Agent based modelling of technological diffusion and network influence

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Outline

1. Study motivation
2. Analytical framework & model description
3. Sample results (agent & systems behaviour)
4. Discussion & next steps

Techno-behavioural dynamic framework

Demand Low

Supply Low

1. Status Quo
- Extrapolation of current macro and micro level trends in demand and supply.
- Conservative policy deployment leading to incremental change.

2. Technological-optimism
- Radical departure from current trends led by accelerated technological diffusion
- Backed by government and industry investment.

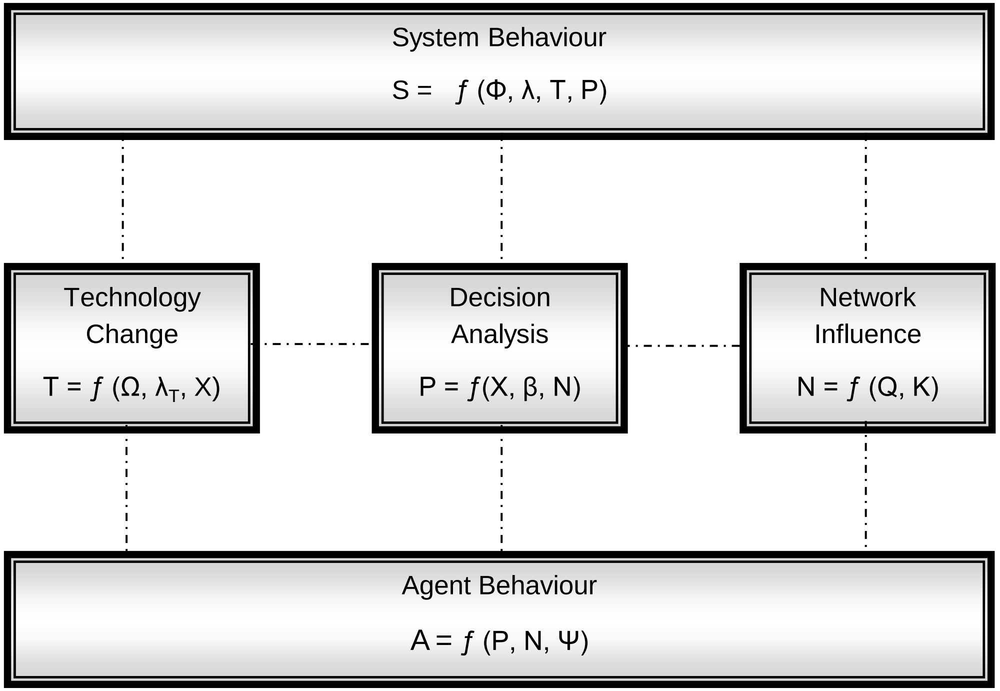
3. Behavioural change
- Focuses on changing individual behaviours and lifestyles (consumption, practices , norms)
- Partly reactionary to the conventional focus on technological solutions without social context.

4. Techno-behavioural Dynamics
- Strategic decision-making and adoption behaviour as a mechanism for behavioural change.
- Technology performance and behaviour as co-evolving coupled dynamical system.

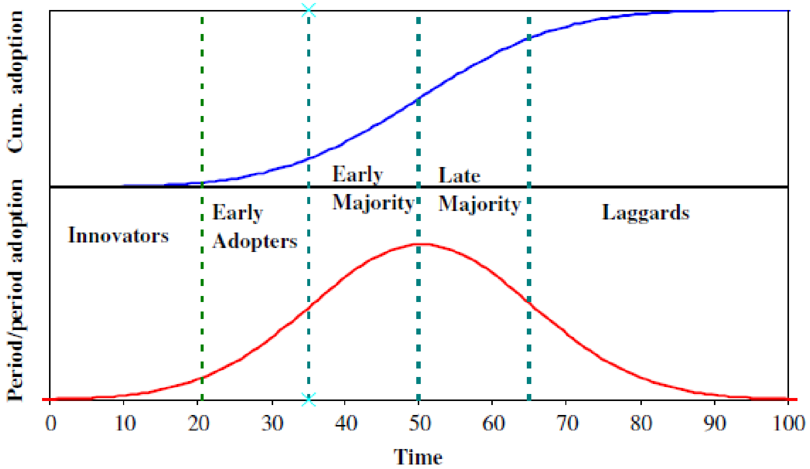
Supply High

Demand High

Implementing the approach – general model description



Conventional technology diffusion models – mean field approaches



$$\frac{dP(t)}{dt} = \alpha P(t)\left(1 - \frac{P(t)}{K}\right)$$

Feedback key but no other explanatory variables

$$\frac{\mathrm{d}n(t)}{\mathrm{d}t} = [\mathrm{M} - n(t)]\left[\mathrm{p} + \frac{\mathrm{q}}{\mathrm{M}}\, n(t)\right], \quad n(0) = 0$$

Additional parameters important but need to disaggregate, *p & q*

Diffusion = *f(A, T, P, N)*

ABM derivation – need to account for variation in individual behaviour and balancing between internal and external influence

ABMs with a general binomial form*:

$$\text{Prob}(t) = 1 - (1 - p) * (1 - q) \wedge k(t)$$

$$t(0) = \text{no adopt}$$

$$t + 1 = \text{prob}(t) > U \text{ adopt}$$

Re-specify model to account for technology trade-off behaviour i.e. index into matrix of options, *j* and influences *(P, Q, K)* specific to each individual, *i* :

$$\text{Prob}(t) = 1 - (1 - P_{ij}) * (1 - Q_{ij}) \wedge K_{ij}(t)$$

*Source: Goldenberg & Shapira, 2009

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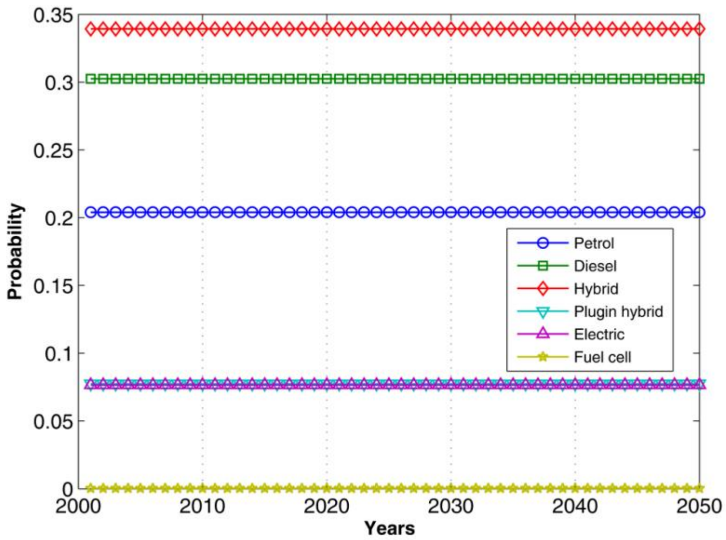
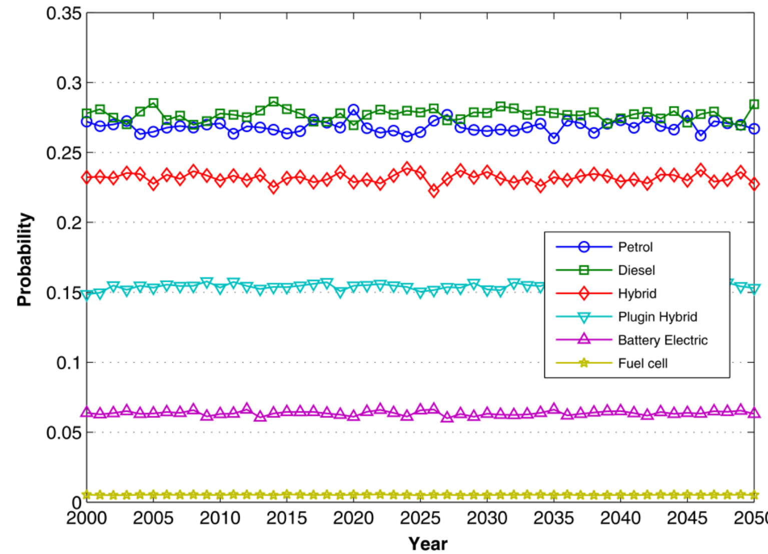
Monte Carlo simulations used for assessing unknown individual preferences (P_{ij})





Static approach,

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_{j=1}^{J} e^{\beta' x_{nj}}}$$

HEV's outcompete ICE's, survey bias?

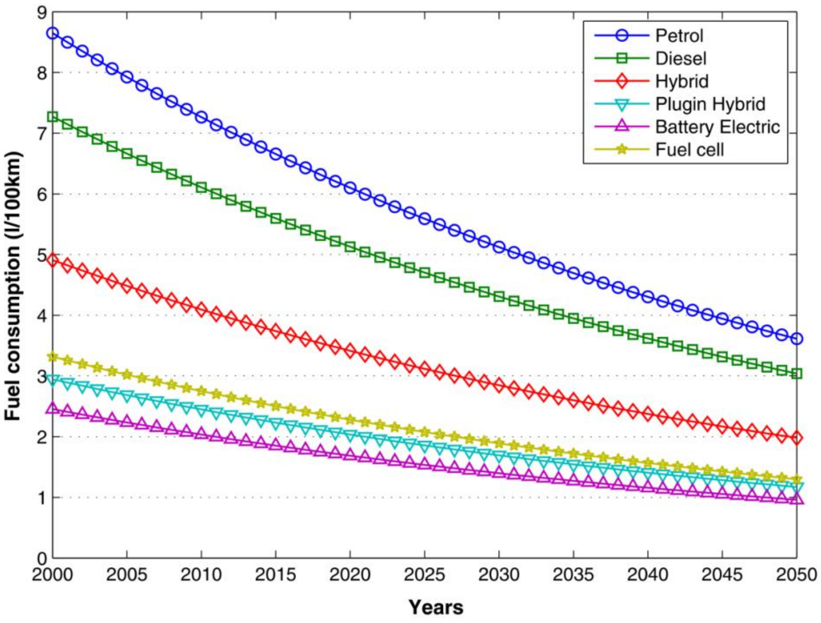
Dynamic approach,

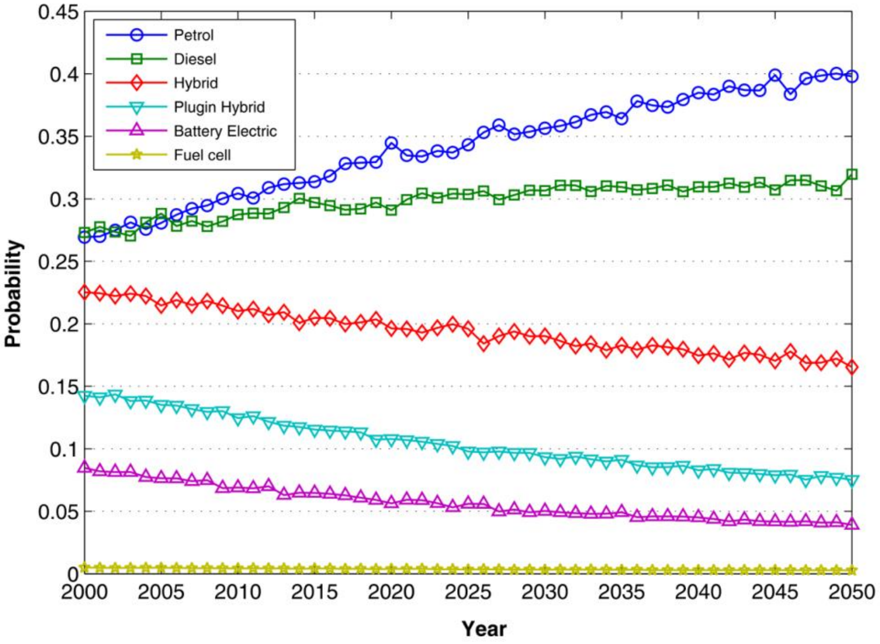
$$P_{ni}(\theta) = \int_{-\infty}^{+\infty} L_{ni}(\beta) f(\beta \mid \theta)\, d(\beta)\,,$$

$$L_{ni}(\beta) = \exp(\beta' x_{ni}) / \sum_{j} \exp(\beta' x_{ni})$$

Accounts for heterogeneity, better approximation

Co-evolution of technological performance and agent behaviour





- Feedback effect between technological change and agent preferences over time
- How do different feedback effects scale up to impact the larger technological system?

Simple assumptions made on network influence *(Q_{ij}, K_{ij})*

Indirect influence, Q_{ij}, based on value estimate, *V* of previous adopters, n_k out of a local population, *n*,

$$Q_{ij} = V(p_k),\ p_k = n_k/n$$

Direct influence, K_{ij} based on previous adopters out of personal contacts, w_{ij} that has influence, y_i on an individual,

$$K_{ij}(t) = \sum w_{ij}y_i/\sum w_i$$

Therefore the master function is,

$$\mathrm{Prob}(t) = 1 - (1 - [\tfrac{1}{R} * \textstyle\sum_{r=1}^{R} L_{ij}\,(\beta^{r})]) * (1 - [n_k/n])\ \hat{}\ (\sum w_{ij}y_i/\sum w_i)$$

See Tran, 2012 for full derivation

Technology data and assumptions

Technologies	Purchase Price (2011 USD)	Fuel Price (USD/ 160 km)	Fuel Consumption (L/100 km)	Performance (Acceleration 0-100 km/hr in seconds)	Range (Km on 1 tank/charge)	Environment (Annual WTW GHG CO_2-eq emission, metric tonnes)	Refuelling Availability (%)
Petrol	16640	12.9	8.1	6.5	567	5.9	100
Diesel	20180	11.5	6.9	8.7	714	5.7	100
HEV	26155	8.45	4.7	10	862	3.9	100
PHEV	40280	7.63	4.5	12	764	4.0	30
BEV	32780	3.74	2.4	11	117	3.6	1
FC	100000	5.00	3.9	12	384	3.2	1

Rewire for random and small world network influence and sensitivity analysis

Simulations	P	Q	K
1	0.1	0.1	0.1
2	0.9	0.1	0.1
3	0.1	0.9	0.1
4	0.1	0.1	0.9
5	0.1	0.9	0.9

Sources: See Tran, M. 2012 for full references

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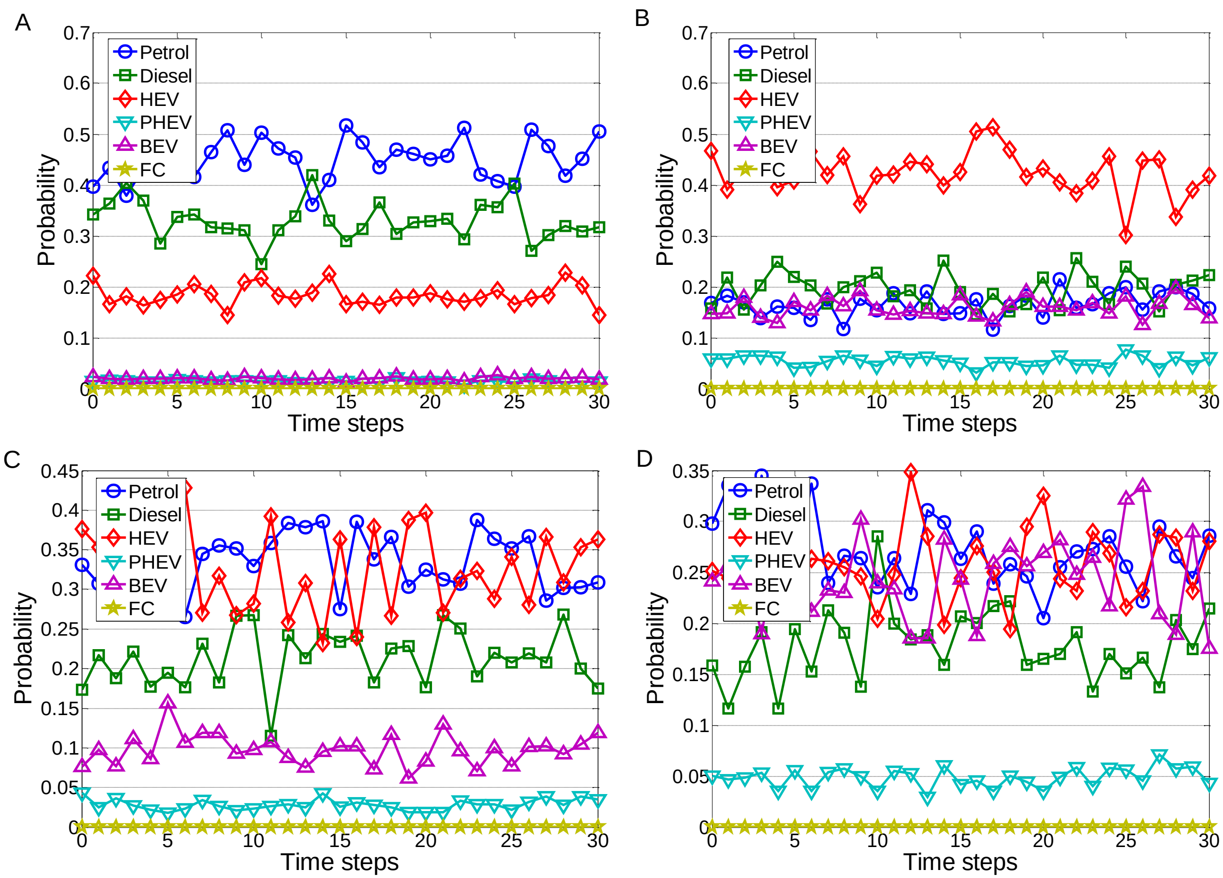
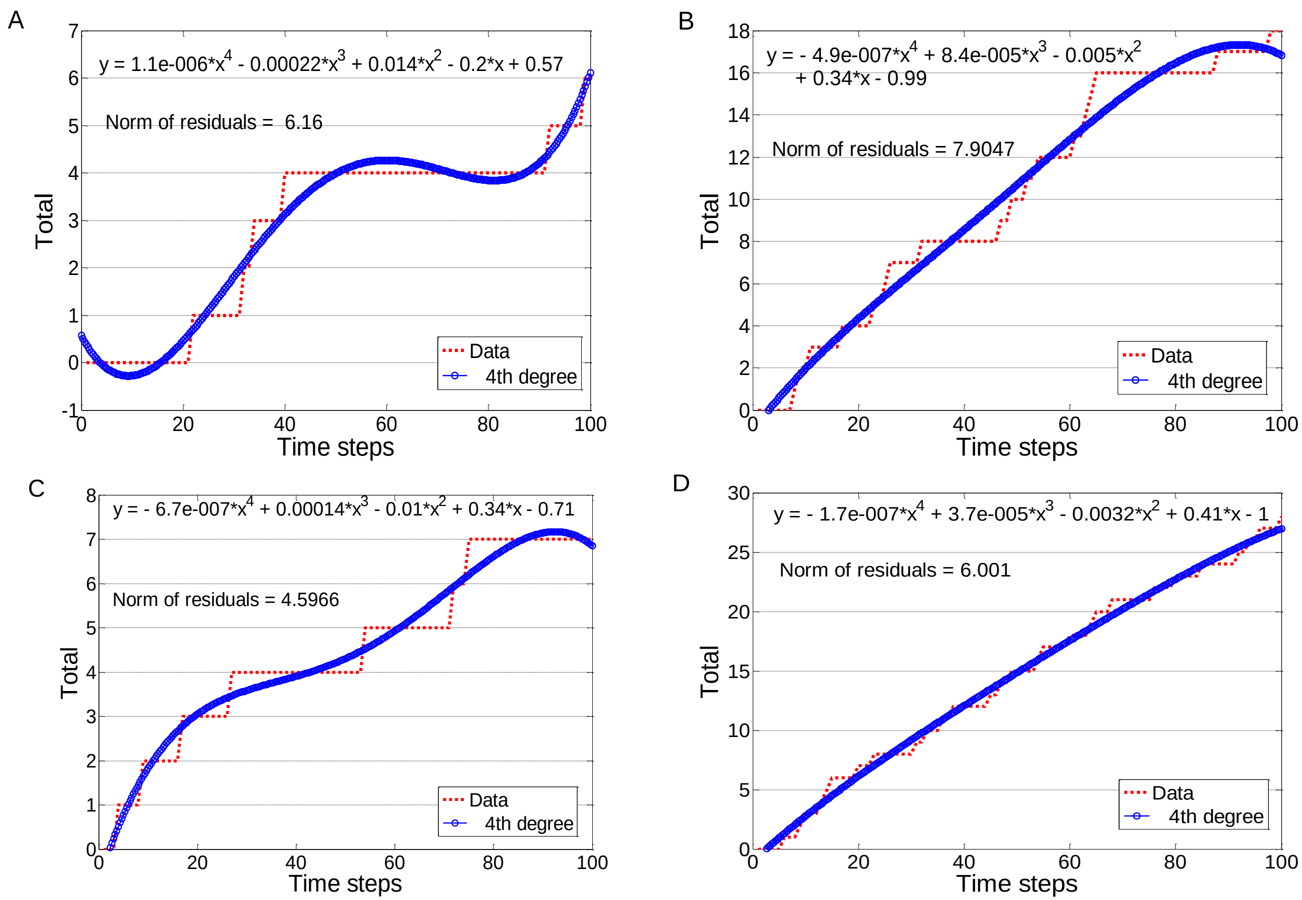
Captures heterogeneous behaviour, distribution and trend effects over time



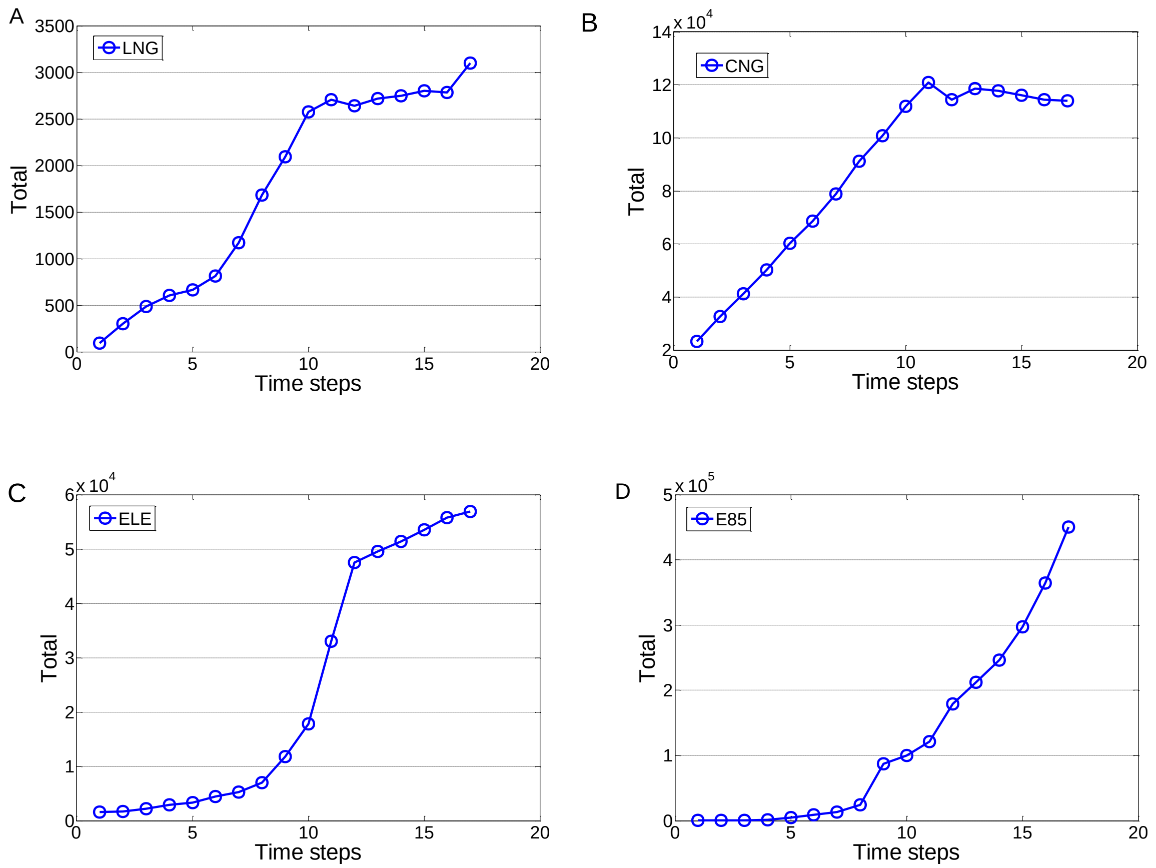
A) Mass market (price, reliability), B) Early adopter (CO_2 , fuel economy) C) Trade-offs (performance vs. environment) D) Exogenous effects (refuelling infrastructure)

High variability during early phases of diffusion, better approximation to empirical evidence



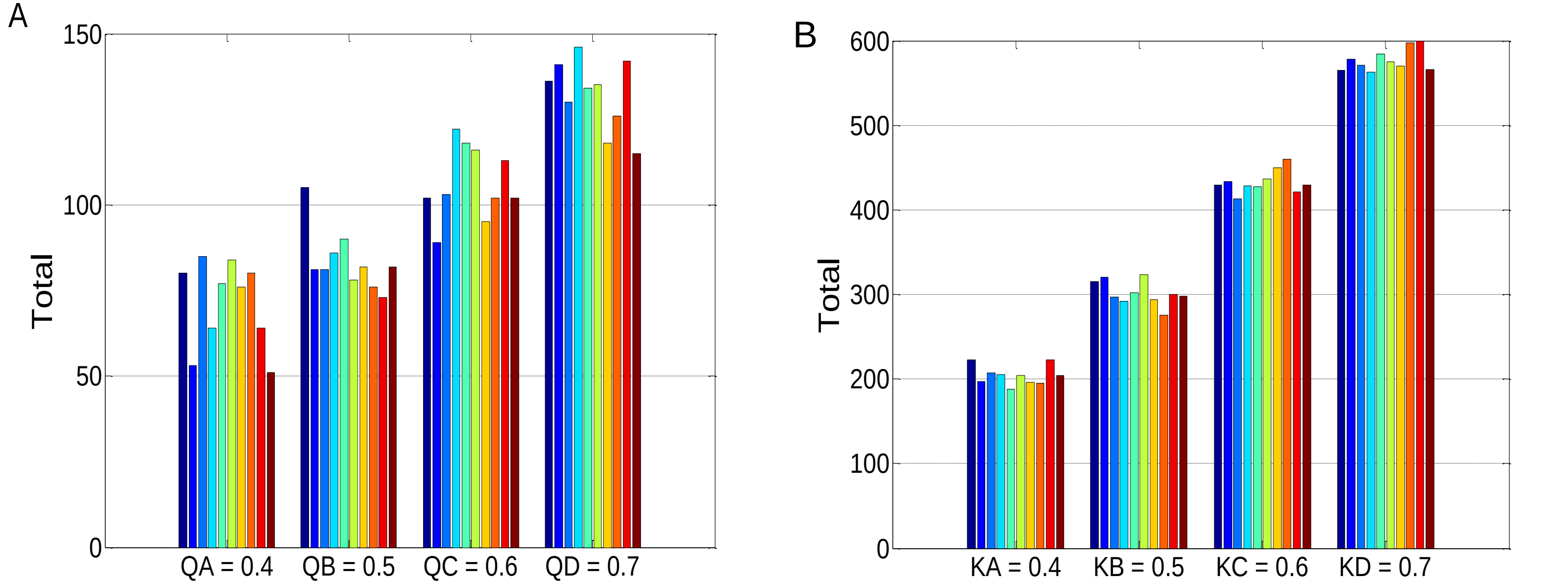
Battery electric vehicle preferences: A) Mass market (price, reliability), B) Early adopter (CO_2 , fuel economy) C) Trade-offs (acceleration) D) Exogenous effects (increasing refuelling). Network effects held constant

ABM can capture a range of outcomes – more consistent with empirical evidence showing multiple trajectories



Cumulative adoption for A) Liquefied natural gas (LNG), B) Compressed natural gas (CNG), C) Full battery electric, D) Ethanol-85 (E85), US 1992 – 2008 (DOE, 2008)

Accounting for evolving social network influence – clustering effects for indirect and direct network influence

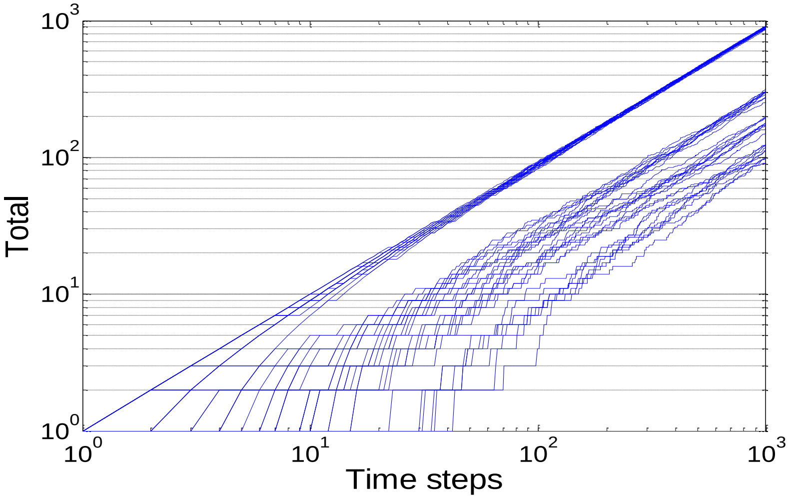


A) Increasing indirect influence (Q), direct influence held constant (K=0.1), low individual preference (P=0.02) held constant

B) Assume personal contacts (K) reflect local population behaviour and exerts influence on individual

Combined influence can have non-linear effects on individual adoption

Sensitivity analysis on all parameters



Parameters	S1	S2	S3	S4	S5
P	0.1	0.9	0.1	0.1	0.1
Q	0.1	0.1	0.9	0.1	0.9
K	0.1	0.1	0.1	0.9	0.9
Cumulative adoption range	100 - 150	850 - 950	250 - 300	150 - 200	850 - 950

S1 = Ref, S2 = Pref, S3 = Indirect, S4 =Direct, S5 = Combined

- High variability in short term but clear diffusion pattern over longer term
- Combined network effects can have as much influence as individual preference
- Indirect influence can have greater effect than direct personal contacts (‘influence through numbers effect’)
- **Indicates a mechanism to change risk averse behaviour?**

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Discussion and next steps

Constraints:

- Lack of network data (esp. on high investment technologies e.g. energy technologies)

Potential:

- Framework has wide ranging applications for technological and behavioural interactions
- ABM can give a distribution of possible outcomes instead of locking into single trajectories (‘magic number solutions’), can deal with future uncertainty rather than prediction
- How do agents balance internal strategy/preferences (profit maximization for service provision) and external influence (networked behaviour of competitors, changing consumer preferences, macro-level signals e.g. investment climate, policy incentives, etc.)
- How do personal (or firm-level) networks evolve with population level behaviour (larger network of service providers)? What is the direction and magnitude of the feedback effect?
- Can individual behaviour (habits, risk aversion, preferences, etc.) be outweighed by external network influence over time?
- What network topologies amplify behavioural signals at the individual, local and population levels?

How does agent behaviour scale up to impact the larger system e.g. disruptive technological change?

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Thank you!

Questions?

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