# The Market for Electric Vehicle Charging
# Innovation and Technology Adoption in Transportation

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# Technology Transitions in Transportation

- "A Tale of Two Market Failures" Jaffe, Newell, and Stavins (2005)
- Technological change in complex systems depends on complementary decisions
- For alternative fuel transport: refueling infrastructure essential but seemingly suboptimal
- This project: network competition in the electric vehicle (EV) charging industry
  1. What is the socially optimal spatial allocation of EV charging locations?
  2. What is the extent of inefficiency in spatial allocation of EV charging locations?
  3. How can policy correct any inefficiency that exists?

# Many trips in EVs would still deviate from fastest gas car route

Figure: 555 miles in gas car, 8.5 hrs

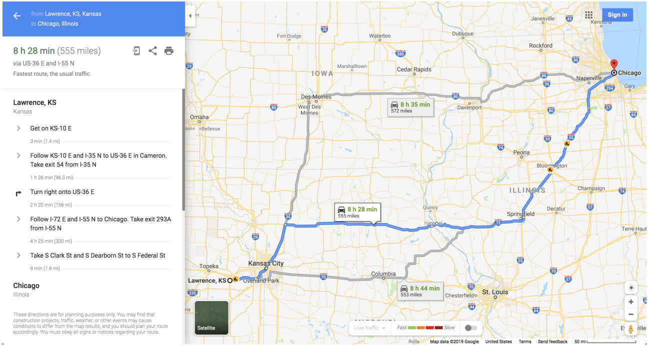
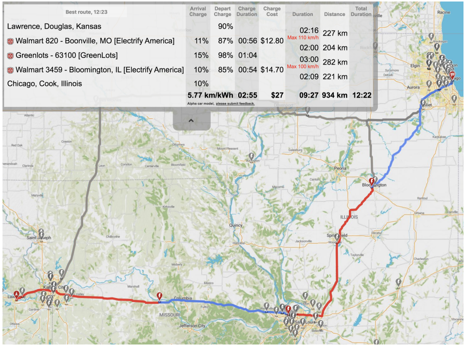
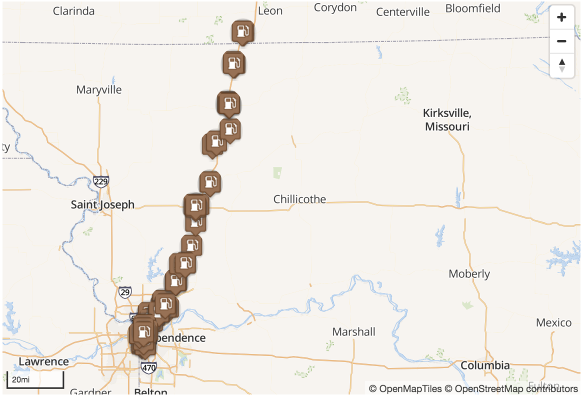



Figure: 580 miles in EV, 12 hrs 22 min




Lawrence, KS to Chicago, IL; Left - Google Maps; Right: abetterrouteplanner.com

# Dramatic difference in density of charging and gas stations along highways



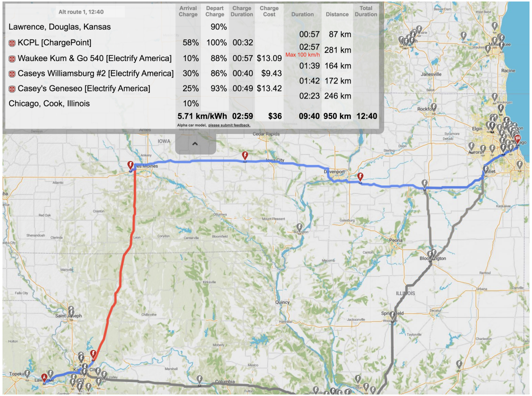



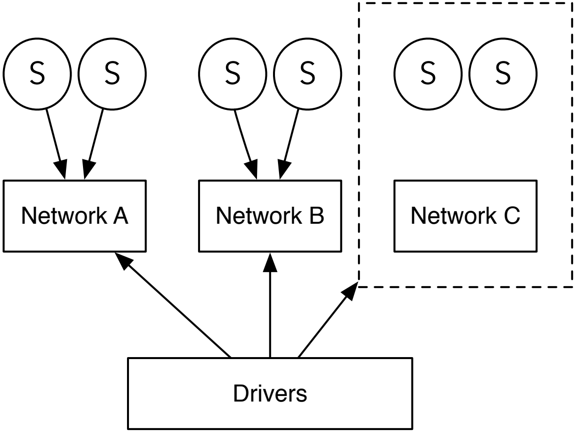

Figure: Interstate 35 between Kansas City and Des Moines

# Two potential coordination failures

1. Coordination between potential EV drivers and stations on a route (classic indirect network effect applied to routes rather than the overall market)

2. Coordination between potential station entrants along a route (coordination among producers of complementary goods)

# Vertically integrated or planned networks in the EV charging industry




Financing
Siting and install
Operational logistics

Payment logistics
Map and search

# Planned vs. open networks

- Planned network examples:
    - Electrify America - 143 locations, Volkswagen spinoff
    - AeroVironment - 61 locations operator of West Coast Electric Highway (Washington, Oregon, California governments, Nissan involvement in early years)
    - Seemingly deliberate siting choices

- Open network example:
    - ChargePoint - 8217 locations
    - ChargePoint has a few 'Express Charging Corridors' in collaboration with BMW and VW - a planned component in the network
    - Potential misallocation of stations across space
    - Potential over-entry due to business-stealing and inefficient subsidy allocation

# Compare three EV charging station allocations

1. Socially optimal allocation of EV charging stations
   - Preferences over trips
   - Preferences over fuel type
   - Social costs of EV station entry, environmental benefits
2. Private equilibrium - planned networks
3. Private equilibrium - no coordination among potential entrants

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- Policy questions
  - How different are the equilibria from each other?
  - How would we move the private equilibria closer to the socially optimal?

Thank you! Comments welcome.

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# R&D with Correlation and Learning

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# Motivation

- Combating climate change requires long-term investment in a diverse set of technologies
- How should we allocate R&D resources over time and among technologies?
  - Policy interest: Mission Innovation ($30b), Breakthrough Energy Venture ($22b), DoE ($8b), etc.
- How have governments allocated R&D resources?
  - Lessons for climate R&D funding

# This Paper

1. How do government R&D programs optimally allocate funding across projects and over time?
    - Theory: a simple model of dynamic decision making with 1) correlations in R&D outcomes among projects and 2) gradual resolution of the deployment benefit
2. How are we doing in practice?
    - Empirics: test how effectively DoE has allocated funding among nuclear energy R&D programs
        - Program-level R&D funding data from Abdulla et al. (2017)
        - To be combined with text data and contextual knowledge

# Literature

- Theory:
  - Markowitz (1952), Gibbons, Ross & Shanken (1989)
  - Roberts & Weitzman (1981), Pindyck (2002)
  - This paper: a simple multi-stage R&D allocation model
- Empirics:
  - Effect of government R&D on energy patents or publication: Johnstone et al. (2010), Verdolini & Gaelotti (2011), Peters et al. (2012), Dechezleprêtre & Glachant (2014), Nesta et al. (2014), Costantini et al. (2015), Popp (2016)
  - Determinants of government R&D effectiveness: Wuchty et al. (2007), Costantini et al. (2015), Canter et al. (2016), Popp (2017), Fabrizi et al. (2018)
  - Simulation based on expert elicitation: Anadon et al. (2016), Verdolini et al. (2018)
  - This paper: testing allocative efficiency of government nuclear energy R&D based on program-level data

# Outline

- Conceptual Model
  1. One technology
  2. Two technologies with correlations
  3. One technology with learning
- Data Source

# One Technology

$t = 1$: invest $x \geq 0$ in R&D given R&D effectiveness $a > 0$
$t = 2$: R&D succeeds with probability $P(x, a) \in [0, 1]$

- If it succeeds: deploy technology at intensity $y \geq 0$, paying cost $C(y) \geq 0$ and receiving benefit $B(y) \geq 0$
- If it fails: do nothing, $C(0) = 0$, $B(0) = 0$

Social planner's problem:

$$\max_{x,y \geq 0} P(x, a)(B(y) - C(y)) + (1 - P(x, a)) \times 0 - x$$

Parametrization:

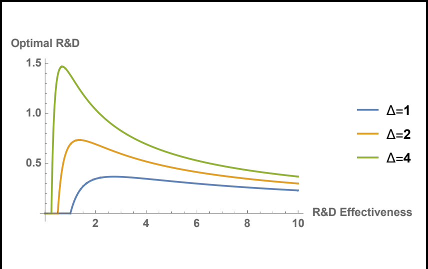
$$B(y) = \frac{y}{1+y}\gamma, \quad \gamma > 0$$
$$C(y) = ky, \quad k \in (0, \gamma]$$
$$P(x, a) = 1 - \exp(-ax)$$

Optimal deployment: $y^* = \sqrt{\frac{\gamma}{k}} - 1$

Net deployment benefit: $\Delta \equiv (\sqrt{\gamma} - \sqrt{k})^2$

Optimal R&D: $x^* = \frac{1}{a}\ln(a\Delta)$

Value of R&D: $V = \Delta - \frac{1}{a} - x^*$



# Two Technologies

Parametrization:

$$B(y_1, y_2) = \frac{y_1 + y_2}{1 + y_1 + y_2}\gamma$$

$$C(y_1, y_2) = k_1 y_1 + k_2 y_2, \quad 0 < k_1 < k_2 \leq \gamma$$

$$\Pr(d_1 = 0, d_2 = 0 | x_1, x_2) = \mu$$

$$\Pr(d_1 = 1, d_2 = 0 | x_1, x_2) = 1 - p_2 - \mu$$

$$\Pr(d_1 = 0, d_2 = 1 | x_1, x_2) = 1 - p_1 - \mu$$

$$\Pr(d_1 = 1, d_2 = 1 | x_1, x_2) = p_1 + p_2 + \mu - 1$$

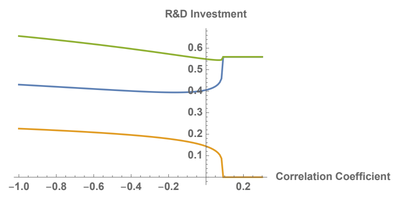
with

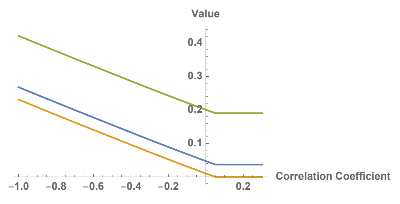
$$p_i \equiv P(x_i, a_i) = 1 - \exp(-a_i x_i) \qquad i = 1, 2$$

$$\mu = (1 - p_1)(1 - p_2) + \rho\sqrt{p_1 p_2 (1 - p_1)(1 - p_2)}$$

where $\rho \in [-1, 1]$ is the correlation coefficient of the two technologies' R&D outcomes.

# Two Technologies with Correlation




( Blue - cheap tech; Orange - expensive tech; Green - total )

# One Technology with Learning

$t = 1$: invest $x_1 \geq 0$ in R&D while facing uncertain $\gamma$
$t = 2$: with probability $p \in [0, 1]$, $\gamma \geq k$; otherwise, $\gamma < k$

- if last-period R&D succeeds, do nothing this period
- if it fails, can invest again this period

$t = 3$: Deploy the technology if it is deployable

Social planner's problem:

$$P(a, x_1) p \Delta + (1 - P(a, x_1)) p [P(a, x_2)\Delta - x_2] - x_1$$

Hence:

$$x_1^* = \frac{1}{a} \ln[p(1 + \ln(a\Delta))]$$
$$x_2^* = \frac{1}{a} \ln(a\Delta)$$
$$V = p\Delta - \frac{1}{a} - x_1^*$$

## Compare with Dixit and Pindyck

Without R&D uncertainty:

- Dixit and Pindyck (1994): wait until the benefit uncertainty resolves
  - Suppose investment $I > 0$ will surely bring R&D success
  - If invest at $t = 2$, get larger expected value:

$$p[(\sqrt{\gamma} - \sqrt{k})^2 - I]$$

  - If invest at $t = 1$, get smaller expected value:

$$p(\sqrt{\gamma} - \sqrt{k})^2 - I$$

With R&D uncertainty:

- invest right away iff $p(1 + \ln(a\Delta)) > 1$

# What Have We Learned from This Toy Model?

#1 Need to diversity the portfolio

#2 Cannot wait until we know the benefit better (under some conditions)

# Empirical Exercise: Testing Allocative Efficiency of the DoE Nuclear Energy Programs

Abdulla et al. (2017):

- Obtained annual budget justification documents from DoE through a Freedom of Information Act and constructed a database that traced both funding levels and project names and designations from 1999-2015

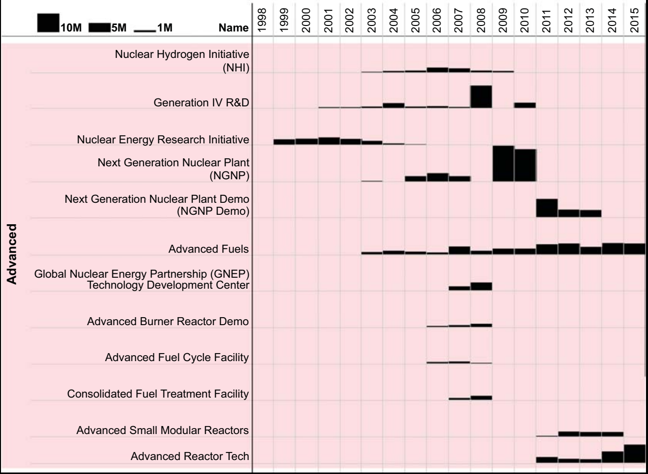



Figure 1: Part I of data from Abdulla et al. (2017)

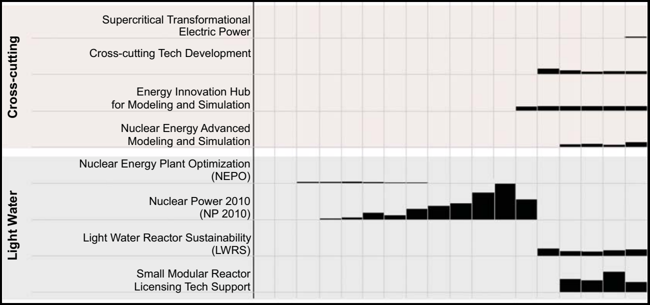



Figure 2: Part II of data from Abdulla et al. (2017)