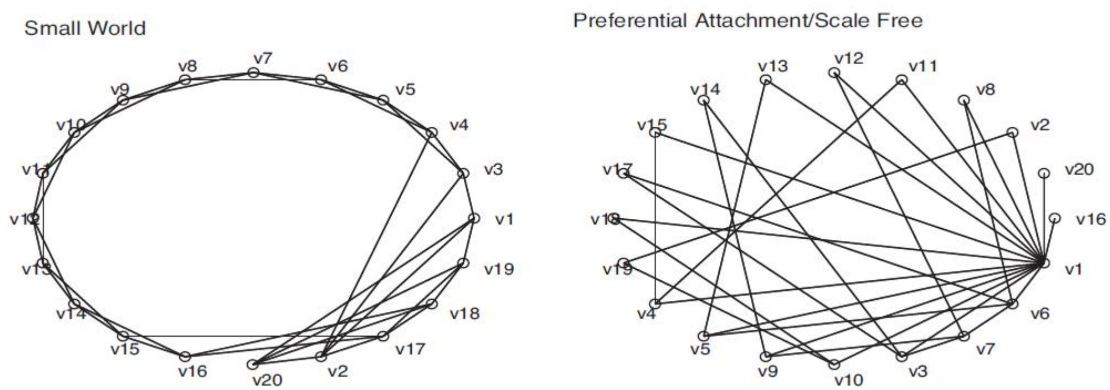
Social Network Structure

- Lack of social network data, so typically random networks generated



- Clustering of adoption can occur with typical human social network structures
  - But the shape can lead to different cluster quantities and sizes (McCoy and Lyons, 2014; Tran 2012)
- Current data likely insufficient to identify nodes to target with currently emphasized consumer groups (McCoy and Lyons, 2014)

Source: McCoy and Lyons, 2011

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Social Threshold Needs

- High thresholds prevent PEV breakout as the attributes of PEVs are not favorable enough
  - Eppstein et al., 2011 observed that vehicle rebate programs had no effect when thresholds were too high
- How are thresholds distributed among the population?
  - No models calibrated their model on using other datasets and methodologies
  - Models reviewed tended to fit best with low thresholds (Adeptu and Keshav, 2015; Adeptu et al., 2016)

Effect Size

- Difficult to compare effect size between studies
  - Variety of time and spatial resolutions and decision sets
- All studies but one found an increase an adoption with most following an S-shaped curve
  - Zhang et al., 2011 found that word of mouth would likely cause a niche market for PEVs, but limited widespread adoption
  - Wolf et al., 2014 predicted no effect

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Maness, Michael, 10/18/2016

Conclusion

- Reviewed the state of computation models of consumer choice behavior for PEV with social adoption effects
- Most models were agent-based models with varying degrees of representing social connections
- S-shaped adoption commonly observed, but with localized clustering
- Most studies found that social effects were significant

Conclusion

- Social network data is lacking limiting the strength of results and conclusions
  - Limited theoretical basis for the neighborhood sizes used
  - New methods need to be used to calibrate thresholds
- Variation in models limits comparison and repeatability
  - Running multiple models would increase robustness
- Still room for more traditional models to increase their social realism using similar techniques

Some Open Questions

1. If rebate policy focuses on social adoption, how will the structure of these programs change? Are current policies less effective due to not accounting for social adoption effects?
2. How easily can the likely pathways for adoption be recognized accurately and can policy makers, manufacturers, and utilities create new policies, vehicles, and investments quick enough to keep up with adoption?
3. Who are the "influential nodes" that can assist most in spreading social influence and social learning through local social networks? Can organizations create programs to effectively target these individuals?

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