Investing in the Batteries and Vehicles of the Future: A View Through the Stock Market

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Disclaimer

All statements today reflect my own personal opinion and do not reflect the official opinion of the Federal Reserve Bank of Dallas nor the Federal Reserve System.

Introduction (1/2)

- Electric vehicles (EVs) and batteries viewed as key for a successful energy transition
- Many companies in the EV and battery supply chain have gone public on a major U.S. exchange since 2020
- Important literature investigates returns of "green" stocks, impact of ESG on asset returns
- Much less work focused on clean energy companies
- Essentially none focused on stocks of new EV and battery companies (EV stocks)

Introduction (2/2)

- Broad goal: Shed light on comovement among EV stock returns
- Comovement could be driven by:
  - Systematic factors that explain stock returns generally speaking
  - Factors specific to the EV and battery space
- Leads to two specific research questions:
  1. Do risk factors that affect stocks broadly speaking also help explain EV stock returns?
  2. Is there an "EV" factor present in the idiosyncratic returns of EV companies?
- This paper uses a statistical approach to answer these questions

Methodology

- Compile a novel data set of high-frequency stock returns for companies operating in the EV and battery supply chain
- Decompose EV stock returns into systematic and idiosyncratic components using regression model
  - Systematic components are latent factors extracted from large cross-section of stock returns (Pelger 2019, Pelger 2020)
- Document relationships between EV returns and latent factors
- Use principal components on idiosyncratic returns

Findings

- Risk factors that help explain cross-section of stock returns also explain EV stock returns
  - Market factor and a "tech" factor are most important (similar to tech stocks)
  - Explain about 20 percent of variation for typical EV stock
  - Systematic factors less important in 2023
- There is evidence for an EV factor in the idiosyncratic returns
  - First PC explains about 15 percent of idiosyncratic returns
  - Generates important comovement among most EV stocks
  - Also evidence for a "lithium" factor

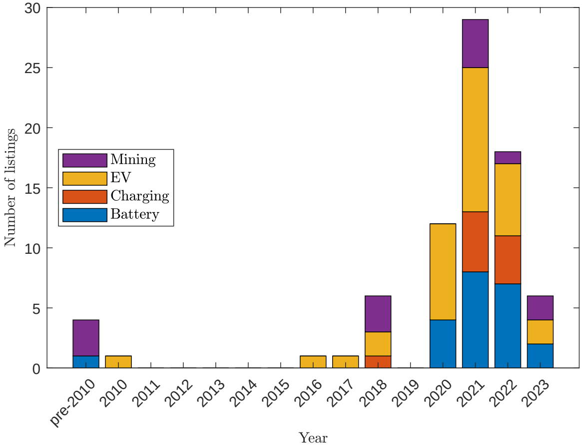
Literature

- "Green" stocks literature
  - Carbon emissions: Bolton and Kacperczyk (2021), Bauer at al. (2022), Aswani et al. (2023)
  - ESG scores: Alessi et al. (2021), Pastor et al. (2022)
- Asset returns of clean energy companies
  - Multi-factor asset pricing models: Henriques and Sadorsky (2008), Sadorsky (2012), Inchauspe et al. (2015)
  - Various other empirical works: Demiralay et al. (2023), Pham et al. (2023)
- What distinguishes my work:
  - Use of firm-level data
  - Focus on EV and battery supply chain
  - Focus on understanding comovement of returns (especially idiosyncratic)
  - Risk factors (statistical vs. observed)

Data

- Intra-daily price data sourced from Polygon.io
- Adjusted for splits and dividends using CRSP method
- Companies grouped into two sets:
  - Panel X: Large cross-section of stocks on S&P500 and Nasdaq 100
  - Panel Y: EV stocks
- EV stocks:
  - Use information from Bloomberg and others to find relevant companies
  - Companies are listed on a major U.S. exchange
  - Covers the entire supply chain: mining, advanced battery, lithium-ion, traditional battery, EV OEM, EV charging

IPO and Uplisting Dates



Practical Issues

1. Choice of frequency: 15 minute return interval
   - Selected based on tests of Ait-Sahalia and Xiu (2019)
2. Sample selection: Data for 2022-2023
   - 38 EV stocks: 8 mining; 9 battery; 17 EV OEMs; 4 charging
   - 12,883 log returns for each company
3. Robustness
   - Frequency and data source: Use daily return data from CRSP
   - Sub-sample analysis: Generate results for 2022, 2023 samples

Estimation of Factors

$$\underset{(T\times N)}{X} = \underset{(T\times K)}{F}\underset{(K\times N)}{\Lambda'} + \underset{(T\times N)}{e_t}$$

- X is the panel of stock returns on S&P 500 and Nasdaq 100
- Estimated loadings, $\hat{\Lambda}$, are eigenvectors associated with the K largest eigenvalues of $\frac{1}{N}X'X$ multiplied by $\sqrt{N}$.
- Estimated factors are $\hat{F} = \frac{1}{N}X\hat{\Lambda}$
- Number of factors, K, determined using test of Pelger (2019)
- Test identifies first five principal components as systematic

Five Systematic Factors Have Industry Interpretation

1. "Market" factor: Loads on all stocks
2. "Cyclical" / "Tech" factor: Loads positively on tech, communications, consumer discretionary, negatively on utilities, real estate, consumer staples
3. Oil and gas/materials/financial factor
4. Oil and gas factor
5. Utilities and real estate factor

Loadings

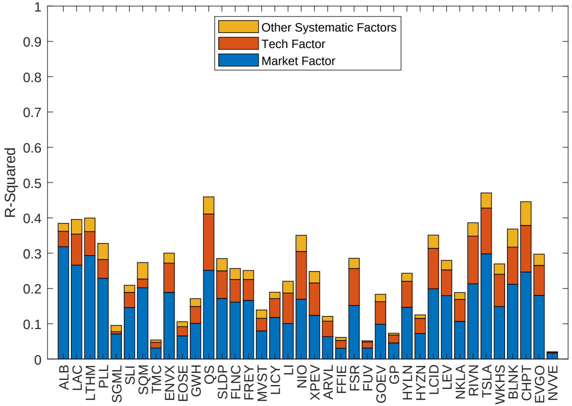
Regression Model for EV Stocks

- Use regression model to decompose returns:

$$r_{it} = \alpha_i + \sum_{j=1}^{\hat{K}} \beta_{ij} f_{jt} + \epsilon_{it},$$

- r_{it} is return on stock i at time t
- f_{jt} is systematic factor j for $j = 1, \ldots, \hat{K}$
- Systematic return: $\sum_{j=1}^{\hat{K}} \beta_{ij} f_{jt}$
- Idiosyncratic return: ϵ_{it}

Variance of EV Returns Explained by Each Factor



Explanatory Power of Market Factor

Table: Median R^2 for each factor across specific groups of companies.

Group	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
GICS10	0.21	0.00	0.19	0.23	0.00
GICS15	0.37	0.00	0.02	0.01	0.00
GICS20	0.39	0.01	0.00	0.01	0.02
GICS25	0.34	0.03	0.01	0.01	0.01
GICS30	0.18	0.18	0.02	0.00	0.01
GICS35	0.21	0.02	0.03	0.00	0.00
GICS40	0.40	0.01	0.06	0.01	0.00
GICS45	0.35	0.07	0.02	0.01	0.00
GICS50	0.28	0.02	0.01	0.01	0.01
GICS55	0.20	0.33	0.02	0.00	0.06
GICS60	0.34	0.03	0.02	0.01	0.08
All firms in X	**0.33**	**0.02**	**0.02**	**0.01**	**0.01**
Mining	0.22	0.04	0.00	0.01	0.01
Advanced battery	0.17	0.08	0.00	0.00	0.02
Lithium-ion battery	0.16	0.06	0.00	0.00	0.02
EV	0.12	0.07	0.00	0.00	0.02
EV charging	0.20	0.10	0.00	0.00	0.04
All firms in Y	**0.15**	**0.06**	**0.00**	**0.00**	**0.02**

Explanatory Power of Tech Factor

Table: Median R^2 for each factor across specific groups of companies.

Group	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
GICS10	0.21	0.00	0.19	0.23	0.00
GICS15	0.37	0.00	0.02	0.01	0.00
GICS20	0.39	0.01	0.00	0.01	0.02
GICS25	0.34	0.03	0.01	0.01	0.01
GICS30	0.18	0.18	0.02	0.00	0.01
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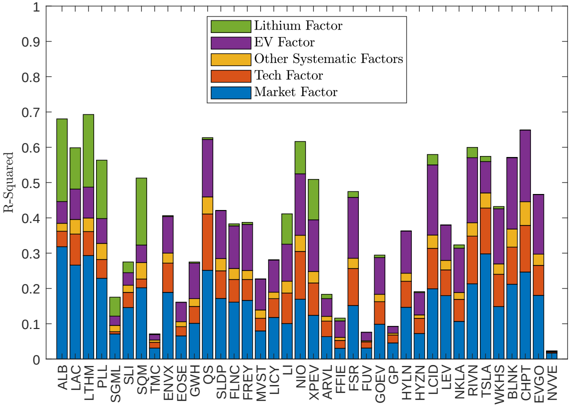
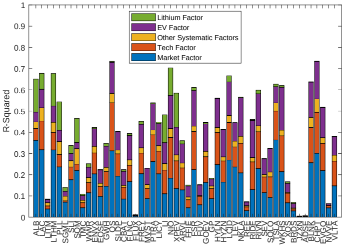
EV	0.12	0.07	0.00	0.00	0.02
EV charging	0.20	0.10	0.00	0.00	0.04
All firms in Y	**0.15**	**0.06**	**0.00**	**0.00**	**0.02**

Idiosyncratic Returns

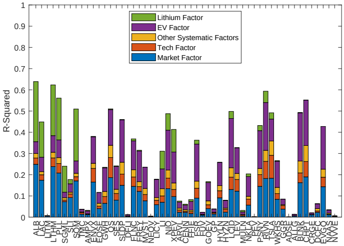
- Use PCA to extract latent factors from idiosyncratic returns
- Define "EV" factor as first principal component
  - Loads on all idiosyncratic returns
  - Explains about 15 percent of variation of that panel
- Second component loads heavily on lithium companies
- Repeat previous regressions but include EV and lithium factors

High Explanatory Power for Idiosyncratic Factors





(a) 2022 Sample



(b) 2023 Sample

Additional Results

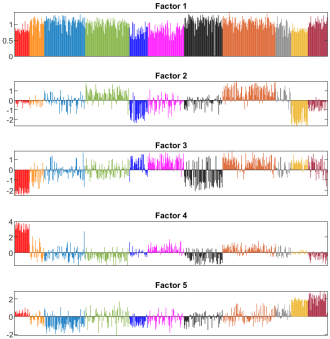
1. Frequency and data quality
    - Use daily return data from CRSP
    - Main findings hold
2. Sample
    - Consider 2021-2023
    - Full data for 23 companies
    - Results broadly similar to 2022-2023 sample

CRSP data Longer sample

Conclusions

- Investigated ability of statistical factors to explain EV stock returns
- Market and tech factors drive comovement with broader market (similar to tech stocks)
- EV and lithium factors help explain idiosyncratic variation in EV stock returns
- Future work:
  - Consider broader set of clean energy companies
  - Undertake more structural analysis of comovement

Factor Loadings



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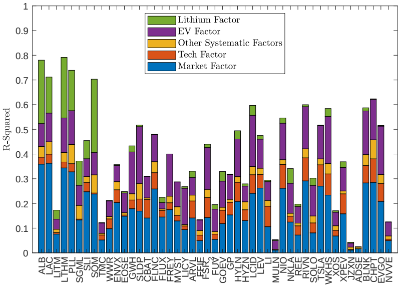
Daily Data



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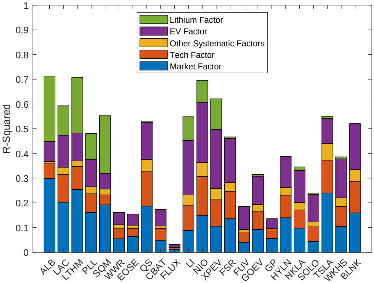
Long Sample



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