Being in the Right Place at the Right Time: Investment Decisions in the Global EV Battery Industry

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Motivation

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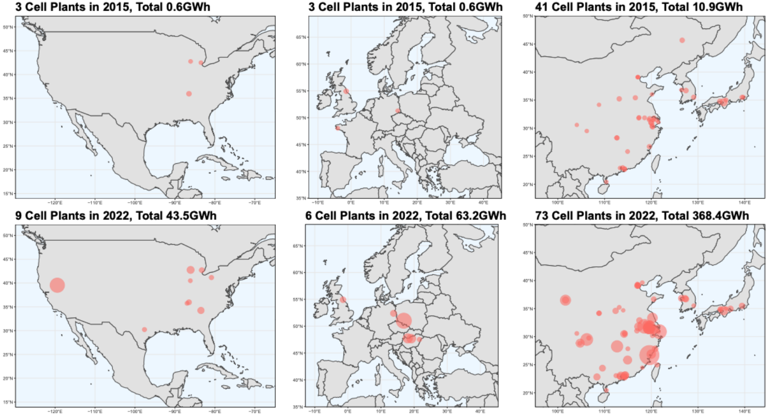
- EV battery is the most expensive part of an EV.
  - It takes up 20% - 60% of the total EV costs.
- Two facts about EV batteries
  - The production volume and installed capacity of EV batteries increased fast since 2015.
  - The distribution of EV battery firms and plants are uneven.

Motivation

Figure 2: Cell plants in the major regions



Source: Head et al., 2024

Motivation

Firm	Country	Market Share (%)
CATL	China	36.8
BYD	China	15.8
LG Energy Solution	South Korea	13.6
Panasonic	Japan	7.3
SK On	South Korea	5.4
Samsung SDI	South Korea	4.7
CALB	China	4.1
Gotion High-Tech	China	2.6
EVE Energy	China	2.3
Sunwoda	China	1.9
Total		**94.5**

Table: Top 10 EV Battery Producers in 2023

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Country	City	Year
China	Liyang	2018
China	Ningde	2019
China	Wuhan	2020
China	Xining	2020
China	Guangzhou	2021
China	Jingzhou	2021
China	Fuding	2022
China	Yibin	2022
Germany	Erfurt	2022
China	Xiamen	2024
China	Yichin	2025
Mexico	Chihuahua	2025
USA	Kentucky	2025
Hungary	Debrecen	2026
Indonesia	Halmahera	2027

Table: CATL Operations

Country	City	Year
South Korea	Ochang, Seoul	2010
USA	Holland, Michigan	2013
China	Nanjing 1st Plant	2016
Poland	Wroclaw	2018
Vietnam	Ha Tinh	2020
China	Ningbo	2021
USA	Lordstown, Ohio	2022
China	Nanjing 2nd Plant	2023
USA	Spring Hill, Tennessee	2023
Canada	Windsor, Ontario	2024
Indonesia	North Maluku	2024
USA	Lansing, Michigan	2024
USA	TBA	2025
USA	Arizona	2025
USA	Ohio	2025
Indonesia	Karawang	2026

Table: LG Energy Solution Operations

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- Different firms have different strategies in location choices of the plants.
- The location choice decisions can be affected by multiple factors.
  - Proximity to demand / supply
  - Supply chain stability
  - Factor cost considerations
  - Policy and regulations

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- **Research Questions**
  - how do battery producers make choices in real world?
  - what's the policy implications?

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  - **$3,750**: Foreign Entity of Concern Restrictions
- The Trump Administration: reshoring and trade war between China should continue.

Related Literature

- **Economics of EVs**:
  Barwick, Kwon and Li (2024), Barwick et al., (forthcoming), Remmy (2022)

- **Supply chain analysis**:
  Kukharskyy and Eppinger (2021), Bai et al(2020), Williamson(1979)

- **Dynamic optimization and location choices**:
  Rust(1987), Bajari, Benkard and Levin(2007), Holmes(2011), Houde, Newberry and Seim (2023).

Overview

1. Introduction.
2. Model.
3. Data.
4. Next Steps.

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- The decision of battery producers can be divided to two parts: static and dynamic
  - Static: In each period, battery producers decide the price and quantity of battery produced in each plant to maximize their profit;
  - Dynamic: The battery producers choose to make investment either to enlarge the capacity of the existing plant or build a new plant.

Static Model

Static Model

— Battery producer's problem

$$\pi^B = \max_{p^B} \sum_{i \in \mathcal{I}} (p_i^B - mc_i^B) q_i(p_i^B) \quad \text{s. t.} \sum_i q_i(p_i^B) \leqslant \bar{q}$$

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- where
  - $mc^B = DC + OC = \tau_1 d^{\text{up}} + \tau_2 d^{\text{down}} + \rho\text{Chem}$

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  - $mc^B = DC + OC = \tau_1 d^{\text{up}} + \tau_2 d^{\text{down}} + \rho \text{Chem}$
- Notations
  - $\mathcal{I}$: the set of batteries i owned by the battery producer;
  - d^{up} : the distance between the producer of raw materials and the EV battery plant;
  - d^{down}: the distance between the EV battery plants and the EV manufacturer.
  - τ_1 and τ_2: parameters for transportation costs;
  - Chem: chemistry type; ρ: cost parameter

Model: Estimation and Challenges

- Estimation
  - Parameters to estimate: τ_1, τ_2, ρ and $q(p_t^B)$.
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- Solutions
  - Nash Bargaining to estimate markup as a whole (Barwick et al., WP).

Model: Bargaining (Barwick et al., WP)

- Assume the Nash-in-Nash bargaining model (Horn and Wolinsky 1988)
- Each EV manufacturer-battery producer pair chooses battery price p_{vb}
- Maximize the Nash product of their net gains from trade, taking as given the battery prices chosen by all other pairs:

$$NP_{vb}(p_{vb}; p_{-vb}) = (\pi^v - d_{vb}^v)^{1-\lambda^b}(\pi^b - d_{vb}^b)^{\lambda^b}$$

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  - λ^b is the bargaining weight of battery supplier b
  - π^v and π^b are profits of EV manufacturer v and battery producer b
  - d^v and d^b are the disagreement payoffs: profits if negotiations fail.

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    * If v and b disagree over p_{vb}, the vehicle is not produced.

Model: Bargaining (Barwick et al., WP)

- EV manufacturers' profit from this pair

$$\begin{aligned}
\pi^{EV}(p) &= \sum_{k \in \mathcal{J}} (p_k - mc_k) q_k(p) \\
&= \sum_{k \in \mathcal{J}} (p_k - p^B - mc_k^v) q_k(p) \\
&= \sum_{k \in \mathcal{J}} mk_k^v q_k(p)
\end{aligned}$$

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  - mk^v: markup of EV manufacturers, can be estimated using BLP.

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- Estimation equation

$$p = mk^v + mk^b + mc^v + mc^b$$

$$p_{jct} - mk^v_{jct} = \frac{\lambda^b}{1-\lambda^b} A \, mk^v_{jct} + x_{jct}\gamma_v + [\tau_1 d^{\text{up}} + \tau_2 d^{\text{down}} + \rho \text{Chem}_{bjct}]\kappa_{bjct} + \text{FEs} + \omega_{jct}$$

  - x_{jct}: vehicle attributes
  - FEs: country FE, year FE, EV manufacturer FE and battery supplier FE
  - ω_{jct}: unobserved cost shocks or quality for battery and vehicle.

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- where
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- Notations
  - FC^e: the fixed cost to build the first plant at a location;
  - I_t: Investment level; k: Investment costs.
  - r : cost of running the capacity

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- Notations
  - FC^e: the fixed cost to build the first plant at a location;
  - I_t: Investment level; k: Investment costs.
  - r : cost of running the capacity
- Benefit of investment:
  - enlarge the set $\mathcal{J}$ and choose new location;
  - raise the capacity constraint: $\bar{q}_{t+1} = \bar{q}_t + I_t$

Dynamic Model: Identification (TBC)

- Possible ways to identify k, r and FC^e
  - Bajari, Benkard and Levin (2007)
    - Extended from Rust (1987)
    - Applied to oligopoly industry
    - Key insight: firms' equilibrium choices are observed in data
  - Holmes (2011)
    - Revealed preference approach
    - Identification strategy: **swap** the strategy to construct partial inequality moments

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Data

- **EV battery plant level data (2015-2023, 2024-2030) : ownership, location, capacity**
- EV battery data : attributes (chemistry, capacity)
- EV model level data : sales, attributes, price (2012-2022)
- Battery - EV pair data

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— Counterfactual analysis: the impact of Inflation Reduction Act (IRA) on the global EV battery industry

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- Counterfactual analysis: the impact of Inflation Reduction Act (IRA) on the global EV battery industry
- Real next steps
  - Collect the necessary data and explore the some facts;
  - Learn more about the theory and industry to finish the model and the estimation.

Thank you!

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