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

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

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Abstract

A large number of companies operating in the EV and battery supply chain have listed on a major U.S. stock exchange in recent years. This paper investigates 1) how these companies' stock returns are related to systematic risk factors that can explain movements in the stock market and 2) how these companies' idiosyncratic returns are related to one another. To do so, I compile a unique data set of intradaily stock returns that spans the supply chain, including companies focused on the mining of battery and EV-related critical minerals, advanced battery technology, lithium-ion battery production, EV original equipment manufacturers (EV OEMs) and EV charging companies. The returns are decomposed into a systematic and idiosyncratic component, with the systematic component given by latent factors extracted from a large panel of stock returns using high-frequency principal components. A key feature of the returns of interest is that they can be explained not only by a market factor but also by a second factor that loads on tech and consumer discretionary stocks. There is evidence for cross-sectional dependence in the idiosyncratic returns but correlations are generally low, except for some specific groups, e.g., lithium mining companies. The first principal component of the idiosyncratic returns, which can be viewed as an "EV" factor, explains only about 13 percent of their variation.

Keywords: stock returns; principal components; electric vehicles; batteries; high-frequency data

JEL Classifications: G10; Q40; C55

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1 INTRODUCTION

The energy transition is expected to lead to an enormous increase in the demand for electric vehicles and batteries.[1] This is creating opportunity for companies to expand the production of those goods and the key inputs used in their production. Capital is also being deployed to develop new technologies in these areas. Not surprisingly, there has been a proliferation of companies that operate in the electric vehicle (EV) and battery supply chain and, in recent years, a growing number of them have listed on a major U.S. stock exchange to take advantage of increased commercial interest.[2]

In this paper, I seek to answer several important and inter-related questions about the stock returns of these companies that have not been previously addressed in the literature. First, can these returns be explained by systematic (i.e. pervasive) risk factors that affect stock returns more generally? Second, if so, are there any specific patterns with respect to which of these factors are important? Do those patterns resemble other sectors in the economy or are they unique to companies operating in the EV and battery supply chain? Finally, how are the idiosyncratic returns of these companies related to each other? Is there any evidence for a systematic factor that specifically affects companies operating in the EV and battery supply chain?

To address these questions, I compile a unique data set of intradaily stock returns for almost 70 companies involved in the EV and battery supply chain that are listed on a major U.S. stock exchange. This data set spans the supply chain and includes companies focused on the mining of battery and EV-related critical minerals, advanced battery technology, lithium-ion battery production, EV original equipment manufacturers (EV OEMs) and EV charging companies. One challenge is that most of these companies have only gone public in the past few years, so data is limited. To overcome this challenge, I make use of high-frequency stock price data. This significantly expands the sample size and allows me to use recently developed methods for applying

[1] See, for example, projections and forecasts in IEA (2023) and Bloomberg (2023).

[2] This listing boom has coincided with a more general surge in the number of initial public offerings since 2020. See Dobridge et al. (2022) for details.

principal components analysis (PCA) to high-frequency data sets (Pelger, 2019 and Pelger, 2020).

Those works have shown that a small number of latent factors estimated using high-frequency principal components can explain stock returns. Following suit, I extract latent factors from a panel of stock returns that includes a large number of stocks found on the S&P 500 or the Nasdaq 100.[3] Statistical tests show that the first five principal components are important to explain variation in this panel during the sample period considered. Similar to the findings of Pelger (2020), each factor is connected with a specific set of industries. For example, one factor is a "market" factor that affects all stocks while another is an "oil" factor that is important for the returns of oil and gas companies but not other sectors.

I decompose the returns of companies operating in the EV and battery supply chain into systematic and idiosyncratic components by regressing them against the five latent factors. This exercise provides insight into the relationships that exist between the systematic risk factors and the returns of those companies. The regression analysis reveals a common pattern in that only two of the five latent factors have good explanatory power. One is the "market" factor while the other is, for lack of a better word, a "cyclical" or "tech" factor that loads positively on tech and consumer discretionary stocks but negatively on utilities and consumer staples. The relationship between the returns of EV and battery companies and the latent factors most closely resembles the one seen for tech and consumer discretionary stocks but is otherwise distinct when compared to other sectors, with the market factor having a below-average role and the tech factor an above-average influence.

This exercise also allows a comparison with auto and battery companies not heavily involved in the EV space. Doing so shows that the returns of more "traditional" companies have a very different relationship with the latent factors. For example, while the cyclical factor plays an important role for EV manufacturers such as Tesla, Rivian and Lucid it plays only a minor role for Ford and General Motors.[4] Likewise, the tech factor is very important for understanding the returns of companies developing new battery technology or producing lithium-ion batteries but has essentially no

[3]While the application of PCA to high-frequency data is relatively recent, the use of PCA to understand stock returns extends back to at least the 1980s. See, for example, Trzcinka (1986) and Connor and Korajczyk (1993).

[4]While Ford and GM are investing significant capital to expand EV production, EV sales continue to make up a very small fraction of total sales for both firms.

explanatory power for the returns of Energizer and EnerSys, two traditional battery producers.

The regressions also provide estimates for the idiosyncratic returns, which are typically an important component of the total returns of my companies of interest. Tests of cross-sectional dependence strongly reject the null hypothesis of no dependence but, in general, the correlations of the idiosyncratic returns across companies are relatively low. The mean correlation across more than 1,200 pairwise correlations is a little more than 0.09. The correlations of the idiosyncratic returns are stronger when looking at companies in some very specific groups, including lithium companies, a trio of Chinese EV OEMs and EV charging companies. The first principal component of the idiosyncratic returns loads on all of the companies and as such can be viewed as an "EV" factor. It only explains about 13 percent of the variation of the idiosyncratic returns. So, while there is substantial co-movement when looking at the total returns of these companies, a large fraction of that co-movement is due to systematic risk factors that broadly affect the entire stock market.

1.1 RELATED LITERATURE

An influential and growing literature in finance examines the returns from investing in green stocks. In this literature, firms are usually categorized as "green" or "brown" on the basis of some measure of environmental performance. Many works use carbon emissions as a measure. See, for example, Bolton and Kacperczyk (2021), Bauer et al. (2022), Huij et al. (2022), and Aswani et al. (2023). Other works have used environmental scores to categorize firms, e.g. Alessi et al. (2021) and Pástor et al. (2022). The focus of these works is typically on understanding whether the returns of green and brown firms differ and, if so, why. My focus on the EV and battery supply chain distinguishes my work from this literature, as does the specific questions I seek to address about the returns of these companies.[5]

A related strand of literature focuses on asset returns of clean energy companies, which are typically defined as such on the basis of their inclusion in an index with a clean energy focus,

[5]It might seem obvious that companies in the EV and battery supply chain should be "green" stocks but to the best of my knowledge that is a question which does not seem to have been systematically investigated. Works in this literature usually report results based on a large cross-section of stocks across numerous industries.

such as the Nasdaq OMX Green Economy Index or the WilderHill Clean Energy Index.[6] Many empirical works are found in this literature, exploring questions such as the connection between oil prices and the returns to clean energy indexes, risk-return profiles for those indexes, and the ability to forecast clean energy stock prices or index values. Recent examples include Demiralay et al. (2023), Pham et al. (2023), Roy et al. (2022) and Sadorsky (2022).

Among that literature, the most closely related works use multi-factor asset pricing models to understand how various risk factors affect the returns of clean or renewable energy companies. Henriques and Sadorsky (2008) investigate the WilderHill Clean Energy Index using a model that contains a market return, oil prices and interest rates; Sadorsky (2012) use a time-varying parameter version of the CAPM model on a cross-section of stock returns from the WilderHill Clean Energy ETF; Bohl et al. (2013) apply a time-varying parameter version of the Carhart four-factor model to two German renewable energy stock indexes; Inchauspe et al. (2015) investigate the WilderHill New Energy Global Innovation Index using a time-varying parameter CAPM model; Roy et al. (2022) use variants of Fama-French factor models to generate idiosyncratic volatility measures for 95 clean energy stocks; Demiralay et al. (2023) present results using a CAPM model applied to various NASDAQ OMX Green Economy sub-sector indexes.

My work differs from previous works in several important regards. First is the focus on the EV and battery supply chain. Most earlier works, whether using multi-factor models or not, use aggregate indexes that have wide coverage across the renewable/clean energy space. Even in cases where firm-level return data is used, the overlap with my data set appears minimal. For example, Roy et al. (2022) use company level stock returns for 95 companies but less than 5 of them are in my data set. This partially reflects that most of the companies on which I focus on have gone public only in recent years in addition to the more general focus of earlier works on renewable energy more broadly speaking.

Second, the risk factors I use in my analysis are also novel in this literature. Previous studies have used variants of the CAPM or Fama-French models or included observed risk factors, such

[6]The terms clean energy company and renewable energy company are often used interchangeably in this literature.

as the returns of tech stocks and oil prices. I instead work with latent factors extracted from a large panel of stock returns. I view my work as complementary to previous works in that I 1) provide new insights into how an important sub-set of the clean energy space is related to systematic risk factors that affect the broader stock market; and 2) shed light on how the returns of these companies are related to each other after controlling for systematic risk.

Finally, the specific set of questions I seek to address here have not been, to the best of my knowledge, explored in either the green stock or clean energy literature for any grouping of companies. I am also unaware of any works in those literatures that have used high-frequency principal components as a tool to address questions of interest.

My work also makes use of recently developed tools in the high-frequency financial econometrics literature. In particular, I rely on tools developed and used in Aït-Sahalia and Xiu (2019), Pelger (2019) and Pelger (2020).[7] I do not contribute any theoretical insights to this literature but instead join it by applying these tools to address questions about clean energy stocks which, to my knowledge, have not been considered before from this angle.

The rest of the paper proceeds as follows. Section 2 introduces the data set and the methodology used to extract latent factors. Section 3 presents the main results and discusses implications of those results. Section 4 considers some robustness checks and additional results. Section 5 concludes.

2 Data and Methodology

2.1 Data Intradaily stock price data is sourced from Pitrading.com, a private provider of high-frequency stock price data. Stocks prices are adjusted for splits and dividends by the provider using the same method as the Center for Research on Security Prices (CRSP). The price data come in one-minute intervals, although not every company has an observation for every minute. Working with this data requires choosing a frequency to construct returns, which I discuss in the methodology subsection.

I group the companies into two sets. The first set is a broad cross-section of companies that are

[7] See Aït-Sahalia and Jacod (2014) for a detailed introduction to the subject.

on the S&P 500 or the Nasdaq 100. The returns of these companies are stored in a $T \times N_x$ matrix X, where T is the number of time-series observations and N_x is the number of companies in the panel. The second group is composed of companies that operate in the EV and battery supply chain. Their returns are stored in a $T \times N_y$ matrix denoted as Y, where N_y denotes the number of companies in Y. The exact values for T, N_x and N_y will depend upon the sample period but I note here that regardless of the sample I always work with balanced panels.[8]

One contribution of this paper is to assemble a novel data set of stock returns for companies that operate in the EV and battery supply chain. The first step is to determine which firms belong in this data set. I compile a list of potentially relevant companies found on the S&P 500, the Russell 3000 or listed on Nasdaq using information from publicly available sources and from Bloomberg.[9] I identify 69 companies for possible inclusion in the data set. Table 3 lists these companies, their stock ticker, their exchange, as well as a category and sub-category used to help group the companies. The main categories are: mining, battery, electric vehicle, and EV charging. Sub-categories provide additional information, where possible, on the focus of each company.

Most of the firms in the mining group are lithium companies. Among battery companies, the "advanced battery" sub-group develops new battery technology. The "lithium-ion" group focuses on producing lithium-ion batteries. I do not do so but these companies could be further distinguished by their end market, e.g. some produce lithium-ion batteries for use in EVs while some produce batteries used in other applications. The "traditional" battery group includes three companies that do not focus on EVs or lithium-ion batteries but are included because they will make useful comparison points. The "battery materials" group contains three companies that produce inputs used in the production of battery cells.

Among the EV group, I categorize firms into original equipment manufacturers (OEM) or other. Three Chinese OEMs are listed on an American exchange but sell predominantly in the Chinese

[8]The data for the stocks in panel X are sourced from the Historical Intraday Stock Data set from Pitrading while most of the stocks in Y need to be purchased separately.

[9]Bloomberg provides short descriptions of a company's main line of work. Those descriptions were searched for matches with relevant keywords, such as electric vehicle, lithium, and battery. Any company with a match was then manually checked and included in the list if deemed relevant.

market. Only three firms are grouped in the other category. One, JZXN, is a Chinese company that focuses on selling EVs in China, while the other two companies focus on electric scooters.

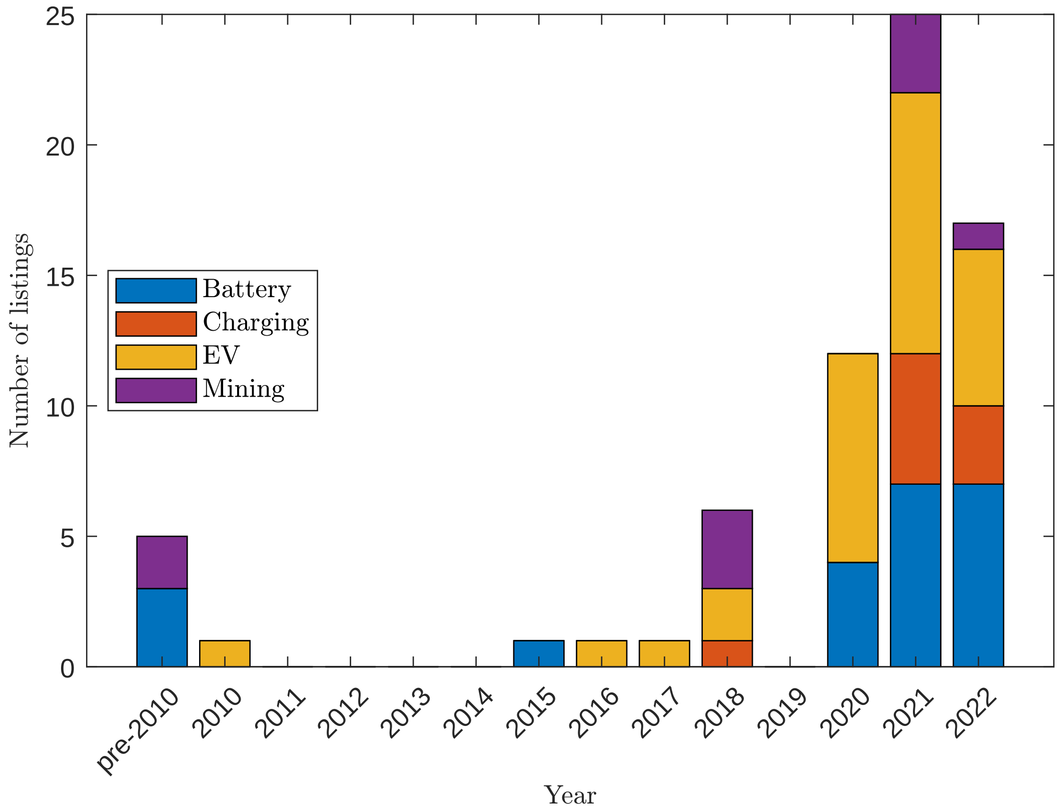
Finally, among the charging group I broadly consider an equipment sub-group and a services sub-group. The former focus more on the production of charging equipment itself while the latter focus more on operating charging stations and providing other services to end-users.

Using information from company announcements, news wires, and other public sources I have compiled the dates when these companies had either their initial public offering (IPO) or were uplisted to a major exchange. Figure 1 shows the number of listings each year through 2022.[10] Reflecting growing interest in electric vehicles and batteries, a large majority of these listings occurred in recent years. The first IPO in my data set directly related to electric mobility occurred much earlier, though, when Tesla had its initial public offering in 2010. Several companies listed before Tesla, although when they did so it would not have been directly linked to electric vehicles. These five are Albemarle (ALB), a lithium company; Ultralife Corporation (ULBI), which sells batteries and communications systems; CBAK Energy (CBAT), a Chinese lithium-ion battery company that produces batteries used in consumer applications; EnerSys (ENS), a battery producer focused on lead-acid batteries; and Westwater Resources (WWR), a mining company focused on graphite.

Many of the companies that have gone public in recent years have done so through mergers with a special purpose acquisition company (SPAC), i.e. through a reverse SPAC. For those companies, I only use price data after the company itself has listed and not the SPAC. For example, QuantumScape (QS) went public on November 27, 2020, merging with Kensington Capital Acquisition Corp. I only consider data for ticker QS starting on November 27. Generally, the behavior of the returns is quite different pre and post-merger. There are also a few companies that have uplisted from over-the-counter (OTC) markets to one of the major exchanges. In that case, I only consider price data for the company when it was on the major exchange, as OTC stocks are typically less

[10] The pace of listings has slowed dramatically in 2023, with one IPO and two uplistings. VinFast Auto (VFS), an EV OEM, had its IPO in August; Electrovaya (ELVA), a lithium-ion battery producer, uplisted to the Nasdaq in July; American Battery Technology Company (ABAT), a battery materials company, uplisted to Nasdaq in September.

Figure 1: Listings per year for EV and battery companies



liquid, have many fewer trades and often have data quality issues.[11]

2.2 METHODOLOGY It is assumed that the stock returns in X can be modeled by an approximate factor model,

$$X = F\Lambda' + e \tag{1}$$

where F is a $T \times K$ matrix of factors, Λ' is a $K \times N_x$ matrix of loadings and e is a $T \times N_x$ matrix of residuals. This assumption decomposes the return of company i at time t into a systematic return, given by the factors, and an idiosyncratic return, given by the residuals.

The factors and loadings are estimated by applying principal components to the variance-covariance matrix of X. The exact method I use is a specific case of a more general method discussed in detail in Pelger (2019) and Pelger (2020). The returns for each stock in X are first

[11] See Eraker and Ready (2015) for a discussion of some issues involved with using price data for OTC stocks.

de-meaned and then standardized to have unit variance. Λ and F are not uniquely identified so the standard assumptions that $\frac{\hat{\Lambda}'\hat{\Lambda}}{N} = I_K$ and $\hat{F}'\hat{F}$ is a diagonal matrix are imposed. The loadings are estimated as the eigenvectors associated with the Kth largest eigenvalues of $\frac{1}{N}X'X$ multiplied by $\sqrt{N}$. The factors are then calculated as $\hat{F} = \frac{1}{N}X\hat{\Lambda}$.

It is necessary to estimate the number of systematic factors, $\hat{K}$. To do so, I employ the perturbed eigenvalue test of Pelger (2019). Define $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_N$ as the ordered eigenvalues from $X'X$. Let $\hat{\lambda}_k = \lambda_k + \sqrt{N}$ be the "perturbed" eigenvalue associated with the kth factor. The perturbed eigenvalue ratio statistic equals

$$ER_k = \frac{\hat{\lambda}_k}{\hat{\lambda}_{k+1}}$$

for $k = 1, ..., N-1$. As discussed in Pelger (2019), the value of ER_k will be well above 1 for factors that are systematically important, while it will tend towards a value of 1 for factors that are relatively unimportant for explaining variation in the panel. The estimate of the number of systematic factors in the panel is then chosen as

$$\hat{K}(\gamma) = max\{k \leq N-1 : ER_k > 1+\gamma\},$$

where $\gamma > 0$ is a cutoff term set to 0.08 following Pelger (2020).

The returns of EV and battery companies are decomposed into a systematic and idiosyncratic component using a simple OLS regression model,

$$r_{it} = \alpha + \sum_{j=1}^{\hat{K}} \beta_j f_{jt} + \epsilon_{it}, \tag{2}$$

where r_{it} is the return of company i at time t, f_{jt} is the value of factor j at time t and ϵ_{it} is the residual for company i at time t. The systematic return is given by $\sum_{j=1}^{\hat{K}} \beta_j f_{jt}$ while the idiosyncratic return is given by the residual.

2.3 SAMPLE AND FREQUENCY

Applying this methodology requires choosing a sample period over which to extract the factors. In general, more data is preferred to less since this provides more observations for estimating the variance-covariance matrix. In my application, though, there is a tradeoff to considering very long samples because the number of EV and battery firms shrinks rapidly, even going back just a few years. Given this, I produce a set of base results using a sample for 2022. Companies are dropped if they do not have a full set of data. The X panel then has a total of 565 companies while there are 51 companies in the panel of EV and battery companies. Of those, there are 8 mining companies, 14 battery companies, 23 EV companies; and 6 EV charging companies. I also report results for a longer sample that starts in 2021.

One also needs to select a frequency at which to construct returns. The original price data allows for returns at a one-minute frequency, but careful consideration needs to be given to issues regarding market microstructure noise and infrequent trading, which can lead to asynchronous returns and a large of number of zero returns. It is common in the high-frequency finance literature to use 5-minute returns but an important concern with my data set is that many of the companies of interest are relatively small and their shares may not be very liquid. As shown in Aït-Sahalia et al. (2020), there are many cases where a five-minute window can be too short.

To provide guidance, I test for the presence of noise using the H_{3n} statistical test of Aït-Sahalia and Xiu (2019). Essentially, the test makes use of the fact that the realized volatility of the returns (the sum of squared log-returns) is both an efficient and a consistent estimator of the volatility when noise is not present whereas it is inconsistent in the presence of noise. Aït-Sahalia and Xiu (2019) propose several alternative estimators that are consistent even in the presence of noise but inefficient when no noise is present. They show that a Hausman test can be constructed using these estimators. The H_{3n} test is one variant that is robust to the presence of jumps in the data. Under the null hypothesis that the data is not contaminated with noise, the test statistic is asymptotically distributed as χ^2_1. This test shows that a 15-minute interval is generally appropriate for most of the EV and battery stocks.

Based on these test results, I construct log-returns for each company using a 15 minute window. I focus strictly on the intradaily returns in my base results. For the 2022 sample, this provides a total of $T = 6461$ returns. I also consider a follow up exercise where I use a sample spanning 2021 and 2022. This includes 26 EV and battery companies with $T = 12922$ for the number of returns.

Table 1: Perturbed eigenvalue test statistics and R^2 values

	Test statistic	R^2
Factor 1	4.67	.37
Factor 2	1.58	.07
Factor 3	1.36	.04
Factor 4	1.29	.02
Factor 5	1.16	.02
Factor 6	1.00	.01

Even given the tests, one might remain concerned about the presence noise in the data or about quality control issues associated with using a third-party data provider. In the robustness section, I consider a check on both of these issues by making use of daily stock returns sourced from CRSP, which is viewed as the highest quality source for stock return data. I find that the results are very similar, providing evidence that neither of these issues play a role in my main findings.

3 RESULTS

3.1 LATENT FACTORS The first step is to select the number systematic factors in X and then provide information on what those factors identify. The second column of Table 1 shows the perturbed eigenvalue test statistics for the first six principal components. The test statistic will tend toward 1 for factors that have little explanatory power for the panel. Using the cutoff value of 1.08 leads to a selection of the first five factors as being systematic in the 2022 sample. The variance explained by each factor is reported in the third column of table. In total, the first five factors explain roughly 52 percent of the variation of the panel. The first factor explains about 37 percent, the second 7 percent, the third about 4 percent and the fourth and fifth about 2 percent each.

One method for understanding what the factors represent is to plot their loadings, which are shown in Figure 2. The companies have been sorted, left-to-right, by their two-digit Global Industry Classification System (GICS) codes.[12] The two-digit codes are color-coded.

[12]The GICS groups companies into 11 different sectors: energy (code 10); materials (code 15); industrials (code 20); consumer discretionary (code 25); consumer staples (code 30); health care (code 35); financial (code 40); information technology (code 45); communication services (code 50); utilities (code 55); real estate (code 60).

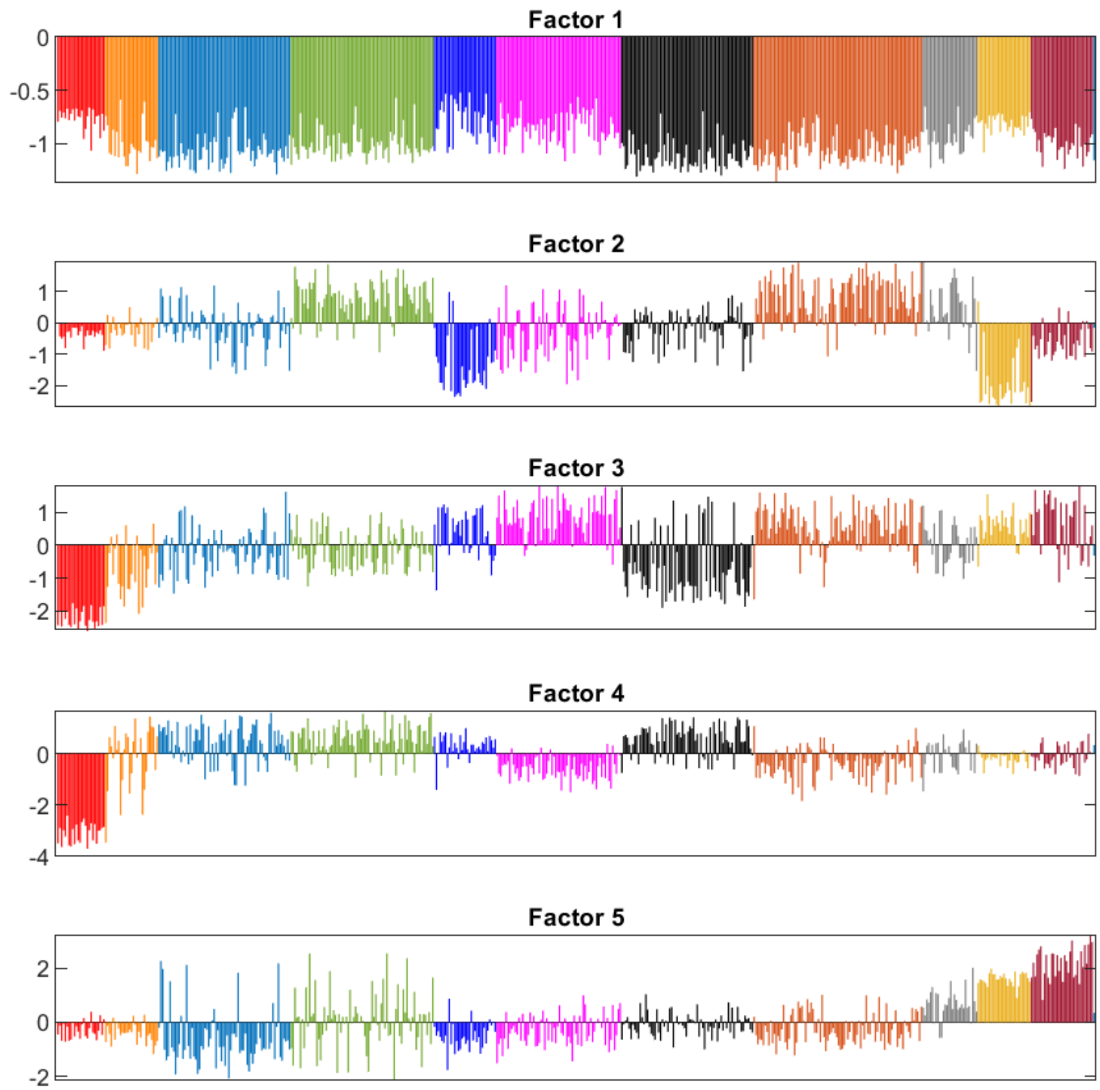


Figure 2: Loadings of the five systematic factors. Stocks are sorted by their two-digit GICS code. In order these are energy (red); materials (orange); industrials (light blue); consumer discretionary (green); consumer staples (dark blue); health care (pink); financials (black); tech (dark organge); communications (gray); utilities (yellow); real estate (maroon).

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

Group	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
GICS10	0.20	0.01	0.20	0.21	0.01
GICS15	0.39	0.01	0.03	0.01	0.00
GICS20	0.43	0.01	0.01	0.02	0.01
GICS25	0.41	0.03	0.01	0.01	0.00
GICS30	0.20	0.18	0.02	0.00	0.00
GICS35	0.26	0.02	0.03	0.01	0.01
GICS40	0.47	0.01	0.05	0.01	0.00
GICS45	0.44	0.05	0.02	0.00	0.01
GICS50	0.36	0.02	0.01	0.00	0.01
GICS55	0.22	0.33	0.02	0.01	0.06
GICS60	0.35	0.04	0.04	0.00	0.06
All firms in X	0.37	0.03	0.02	0.01	0.01
Mining	0.18	0.06	0.00	0.03	0.00
Advanced battery	0.21	0.11	0.00	0.01	0.02
Lithium-ion battery	0.10	0.06	0.00	0.01	0.02
Traditional battery	0.28	0.01	0.00	0.01	0.00
EV	0.15	0.14	0.00	0.01	0.02
EV other	0.01	0.00	0.00	0.00	0.00
EV charging	0.20	0.14	0.00	0.01	0.03
All firms in Y	0.14	0.08	0.00	0.01	0.01

The first factor is easily understood as a market factor that loads on all stocks in the same direction and reflects broad stock-price movements regardless of industry. The second factor loads positively on consumer discretionary stocks (GICS code 25), tech stocks (GICS code 45) and communications companies (GICS 50). It loads negatively on other sectors, in particular consumer staples (GICS code 30), utilities (GICS code 55) and real estate (GICS code 60). Given these loadings, one could loosely view the second factor as a "cyclical" factor, since it reflects periods where returns of industries often referred to as "cyclical", such as tech and consumer discretionary, move in the opposite direction to the returns of utilities and consumer staples, sectors often thought of as "defensive." The third factor loads negatively on oil and gas (GICS code 10), materials (15) and finance companies (40) while the fourth factor loads mainly on oil and gas companies. The fifth factor loads on utilities and real estate, and positively on most other stocks.[13] It is also useful to examine the ability of each factor to explain variation in the returns of the companies in X. To do this, I regress the returns of stock $i = 1, 2, \ldots, N_x$ on a constant and factor j, one-at-a-time for $j = 1, ..., 5$, and store the R^2 for each j. By definition, the factors are orthogonal to each other so

[13]Despite the differences in samples and data sets, the systematic factors that I estimate are similar to those found in Pelger (2020), based on a visual examination of the loadings found in Figure 4 of that paper. The first factor in Pelger (2020) is a market factor that loads on all stocks in the same direction; the second factor loads heavily on oil companies; the third factor loads negatively on energy and finance companies and positively on most other sectors, and the fourth factor loads positively on utilities and negatively on technology stocks.

the sum of the individual contributions to R^2 is exactly the same as a regression of stock i on all j factors.

The upper portion of Table 2 reports the median R^2 for every factor across each GICS code. The first factor has broad explanatory power for all stocks regardless of sector. The second factor has very high explanatory power for utilities (GICS 55), consumer staples (GICS 30) and, to a lesser degree, tech stocks (GICS 45) and consumer discretionary (GICS 25). Based on its ability to explain returns, the third factor is primarily an oil and gas factor, although it has some explanatory power for finance companies and several other sectors. The fourth factor, however, appears to be a pure oil and gas factor. The fifth factor explains mainly the returns of utilities and real estate.

3.2 Systematic returns of EV and battery companies

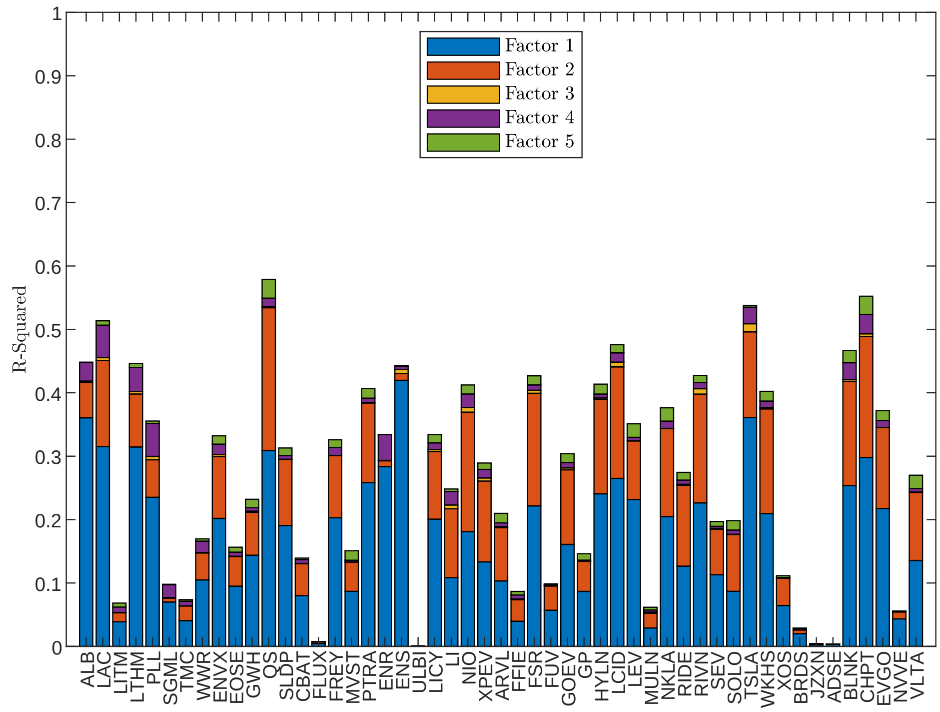
This section investigates the relationship between the latent factors and the returns of companies in the EV and battery supply chain. The main questions of interest are whether the factors can explain those returns and, if so, whether there are any specific patterns that emerge about which factors are important. It is also considered whether those patterns resemble other sectors in the economy or whether they are unique to the companies being considered.

To answer these questions, the returns are first regressed on a constant and the factors, one-at-a-time, to produce R^2 values for each factor and each firm. Figure 3 shows the explanatory power of each factor for each stock. The contribution of the market factor is shown by the blue bar, the "cyclical" factor by red, the third and fourth factors (the oil factors) by yellow and purple, while the green bar is for the fifth factor.

As a group, the factors have explanatory power for most of the stocks. In a few cases, the explanatory power is substantial, with the R^2 exceeding 50 percent.[14] A general pattern that emerges from Figure 3 is that the first two factors are the ones with good explanatory power. To much a lesser degree, the fourth factor plays a modest role, particularly for the lithium companies, Energizer (ENR) and a few other companies. Put differently, most of the companies of interest are

[14] There are also a few stocks for which the factors have essentially no explanatory power. Those all had very large test statistics for the H_{3n} test, evidence that those returns are contaminated with noise.

Figure 3: Breakdown of explanatory of systematic factors for individual stocks



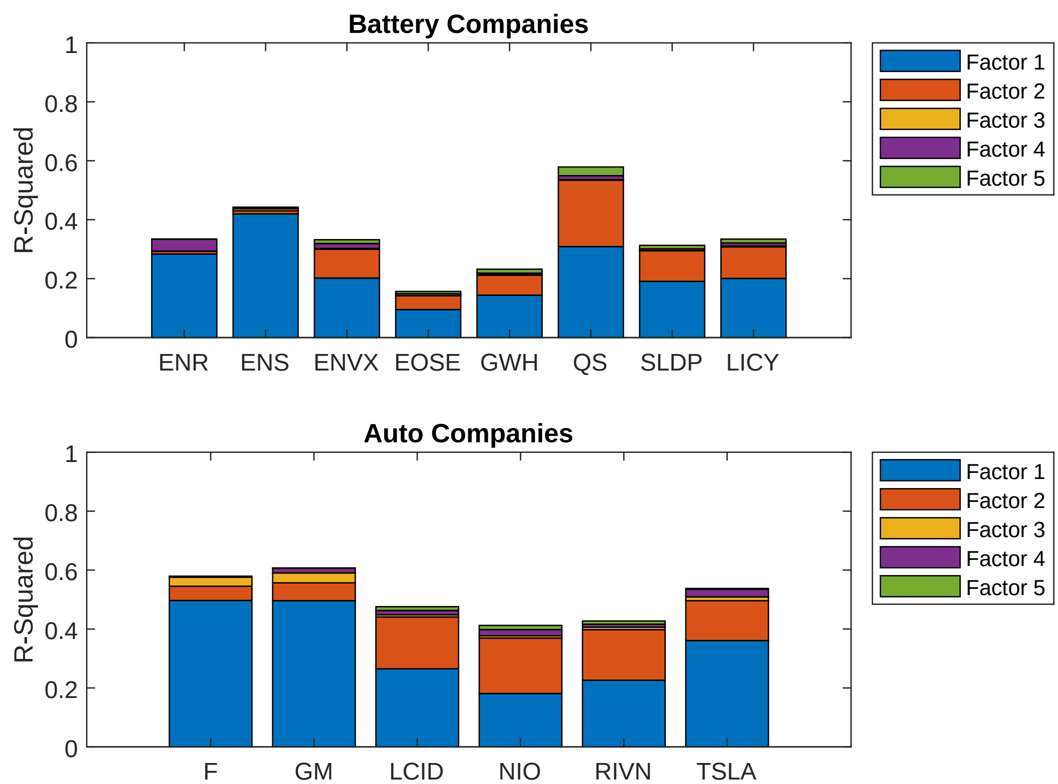
exposed to market risk and also risk associated with cyclical stocks, such as tech companies.

These patterns are more succinctly summarized in the bottom portion of Table 2 which shows the median R^2 of the factors across the specific groups used to categorize the firms in Table 3. The market factor plays a role in explaining the returns although its explanatory power varies across groups. The second factor is also important, particularly for the advanced battery, EV OEM and EV charging groups. The median R^2 of the second factor for these companies is well above the median for most industries, except for utilities and consumer staples. The second factor also has explanatory power for the mining and lithium-ion battery groups, although to a lesser degree.

While the second factor is important, Table 2 does not provide any guidance as to which direction that risk factor loads onto the returns. This is important to know because the loadings show that the second factor loads in opposite directions for cyclical and defensive sectors.[15] The betas from the regressions were investigated and found to be positive for all companies in the panel Y

[15] Of course, "direction" is arbitrary in the sense that the factor could be rotated so that it loads positively on utilities and negatively on tech sectors. More important is the fact that it picks up co-movement in the opposite direction.

Figure 4: Comparing return profiles for traditional vs. EV-focused companies



with exception of two of the "traditional" battery companies. As such, the stock returns of companies in the EV and battery supply chain respond to the cyclical factor in the same direction as tech and consumer discretionary stocks.

Interestingly, the traditional battery group has a very different profile then the other battery groups. The top panel of Figure 4 shows the R^2 of each factor for Energizer and EnerSys, the advanced battery companies, and Li-Cycle (LICY), a startup battery recycling company in the battery materials group. The advanced battery companies and LICY have a distinct pattern compared with Energizer (ENR) and EnerSys (ENS). For the traditional companies, the market factor plays a key role in explaining their returns while the tech factor plays essentially no role.

This type of comparison can also be done for EV OEM companies, because Ford (F) and General Motors (GM) are included in the panel X. The bottom panel of Figure 4 compares the

R^2 for Ford and GM, on the one hand, with Lucid, Nio, Rivian and Tesla, as examples. The patterns are quite distinct across the two groups. The tech factor plays an important role in the EV companies but only a minor role in Ford and GM, while the market factor is the dominating factor in explaining the returns of Ford and GM.[16]

With respect to the relationship between the latent factors, the returns of companies in the EV and battery supply chain most closely resemble tech stocks. *Ex post*, there is some logic to this finding as many of these firms are similar to tech companies and startups in certain important ways: They often have little current revenue and are, essentially, a bet on the success of a particular technology, a particular brand (in the case of an EV company), or a very particular set of assets (in the case of some of the mining companies).

It is worth highlighting that previous works have documented that tech stock returns help explain the returns of many renewable energy companies or indexes. These works typically use multi-factor asset pricing models that include tech stock returns as an observed risk factor. My results are somewhat different in nature from these previous findings. They suggest it is not so much that tech stocks can help explain EV and battery returns; rather, EV and battery stocks ARE tech stocks, at least in terms of how they are exposed to systematic risk factors that affect the entire stock market during the sample period. Another worthwhile difference: the focus here on EV and battery companies, whereas the focus in earlier papers is generally on other parts of the clean energy space.

3.3 IDIOSYNCRATIC RETURNS OF EV AND BATTERY COMPANIES

This section investigates the properties of the idiosyncratic returns, which the bottom portion of Table 2 implies are an important part of the overall returns. I first test for the presence of cross-sectional dependence among the idiosyncratic returns, investigate how correlated those returns are across companies, and then apply principal components to them and discuss what one can accordingly learn about the importance of an "EV" factor.

[16] It would be interesting to undertake a similar comparison for the mining companies but finding a good "placebo" group is more difficult.

I test for the presence of cross-sectional dependence in the idiosyncratic returns using the CD* test of Pesaran and Xie (2022). The CD* test is an extension of the CD test (Pesaran, 2020) that is applicable when the residuals are generated from a regression that includes latent factors estimated using principal components. The null hypothesis of the test is that the sums of the correlation coefficients of the residuals equals zero. Or, more concretely, if we define $\hat{\rho}_{ij}$ as the estimated correlation coefficient between the idiosyncratic return of company i and j, the null is that $\sum_{i=1}^{N_y-1}\sum_{j=i+1}^{N_y}\hat{\rho}_{ij} = 0$. The test statistic has a standard Normal distribution. For the 2022 sample, the test statistic is -34.35; so the test strongly rejects the null of no cross-sectional dependence.[17]

Given strong statistical evidence for cross-sectional dependence among the idiosyncratic returns, I next investigate the correlations in more detail. An important finding is that, in general, the idiosyncratic returns are not highly correlated with each other. With 51 stocks in Y, there are 1275 unique pairwise correlations. The mean correlation across all pairs is just 0.09 while the median is 0.08. The interested reader can find more details in Figure 5, which shows the correlation matrix of the idiosyncratic returns with correlations greater than 0.15 highlighted in red.

The correlation matrix also shows that no individual firm appears to be "pervasive" or "dominant" in the sense of its idiosyncratic returns being extremely correlated with a large number of other companies. A priori, one could have the hypothesis that the idiosyncratic returns of a large and important firm, such as Tesla, would be highly correlated with other firms in the panel but that does not appear to be the case.

Although correlations are low in general, the idiosyncratic returns of companies operating in specific groups can be more strongly correlated. For example, the mean correlation among the lithium companies is 0.19 with the highest correlation being 0.55. Other groups include the trio of Chinese EV OEMs, a handful of U.S. EV OEMs and battery companies, and EV charging companies. This suggests those groups are exposed to a group-specific risk factor.

Finally, principal components is applied to the idiosyncratic returns to provide further detail on

[17] I also considered the cross-sectional dependence test of Juodis and Reese (2021) and reject the null at a one percent level.

common co-movements among them. The first principal component loads in the same direction on all of the returns except for one traditional battery company. Given this, one can view this factor as an "EV" factor since it reflects common movements across all companies in my data set. This factor, though, only explains a little over 13 percent of the variation of the idiosyncratic returns. Factors beyond the first seem to pick up the common movements in certain sub-groups. For example, the second component loads heavily on the three Chinese EV companies while the third loads on the lithium companies. Those two factors each explain about 4 percent of the variation within the panel of idiosyncratic returns.

4 ADDITIONAL RESULTS

4.1 LONGER SAMPLE It is possible to extend the sample to the beginning of 2021 and repeat the analysis for 26 companies. The main results in this case are similar to those of the base case. Details can be found in the appendix. The five factors from this longer sample generally have the same patterns in terms of their explanatory power across industries and across the EV and battery groups. The first factor is a "market" factor, which continues to be important for explaining variation in all stocks. The second factor loads positively on tech and consumer discretionary companies, and continues to play an important role in explaining the stock returns of the EV and battery companies. The relationships of the idiosyncratic returns are similar to those found in the shorter sample. While these results do not imply that the relationships between the latent factors and the returns will continue to hold for the indefinite future, they are evidence that those relationships have been stable over the course of 2021 and 2022.

4.2 DAILY DATA High-frequency stock returns provide significantly more observations to estimate the variance-covariance matrix of the stock returns but can raise concerns about noise and data quality. As a robustness check, I have repeated these exercises using daily stock return data from the CRSP database. This allows me to check whether my results are sensitive to the choice of the frequency and provides a check on the quality of the returns data. I find that my results are not overly sensitive to the choice of frequency. The latent factors extracted from the daily data set have similar interpretations to those from the 15 minute frequency. Additionally, the first and second factors continue to have explanatory power for the returns of the EV and battery companies. The online appendix contains additional details about these results.

5 CONCLUSION

In this paper, I investigate how the stock returns of companies operating in the EV and battery supply chain are related to systematic factors that explain broad movements in the stock market. I find that these systematic factors can help explain stock returns of companies in the EV and battery supply chain. In particular, a market factor and a factor that loads positively on tech and consumer discretionary stocks have good explanatory power. EV and battery companies most closely resemble tech companies in terms of the factors important for explaining their returns. There is evidence of cross-sectional dependence in the idiosyncratic returns of these companies, but those returns are generally not strongly correlated except in a few, smaller sub-groups. The first principal component of the idiosyncratic returns can be interpreted as an "EV" factor but only explains about 13 percent of their variation.

These results will be of interest to investors who want to understand how the returns of these companies are related to systematic risk factors broadly affecting the stock market. They also shed light on how the returns of these companies are related to each other after controlling systematic risk, an important issue given increasing interest in batteries, electric vehicles, and the energy transition, and the increasing ability of investors to get exposure to many of those companies.

Of course, these conclusions are based on a short time window of a few years. It will be interesting to see if the answers to the questions investigated in this paper change in the future as the electric vehicle market grows and more attention is devoted to the companies that operate in the EV and battery supply chain. In ongoing research, I am also investigating whether the relationships uncovered here hold more broadly for other clean energy companies that operate in areas outside of the EV and battery space.

Table 3: Companies in the EV and battery supply-chain.

Company	Ticker	Exchange	Category	Sub-category
Albemarle	ALB	NYSE	Mining	Lithium
Ioneer	IONR	Nasdaq	Mining	Lithium
Lithium Americas	LAC	NYSE	Mining	Lithium
Snow Lake Resources	LITM	Nasdaq	Mining	Lithium
Livent	LTHM	NYSE	Mining	Lithium
Piedmont Lithium	PLL	Nasdaq	Mining	Lithium
Sigma Lithium	SGML	Nasdaq	Mining	Lithium
The Metals Company	TMC	Nasdaq	Mining	Deep-sea
Westwater Resources	WWR	NYSE American	Mining	Graphite
Amprius	AMPX	NYSE	Battery	Advanced battery
Enovix	ENVX	Nasdaq	Battery	Advanced battery
EOS Energy	EOSE	Nasdaq	Battery	Advanced battery
ESS	GWH	NYSE	Battery	Advanced battery
QuantumScape	QS	NYSE	Battery	Advanced battery
SES AI	SES	NYSE	Battery	Advanced battery
SolidPower	SLDP	Nasdaq	Battery	Advanced battery
CBAK Energy	CBAT	Nasdaq	Battery	Lithium-ion
Dragonfly	DFLI	Nasdaq	Battery	Lithium-ion
Flux Power Holdings	FLUX	Nasdaq	Battery	Lithium-ion
Freyr	FREY	NYSE	Battery	Lithium-ion
Microvast	MVST	Nasdaq	Battery	Lithium-ion
Neovolta	NEOV	Nasdaq	Battery	Lithium-ion
ProTerra	PTRA	Nasdaq	Battery	Lithium-ion
Romeo Power	RMO	NYSE	Battery	Lithium-ion
Expion360	XPON	Nasdaq	Battery	Lithium-ion
Energizer	ENR	NYSE	Battery	Traditional
EnerSys	ENS	NYSE	Battery	Traditional
Ultralife Corp.	ULBI	Nasdaq	Battery	Traditional
Electra Battery Materials	ELBM	Nasdaq	Battery	Materials
Li-cycle	LICY	NYSE	Battery	Materials
Novonix	NVX	Nasdaq	Battery	Materials
Li Auto	LI	Nasdaq	EV	OEM (Chinese)
Nio	NIO	NYSE	EV	OEM (Chinese)
Xpeng Inc	XPEV	NYSE	EV	OEM (Chinese)
Atlis Motors	AMV	Nasdaq	EV	OEM
Arrival	ARVL	Nasdaq	EV	OEM
Cenntro Electric Group	CENN	Nasdaq	EV	OEM
Envirotech Vehicles	EVTV	Nasdaq	EV	OEM
Faraday Future	FFIE	Nasdaq	EV	OEM
Fisker	FSR	NYSE	EV	OEM
Arcimoto	FUV	Nasdaq	EV	OEM
Canoo Inc	GOEV	Nasdaq	EV	OEM
GreenPower Motor Company	GP	Nasdaq	EV	OEM
Hylion	HYLN	NYSE	EV	OEM
Lucid Group	LCID	Nasdaq	EV	OEM
Lion Electric	LEV	NYSE	EV	OEM
Mullen Automotive	MULN	Nasdaq	EV	OEM
Nikola	NKLA	Nasdaq	EV	OEM
Pheonix Motor	PEV	Nasdaq	EV	OEM
Polestar	PSNY	Nasdaq	EV	OEM
Lordstown Motor	RIDE	Nasdaq	EV	OEM
Rivian	RIVN	Nasdaq	EV	OEM
Sono Group	SEV	Nasdaq	EV	OEM
Electrameccanica Vehicles	SOLO	Nasdaq	EV	OEM
Tesla	TSLA	Nasdaq	EV	OEM
Workhorse Group Nasdaq	WKHS	Nasdaq	EV	OEM
XOS	XOS	Nasdaq	EV	OEM
Jiuzi Holdings	JZXN	Nasdaq	EV	Other
Bird Global	BRDS	NYSE	EV	Other
Gogoro Inc	GGR	Nasdaq	EV	Other
ADS-TEC Energy	ADSE	Nasdaq	Charging	Equipment
Charge Enterprises	CRGE	Nasdaq	Charging	Equipment
Tritium DCFC	DCFC	Nasdaq	Charging	Equipment
Blink Charging	BLNK	Nasdaq	Charging	Services
ChargePoint Holdings	CHPT	NYSE	Charging	Services
EVGO	EVGO	Nasdaq	Charging	Services
Naas Technology	NAAS	Nasdaq	Charging	Services
Nuvve Holding Corp	NVVE	Nasdaq	Charging	Services
Volta	VLTA	NYSE	Charging	Services

Figure 5: Correlations of residual returns of EV and battery companies.

Row	ALB	LAC	LITM	LTHM	PLL	SGML	TMC	WWR	ENVX	EOSE	GWH	QS	SLDP	CBAT	FLUX	FREY	MVST	PTRA	ENR	ENS	ULBI	LICY	LI	NIO	XPEV
ALB	1.00	0.32	0.02	0.55	0.25	0.10	0.03	0.07	0.13	0.06	0.09	0.10	0.08	0.08	0.00	0.14	0.05	0.08	-0.05	0.05	0.00	0.11	0.09	0.09	0.08
LAC	0.32	1.00	0.07	0.41	0.31	0.13	0.07	0.14	0.12	0.09	0.11	0.22	0.11	0.12	0.02	0.15	0.09	0.17	-0.01	0.06	0.01	0.13	0.14	0.16	0.14
LITM	0.02	0.07	1.00	0.05	0.05	0.05	0.04	0.07	0.04	0.04	0.04	0.04	0.05	0.08	0.02	0.04	0.03	0.02	0.03	0.02	0.03	0.05	0.03	0.05	0.05
LTHM	0.55	0.41	0.05	1.00	0.28	0.12	0.05	0.09	0.14	0.07	0.10	0.17	0.12	0.09	0.01	0.18	0.07	0.11	-0.01	0.09	0.01	0.13	0.09	0.12	0.10
PLL	0.25	0.31	0.05	0.28	1.00	0.11	0.06	0.09	0.12	0.05	0.11	0.11	0.11	0.08	0.01	0.13	0.10	0.13	-0.01	0.04	0.03	0.12	0.04	0.04	0.04
SGML	0.10	0.13	0.05	0.12	0.11	1.00	0.03	0.05	0.07	0.02	0.05	0.06	0.00	0.06	0.00	0.07	0.00	0.08	0.01	0.04	0.02	0.03	0.07	0.07	0.06
TMC	0.03	0.07	0.04	0.05	0.06	0.03	1.00	0.08	0.05	0.08	0.06	0.05	0.06	0.11	0.03	0.04	0.03	0.07	0.05	0.01	-0.02	0.07	0.02	0.05	0.03
WWR	0.07	0.14	0.07	0.09	0.09	0.05	0.08	1.00	0.09	0.06	0.06	0.12	0.08	0.14	0.03	0.10	0.06	0.09	0.01	0.04	0.02	0.08	0.06	0.06	0.05
ENVX	0.13	0.12	0.04	0.14	0.12	0.07	0.05	0.09	1.00	0.09	0.15	0.20	0.13	0.09	0.01	0.19	0.11	0.16	0.01	0.06	0.00	0.18	0.11	0.13	0.12
EOSE	0.06	0.09	0.04	0.07	0.05	0.02	0.08	0.06	0.09	1.00	0.12	0.14	0.08	0.08	0.02	0.10	0.06	0.11	0.06	0.05	0.00	0.10	0.06	0.07	0.06
GWH	0.09	0.11	0.04	0.10	0.11	0.05	0.06	0.06	0.15	0.12	1.00	0.17	0.18	0.07	0.02	0.16	0.11	0.18	0.04	0.08	-0.01	0.16	0.04	0.10	0.07
QS	0.10	0.22	0.04	0.17	0.11	0.06	0.05	0.12	0.20	0.14	0.17	1.00	0.23	0.11	0.02	0.23	0.15	0.24	0.07	0.02	0.00	0.21	0.18	0.31	0.23
SLDP	0.08	0.11	0.05	0.12	0.11	0.00	0.06	0.08	0.13	0.08	0.18	0.23	1.00	0.09	0.01	0.15	0.11	0.16	0.05	0.05	-0.01	0.13	0.06	0.12	0.08
CBAT	0.08	0.12	0.08	0.09	0.08	0.06	0.11	0.14	0.09	0.08	0.07	0.11	0.09	1.00	0.05	0.10	0.06	0.10	0.01	0.05	-0.01	0.11	0.09	0.11	0.06
FLUX	0.00	0.02	0.02	0.01	0.01	0.00	0.03	0.03	0.01	0.02	0.02	0.02	0.01	0.05	1.00	0.03	0.00	0.01	0.03	0.03	0.03	0.04	-0.01	-0.02	-0.02
FREY	0.14	0.15	0.04	0.18	0.13	0.07	0.04	0.10	0.19	0.10	0.16	0.23	0.15	0.10	0.03	1.00	0.13	0.20	0.00	0.06	0.00	0.18	0.09	0.14	0.09
MVST	0.05	0.09	0.03	0.07	0.10	0.00	0.03	0.06	0.11	0.06	0.11	0.15	0.11	0.06	0.00	0.13	1.00	0.15	-0.01	0.06	-0.04	0.17	0.10	0.11	0.08
PTRA	0.08	0.17	0.02	0.11	0.13	0.08	0.07	0.09	0.16	0.11	0.18	0.24	0.16	0.10	0.01	0.20	0.15	1.00	0.05	0.08	-0.01	0.25	0.06	0.12	0.09
ENR	-0.05	-0.01	0.03	-0.01	-0.01	0.01	0.05	0.01	0.01	0.06	0.04	0.07	0.05	0.01	0.03	0.00	-0.01	0.05	1.00	0.12	-0.01	0.08	0.00	0.01	0.01
ENS	0.05	0.06	0.02	0.09	0.04	0.04	0.01	0.04	0.06	0.05	0.08	0.02	0.05	0.05	0.03	0.06	0.06	0.08	0.12	1.00	0.00	0.07	0.00	-0.01	-0.02
ULBI	0.00	0.01	0.03	0.01	0.03	0.02	-0.02	0.02	0.00	0.00	-0.01	0.00	-0.01	-0.01	0.03	0.00	-0.04	-0.01	-0.01	0.00	1.00	0.01	0.01	0.00	0.01
LICY	0.11	0.13	0.05	0.13	0.12	0.03	0.07	0.08	0.18	0.10	0.16	0.21	0.13	0.11	0.04	0.18	0.17	0.25	0.08	0.07	0.01	1.00	0.09	0.13	0.11
LI	0.09	0.14	0.03	0.09	0.04	0.07	0.02	0.06	0.11	0.06	0.04	0.18	0.06	0.09	-0.01	0.09	0.10	0.06	0.00	0.00	0.01	0.09	1.00	0.59	0.61
NIO	0.09	0.16	0.05	0.12	0.04	0.07	0.05	0.06	0.13	0.07	0.10	0.31	0.12	0.11	-0.02	0.14	0.11	0.12	0.01	-0.01	0.00	0.13	0.59	1.00	0.66
XPEV	0.08	0.14	0.05	0.10	0.04	0.06	0.03	0.05	0.12	0.06	0.07	0.23	0.08	0.06	-0.02	0.09	0.08	0.09	0.01	-0.02	0.01	0.11	0.61	0.66	1.00
ARVL	0.01	0.05	0.07	0.02	0.03	0.01	0.04	0.06	0.07	0.08	0.09	0.20	0.12	0.07	0.02	0.08	0.09	0.13	0.03	0.03	0.00	0.10	0.07	0.14	0.12
FFIE	0.01	0.08	0.07	0.02	0.06	0.00	0.04	0.05	0.06	0.04	0.07	0.11	0.09	0.04	0.03	0.08	0.08	0.09	0.02	0.03	0.02	0.07	0.11	0.10	0.12
FSR	0.09	0.19	0.03	0.16	0.10	0.05	0.06	0.09	0.14	0.10	0.14	0.35	0.19	0.10	0.04	0.18	0.12	0.22	0.03	0.02	0.01	0.17	0.19	0.27	0.24
FUV	0.08	0.09	0.05	0.08	0.05	0.06	0.05	0.04	0.06	0.08	0.05	0.09	0.04	0.06	0.01	0.08	0.03	0.07	0.03	0.00	-0.01	0.05	0.08	0.13	0.09
GOEV	0.06	0.12	0.05	0.08	0.09	0.04	0.04	0.06	0.12	0.12	0.14	0.22	0.13	0.10	0.01	0.13	0.12	0.15	0.02	0.04	-0.01	0.14	0.12	0.19	0.16
GP	0.02	0.05	0.05	0.05	0.05	0.01	0.05	0.08	0.06	0.07	0.12	0.09	0.07	0.08	0.03	0.08	0.04	0.09	0.03	0.05	0.01	0.08	0.01	0.03	0.02
HYLN	0.06	0.16	0.04	0.11	0.08	0.04	0.07	0.10	0.15	0.12	0.15	0.25	0.11	0.08	0.01	0.15	0.15	0.27	0.05	0.09	-0.04	0.16	0.06	0.16	0.10
LCID	0.08	0.17	0.04	0.14	0.08	0.08	0.04	0.08	0.16	0.08	0.13	0.37	0.17	0.07	0.02	0.17	0.11	0.21	0.03	-0.02	0.00	0.15	0.21	0.33	0.25
LEV	0.06	0.11	0.06	0.09	0.07	0.04	0.06	0.08	0.11	0.13	0.17	0.17	0.13	0.11	0.02	0.12	0.07	0.18	0.04	0.04	0.02	0.15	0.09	0.11	0.11
MULN	0.03	0.03	0.02	0.04	0.05	-0.01	0.06	0.04	0.01	0.05	0.01	0.06	0.07	0.02	0.03	0.03	0.01	0.04	0.01	0.00	0.02	0.04	0.05	0.04	0.04
NKLA	0.11	0.17	0.05	0.12	0.12	0.10	0.06	0.08	0.15	0.10	0.17	0.31	0.15	0.11	0.04	0.17	0.15	0.27	0.03	0.06	-0.02	0.19	0.16	0.25	0.21
RIDE	0.08	0.14	0.06	0.11	0.09	0.04	0.06	0.09	0.11	0.14	0.16	0.26	0.14	0.07	0.02	0.14	0.13	0.21	0.03	0.04	-0.03	0.16	0.10	0.18	0.15
RIVN	0.11	0.19	0.04	0.16	0.08	0.07	0.08	0.09	0.15	0.10	0.11	0.33	0.19	0.11	0.03	0.17	0.08	0.18	0.03	0.00	0.00	0.16	0.20	0.30	0.25
SEV	0.08	0.10	0.06	0.09	0.06	0.01	0.09	0.08	0.05	0.07	0.08	0.14	0.13	0.10	0.01	0.12	0.06	0.10	0.04	0.04	-0.01	0.10	0.10	0.14	0.14
SOLO	0.07	0.09	0.04	0.08	0.06	0.02	0.06	0.08	0.10	0.08	0.11	0.16	0.06	0.09	0.03	0.12	0.08	0.11	0.03	0.04	0.03	0.13	0.11	0.16	0.14
TSLA	0.12	0.15	0.02	0.15	0.09	0.04	0.04	0.05	0.09	0.07	0.07	0.21	0.15	0.09	0.00	0.12	0.08	0.10	-0.02	-0.01	0.01	0.08	0.16	0.30	0.22
WKHS	0.08	0.18	0.04	0.13	0.09	0.05	0.05	0.09	0.16	0.15	0.18	0.31	0.17	0.12	0.03	0.20	0.16	0.26	0.02	0.06	-0.02	0.17	0.15	0.27	0.21
XOS	0.03	0.06	0.02	0.06	0.05	0.02	0.05	0.07	0.06	0.09	0.09	0.10	0.09	0.08	0.02	0.08	0.05	0.11	0.04	0.04	0.02	0.06	0.04	0.04	0.02
BRDS	0.01	0.05	0.03	0.02	0.03	0.01	0.04	0.05	0.02	0.04	0.07	0.08	0.03	0.05	0.04	0.05	0.04	0.05	0.00	0.03	0.00	0.06	0.01	0.01	0.02
JZXN	-0.01	0.02	0.00	-0.01	0.01	-0.02	0.00	0.01	0.02	0.00	0.01	0.02	0.03	0.00	0.01	0.00	0.01	-0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.00
ADSE	0.00	0.03	0.00	0.00	0.02	-0.01	0.04	0.04	0.00	0.04	0.04	0.03	0.01	0.01	0.02	0.03	0.02	0.01	0.00	0.01	-0.01	0.01	0.00	0.00	-0.01
BLNK	0.16	0.21	0.03	0.20	0.15	0.08	0.06	0.10	0.19	0.16	0.19	0.32	0.16	0.10	0.02	0.22	0.17	0.21	0.01	0.08	0.00	0.21	0.14	0.25	0.19
CHPT	0.17	0.27	0.02	0.24	0.16	0.12	0.06	0.12	0.22	0.16	0.23	0.40	0.19	0.13	0.02	0.26	0.21	0.28	0.03	0.07	-0.01	0.23	0.16	0.30	0.20
EVGO	0.06	0.17	0.06	0.12	0.12	0.06	0.05	0.10	0.14	0.13	0.16	0.27	0.18	0.09	0.03	0.20	0.13	0.23	0.03	0.07	-0.01	0.18	0.09	0.17	0.13
NVVE	-0.03	0.01	0.05	-0.02	0.02	0.00	0.03	0.07	0.02	0.05	0.04	0.03	0.03	0.02	0.03	0.03	0.02	0.05	0.02	0.04	0.02	0.02	0.00	0.01	0.00
VLTA	0.04	0.10	0.03	0.09	0.09	0.05	0.05	0.08	0.08	0.08	0.15	0.20	0.15	0.07	0.03	0.11	0.07	0.14	0.06	0.05	0.00	0.11	0.04	0.11	0.08

Row	ARVL	FFIE	FSR	FUV	GOEV	GP	HYLN	LCID	LEV	MULN	NKLA	RIDE	RIVN	SEV	SOLO	TSLA	WKHS	XOS	BRDS	JZXN	ADSE	BLNK	CHPT	EVGO	NVVE	VLTA
ALB	0.01	0.01	0.09	0.08	0.06	0.02	0.06	0.08	0.06	0.03	0.11	0.08	0.11	0.08	0.07	0.12	0.08	0.03	0.01	-0.01	0.00	0.16	0.17	0.06	-0.03	0.04
LAC	0.05	0.08	0.19	0.09	0.12	0.05	0.16	0.17	0.11	0.03	0.17	0.14	0.19	0.10	0.09	0.15	0.18	0.06	0.05	0.02	0.03	0.21	0.27	0.17	0.01	0.10
LITM	0.07	0.07	0.03	0.05	0.05	0.05	0.04	0.04	0.06	0.02	0.05	0.06	0.04	0.06	0.04	0.02	0.04	0.02	0.03	0.00	0.00	0.03	0.02	0.06	0.05	0.03
LTHM	0.02	0.02	0.16	0.08	0.08	0.05	0.11	0.14	0.09	0.04	0.12	0.11	0.16	0.09	0.08	0.15	0.13	0.06	0.02	-0.01	0.00	0.20	0.24	0.12	-0.02	0.09
PLL	0.03	0.06	0.10	0.05	0.09	0.05	0.08	0.08	0.07	0.05	0.12	0.09	0.08	0.06	0.06	0.09	0.09	0.05	0.03	0.01	0.02	0.15	0.16	0.12	0.02	0.09
SGML	0.01	0.00	0.05	0.06	0.04	0.01	0.04	0.08	0.04	-0.01	0.10	0.04	0.07	0.01	0.02	0.04	0.05	0.02	0.01	-0.02	-0.01	0.08	0.12	0.06	0.00	0.05
TMC	0.04	0.04	0.06	0.05	0.04	0.05	0.07	0.04	0.06	0.06	0.06	0.06	0.08	0.09	0.06	0.04	0.05	0.05	0.04	0.00	0.04	0.06	0.06	0.05	0.03	0.05
WWR	0.06	0.05	0.09	0.04	0.06	0.08	0.10	0.08	0.08	0.04	0.08	0.09	0.09	0.08	0.08	0.05	0.09	0.07	0.05	0.01	0.04	0.10	0.12	0.10	0.07	0.08
ENVX	0.07	0.06	0.14	0.06	0.12	0.06	0.15	0.16	0.11	0.01	0.15	0.11	0.15	0.05	0.10	0.09	0.16	0.06	0.02	0.02	0.00	0.19	0.22	0.14	0.02	0.08
EOSE	0.08	0.04	0.10	0.08	0.12	0.07	0.12	0.08	0.13	0.05	0.10	0.14	0.10	0.07	0.08	0.07	0.15	0.09	0.04	0.00	0.04	0.16	0.16	0.13	0.05	0.08
GWH	0.09	0.07	0.14	0.05	0.14	0.12	0.15	0.13	0.17	0.01	0.17	0.16	0.11	0.08	0.11	0.07	0.18	0.09	0.07	0.01	0.04	0.19	0.23	0.16	0.04	0.15
QS	0.20	0.11	0.35	0.09	0.22	0.09	0.25	0.37	0.17	0.06	0.31	0.26	0.33	0.14	0.16	0.21	0.31	0.10	0.08	0.02	0.03	0.32	0.40	0.27	0.03	0.20
SLDP	0.12	0.09	0.19	0.04	0.13	0.07	0.11	0.17	0.13	0.07	0.15	0.14	0.19	0.13	0.06	0.15	0.17	0.09	0.03	0.03	0.01	0.16	0.19	0.18	0.03	0.15
CBAT	0.07	0.04	0.10	0.06	0.10	0.08	0.08	0.07	0.11	0.02	0.11	0.07	0.11	0.10	0.09	0.09	0.12	0.08	0.05	0.00	0.01	0.10	0.13	0.09	0.02	0.07
FLUX	0.02	0.03	0.04	0.01	0.01	0.03	0.01	0.02	0.02	0.03	0.04	0.02	0.03	0.01	0.03	0.00	0.03	0.02	0.04	0.01	0.02	0.02	0.02	0.03	0.03	0.03
FREY	0.08	0.08	0.18	0.08	0.13	0.08	0.15	0.17	0.12	0.03	0.17	0.14	0.17	0.12	0.12	0.12	0.20	0.08	0.05	0.00	0.03	0.22	0.26	0.20	0.03	0.11
MVST	0.09	0.08	0.12	0.03	0.12	0.04	0.15	0.11	0.07	0.01	0.15	0.13	0.08	0.06	0.08	0.08	0.16	0.05	0.04	0.01	0.02	0.17	0.21	0.13	0.02	0.07
PTRA	0.13	0.09	0.22	0.07	0.15	0.09	0.27	0.21	0.18	0.04	0.27	0.21	0.18	0.10	0.11	0.10	0.26	0.11	0.05	-0.01	0.01	0.21	0.28	0.23	0.05	0.14
ENR	0.03	0.02	0.03	0.03	0.02	0.03	0.05	0.03	0.04	0.01	0.03	0.03	0.03	0.04	0.03	-0.02	0.02	0.04	0.00	0.00	0.00	0.01	0.03	0.03	0.02	0.06
ENS	0.03	0.03	0.02	0.00	0.04	0.05	0.09	-0.02	0.04	0.00	0.06	0.04	0.00	0.04	0.04	-0.01	0.06	0.04	0.03	0.00	0.01	0.08	0.07	0.07	0.04	0.05
ULBI	0.00	0.02	0.01	-0.01	-0.01	0.01	-0.04	0.00	0.02	0.02	-0.02	-0.03	0.00	-0.01	0.03	0.01	-0.02	0.02	0.00	0.01	-0.01	0.00	-0.01	-0.01	0.02	0.00
LICY	0.10	0.07	0.17	0.05	0.14	0.08	0.16	0.15	0.15	0.04	0.19	0.16	0.16	0.10	0.13	0.08	0.17	0.06	0.06	0.01	0.01	0.21	0.23	0.18	0.02	0.11
LI	0.07	0.11	0.19	0.08	0.12	0.01	0.06	0.21	0.09	0.05	0.16	0.10	0.20	0.10	0.11	0.16	0.15	0.04	0.01	0.01	0.00	0.14	0.16	0.09	0.00	0.04
NIO	0.14	0.10	0.27	0.13	0.19	0.03	0.16	0.33	0.11	0.04	0.25	0.18	0.30	0.14	0.16	0.30	0.27	0.04	0.01	0.01	0.00	0.25	0.30	0.17	0.01	0.11
XPEV	0.12	0.12	0.24	0.09	0.16	0.02	0.10	0.25	0.11	0.04	0.21	0.15	0.25	0.14	0.14	0.22	0.21	0.02	0.02	0.00	-0.01	0.19	0.20	0.13	0.00	0.08
ARVL	1.00	0.09	0.16	0.08	0.14	0.12	0.16	0.17	0.10	0.04	0.12	0.13	0.15	0.11	0.09	0.11	0.16	0.07	0.04	0.01	0.02	0.13	0.16	0.13	0.05	0.09
FFIE	0.09	1.00	0.12	0.04	0.11	0.06	0.09	0.13	0.05	0.05	0.10	0.11	0.08	0.07	0.08	0.08	0.12	0.07	0.04	0.05	0.01	0.09	0.11	0.09	0.04	0.05
FSR	0.16	0.12	1.00	0.10	0.22	0.08	0.24	0.35	0.14	0.06	0.29	0.28	0.31	0.14	0.19	0.26	0.33	0.09	0.03	0.00	0.03	0.23	0.29	0.22	0.00	0.15
FUV	0.08	0.04	0.10	1.00	0.09	0.08	0.07	0.13	0.08	0.03	0.08	0.11	0.14	0.10	0.12	0.10	0.11	0.07	0.07	0.02	0.01	0.09	0.11	0.10	0.02	0.08
GOEV	0.14	0.11	0.22	0.09	1.00	0.09	0.19	0.23	0.13	0.05	0.20	0.27	0.23	0.13	0.15	0.18	0.26	0.07	0.07	0.02	0.00	0.22	0.22	0.21	0.04	0.14
GP	0.12	0.06	0.08	0.08	0.09	1.00	0.07	0.05	0.10	0.02	0.07	0.07	0.06	0.06	0.09	0.03	0.09	0.08	0.06	0.02	0.04	0.09	0.10	0.09	0.03	0.06
HYLN	0.16	0.09	0.24	0.07	0.19	0.07	1.00	0.21	0.21	0.03	0.38	0.24	0.18	0.09	0.16	0.14	0.32	0.11	0.06	0.02	0.00	0.26	0.29	0.23	0.05	0.15
LCID	0.17	0.13	0.35	0.13	0.23	0.05	0.21	1.00	0.14	0.04	0.27	0.25	0.47	0.15	0.16	0.33	0.30	0.05	0.04	0.00	0.01	0.24	0.31	0.22	0.04	0.15
LEV	0.10	0.05	0.14	0.08	0.13	0.10	0.21	0.14	1.00	0.06	0.21	0.19	0.13	0.08	0.14	0.11	0.21	0.09	0.04	-0.01	0.00	0.20	0.20	0.14	0.02	0.11
MULN	0.04	0.05	0.06	0.03	0.05	0.02	0.03	0.04	0.06	1.00	0.02	0.03	0.07	0.04	0.05	0.06	0.02	0.04	0.01	0.01	0.01	0.04	0.05	0.05	0.00	0.07
NKLA	0.12	0.10	0.29	0.08	0.20	0.07	0.38	0.27	0.21	0.02	1.00	0.26	0.22	0.11	0.16	0.18	0.33	0.08	0.04	0.01	0.00	0.29	0.34	0.21	0.03	0.14
RIDE	0.13	0.11	0.28	0.11	0.27	0.07	0.24	0.25	0.19	0.03	0.26	1.00	0.21	0.13	0.19	0.15	0.42	0.09	0.05	0.01	0.01	0.24	0.24	0.22	0.03	0.15
RIVN	0.15	0.08	0.31	0.14	0.23	0.06	0.18	0.47	0.13	0.07	0.22	0.21	1.00	0.17	0.14	0.29	0.26	0.07	0.04	0.00	0.04	0.21	0.27	0.19	0.04	0.14
SEV	0.11	0.07	0.14	0.10	0.13	0.06	0.09	0.15	0.08	0.04	0.11	0.13	0.17	1.00	0.08	0.13	0.14	0.08	0.03	0.03	0.03	0.13	0.14	0.12	0.04	0.11
SOLO	0.09	0.08	0.19	0.12	0.15	0.09	0.16	0.16	0.14	0.05	0.16	0.19	0.14	0.08	1.00	0.15	0.21	0.08	0.07	0.00	0.02	0.18	0.18	0.13	0.05	0.12
TSLA	0.11	0.08	0.26	0.10	0.18	0.03	0.14	0.33	0.11	0.06	0.18	0.15	0.29	0.13	0.15	1.00	0.21	0.03	0.01	0.00	0.03	0.21	0.22	0.15	0.03	0.08
WKHS	0.16	0.12	0.33	0.11	0.26	0.09	0.32	0.30	0.21	0.02	0.33	0.42	0.26	0.14	0.21	0.21	1.00	0.11	0.07	0.01	0.01	0.33	0.31	0.26	0.05	0.13
XOS	0.07	0.07	0.09	0.07	0.07	0.08	0.11	0.05	0.09	0.04	0.08	0.09	0.07	0.08	0.08	0.03	0.11	1.00	0.09	0.02	-0.01	0.08	0.11	0.13	0.04	0.08
BRDS	0.04	0.04	0.03	0.07	0.07	0.06	0.06	0.04	0.04	0.01	0.04	0.05	0.04	0.03	0.07	0.01	0.07	0.09	1.00	0.00	0.00	0.10	0.09	0.07	0.00	0.05
JZXN	0.01	0.05	0.00	0.02	0.02	0.02	0.02	0.00	-0.01	0.01	0.01	0.01	0.00	0.03	0.00	0.00	0.01	0.02	0.00	1.00	0.01	-0.02	0.00	0.00	0.01	-0.01
ADSE	0.02	0.01	0.03	0.01	0.00	0.04	0.00	0.01	0.00	0.01	0.00	0.01	0.04	0.03	0.02	0.03	0.01	-0.01	0.00	0.01	1.00	0.01	0.00	0.01	0.01	0.03
BLNK	0.13	0.09	0.23	0.09	0.22	0.09	0.26	0.24	0.20	0.04	0.29	0.24	0.21	0.13	0.18	0.21	0.33	0.08	0.10	-0.02	0.01	1.00	0.46	0.29	0.03	0.18
CHPT	0.16	0.11	0.29	0.11	0.22	0.10	0.29	0.31	0.20	0.05	0.34	0.24	0.27	0.14	0.18	0.22	0.31	0.11	0.09	0.00	0.00	0.46	1.00	0.33	0.06	0.21
EVGO	0.13	0.09	0.22	0.10	0.21	0.09	0.23	0.22	0.14	0.05	0.21	0.22	0.19	0.12	0.13	0.15	0.26	0.13	0.07	0.00	0.01	0.29	0.33	1.00	0.03	0.23
NVVE	0.05	0.04	0.00	0.02	0.04	0.03	0.05	0.04	0.02	0.00	0.03	0.03	0.04	0.04	0.05	0.03	0.05	0.04	0.00	0.01	0.01	0.03	0.06	0.03	1.00	0.03
VLTA	0.09	0.05	0.15	0.08	0.14	0.06	0.15	0.15	0.11	0.07	0.14	0.15	0.14	0.11	0.12	0.08	0.13	0.08	0.05	-0.01	0.03	0.18	0.21	0.23	0.03	1.00

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NOT FOR PUBLICATION APPENDIX

A 2021 TO 2022 SAMPLE

This section includes results for the longer sample that includes data from the start of 2021 to the end of 2022. Figure 6 shows the loadings on the factors. Figure 7 shows the explanatory power of each factor for the stocks which have a full sample available over the entire sample. Finally, Figure 8 performs the comparison between the "traditional" companies and the companies included in panel Y.

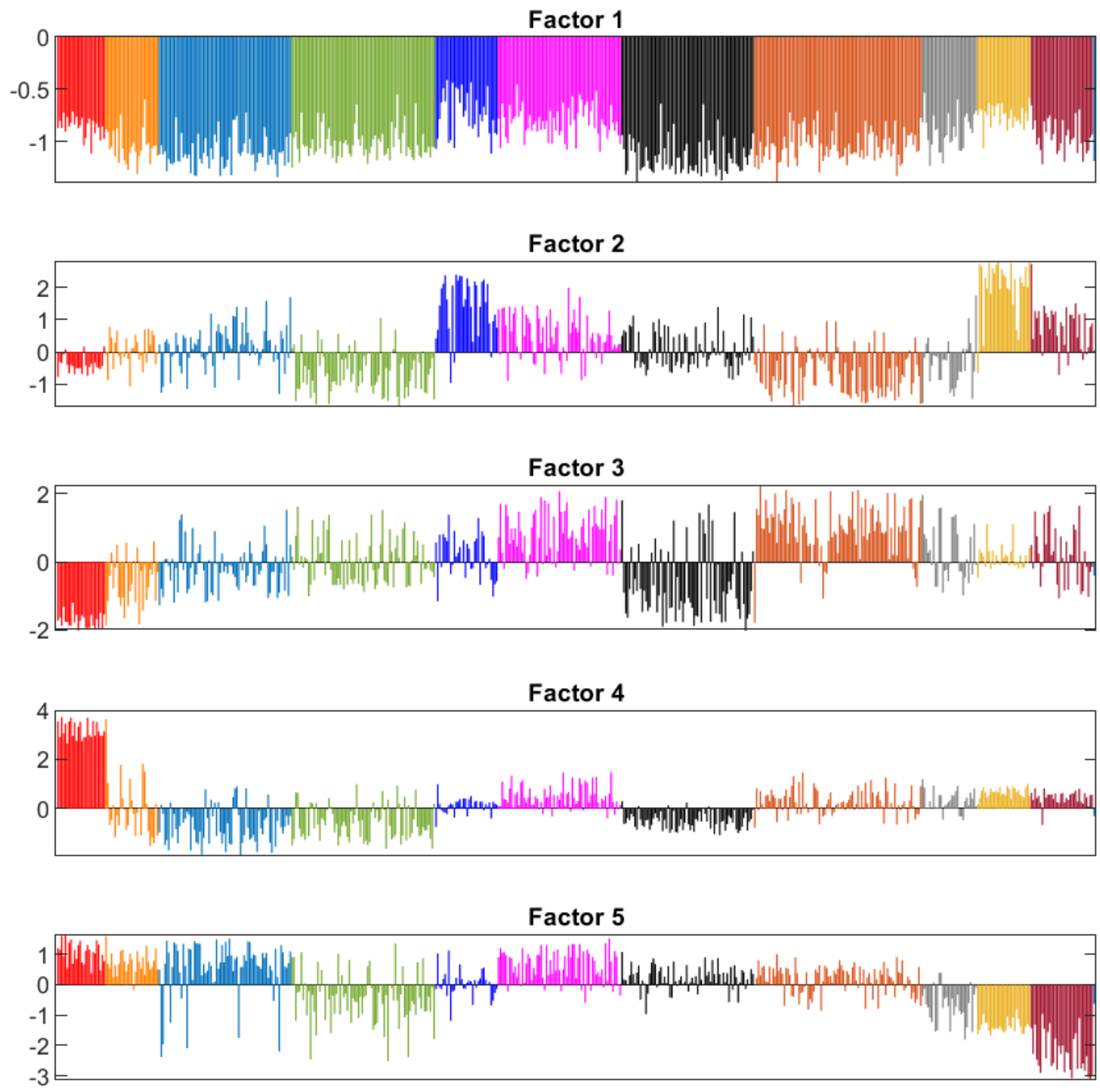


Figure 6: Loadings of the five systematic factors. Stocks are sorted by their two-digit GICS code. In order these are energy (red); materials (orange); industrials (light blue); consumer discretionary (green); consumer staples (dark blue); health care (pink); financials (black); tech (dark organge); communications (gray); utilities (yellow); real estate (maroon).

Figure 7: Breakdown of explanatory of systematic factors for individual stocks

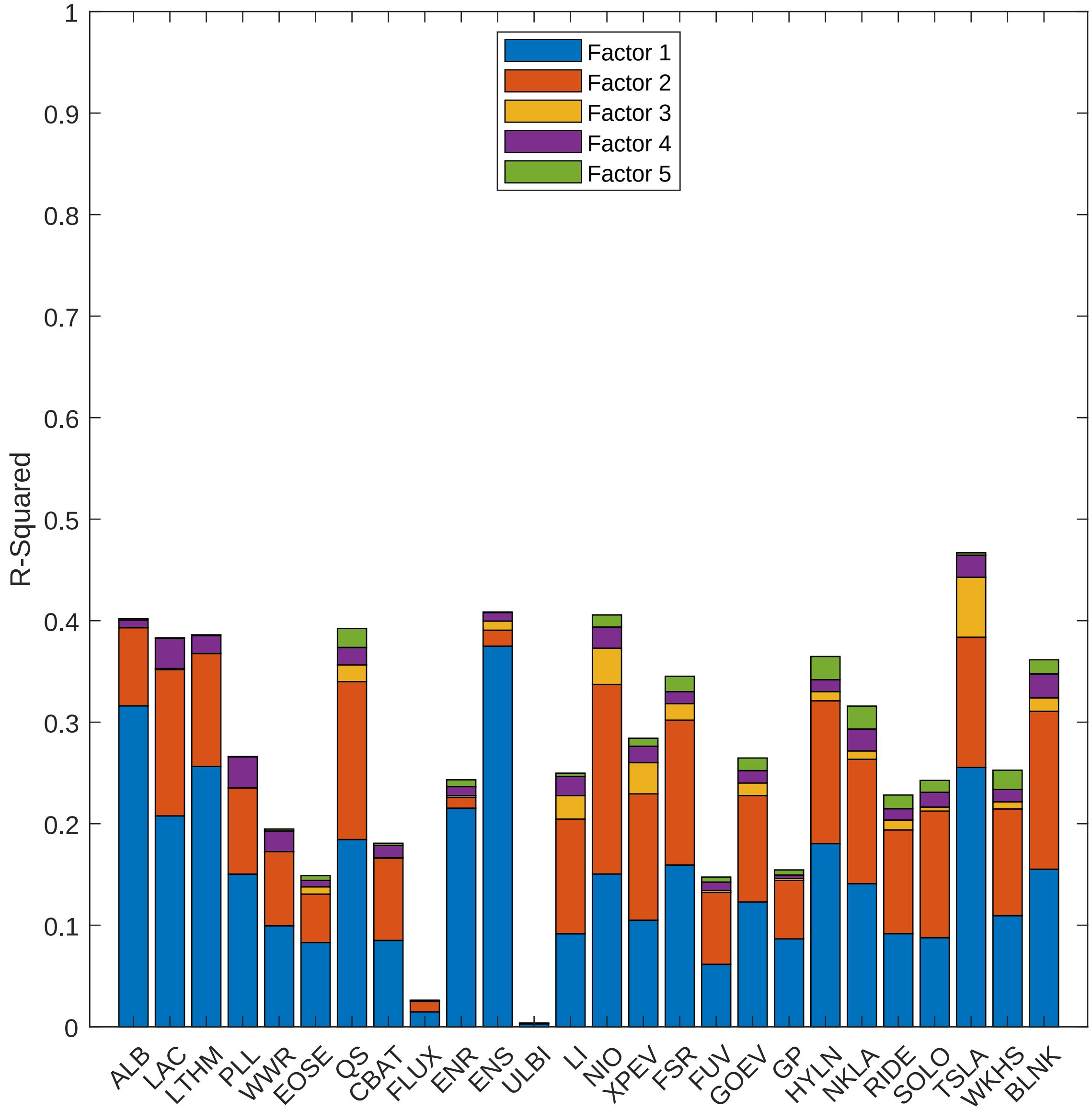
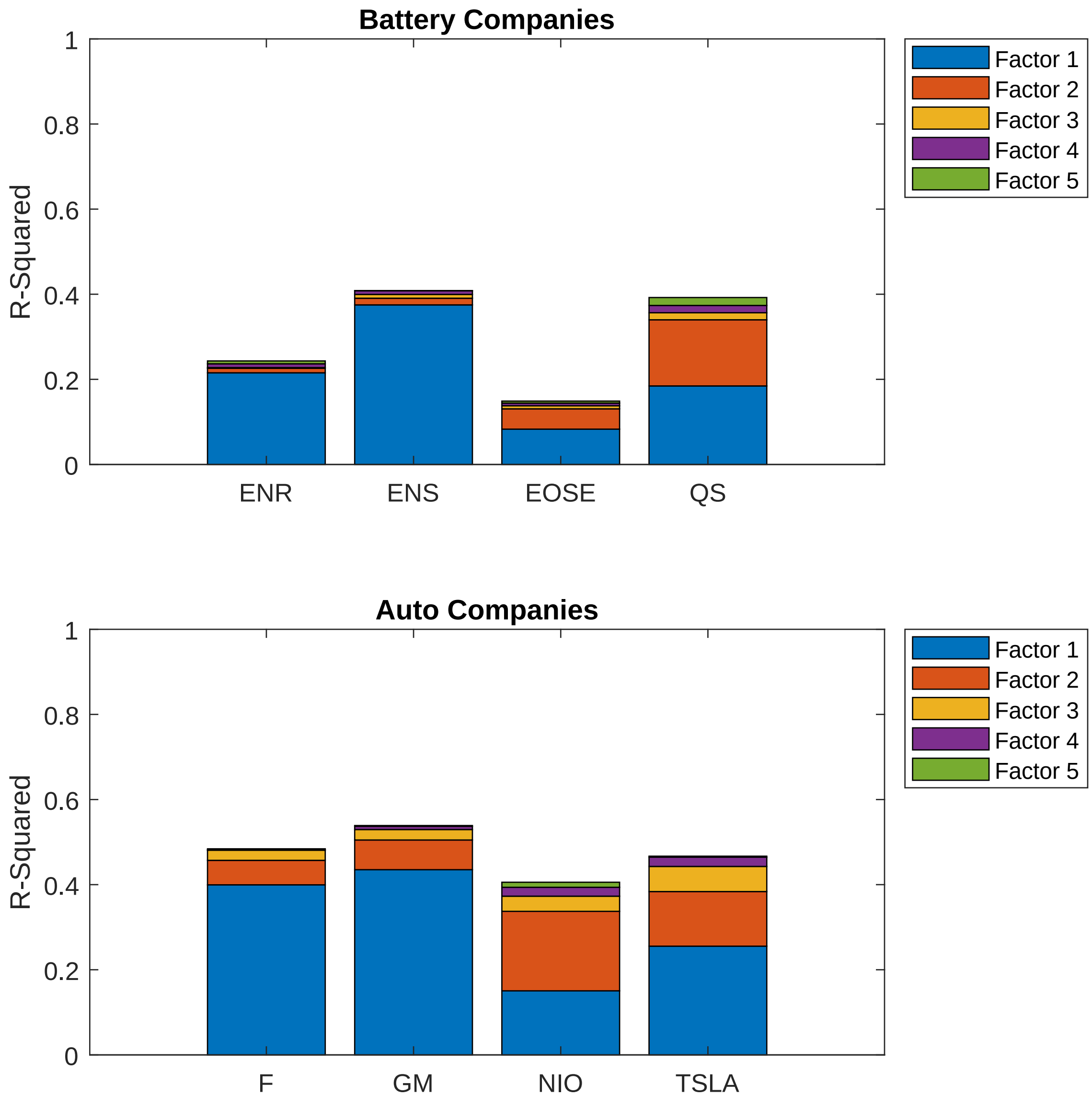


Figure 8: Comparing return profiles for traditional vs. EV-focused companies



B DAILY DATA

This section includes results for using daily data for 2022. Overall, these results are broadly similar to the results using the high-frequency data. Figure 9 shows the loadings on the factors. Figure 10 shows the explanatory power of each factor for the stocks which have a full sample available over the entire sample. In the daily data, the "cyclical" factor (factor 2) has somewhat more explanatory power for many of the EV and battery companies but somewhat less power for the lithium companies. On the other hand, factor x has more explanatory power for the lithium companies. Figure 11 performs the comparison between the "traditional" companies and the companies included in panel Y.

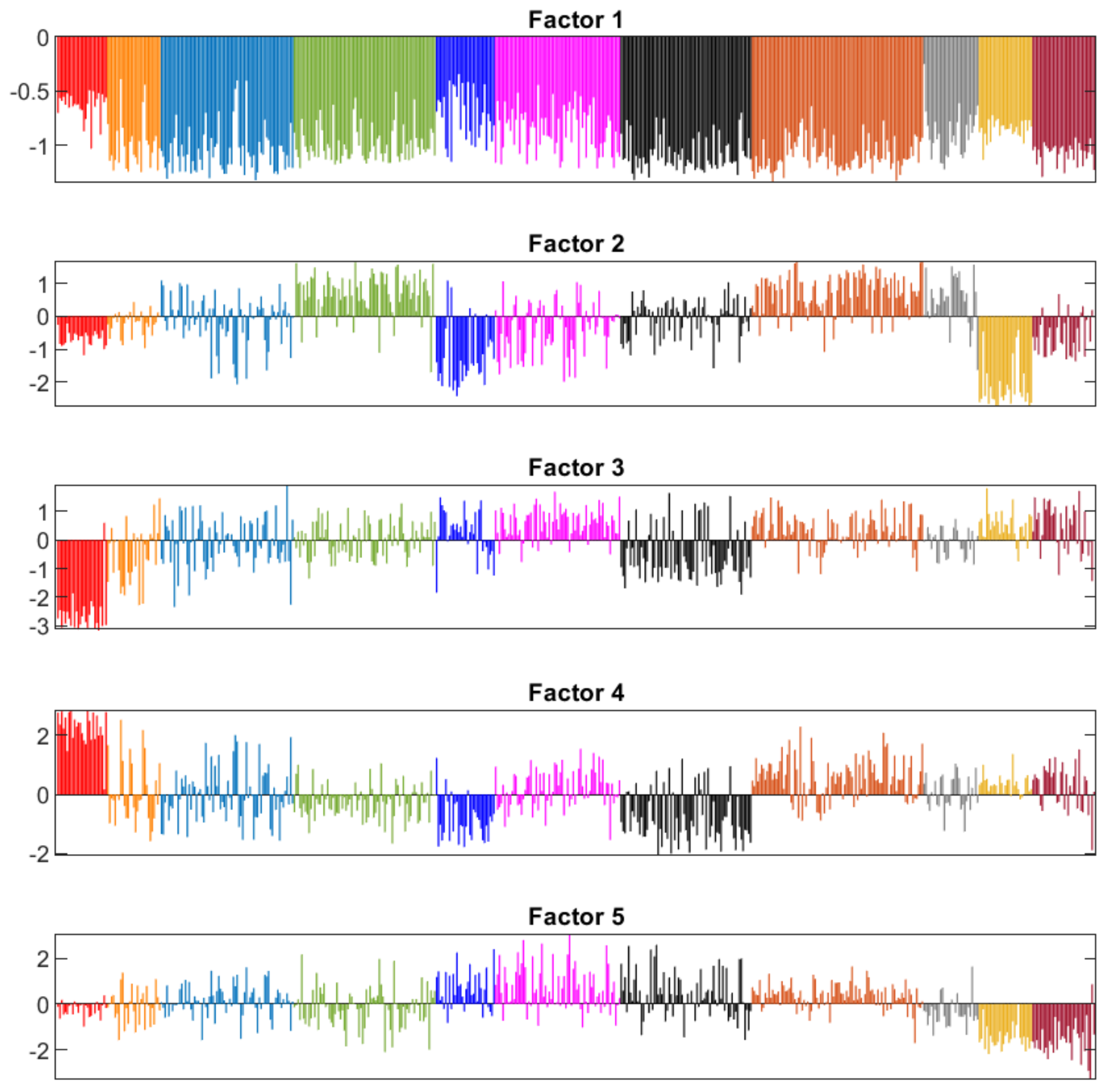


Figure 9: Loadings of the five systematic factors. Stocks are sorted by their two-digit GICS code. In order these are energy (red); materials (orange); industrials (light blue); consumer discretionary (green); consumer staples (dark blue); health care (pink); financials (black); tech (dark organge); communications (gray); utilities (yellow); real estate (maroon).

Figure 10: Breakdown of explanatory of systematic factors for individual stocks

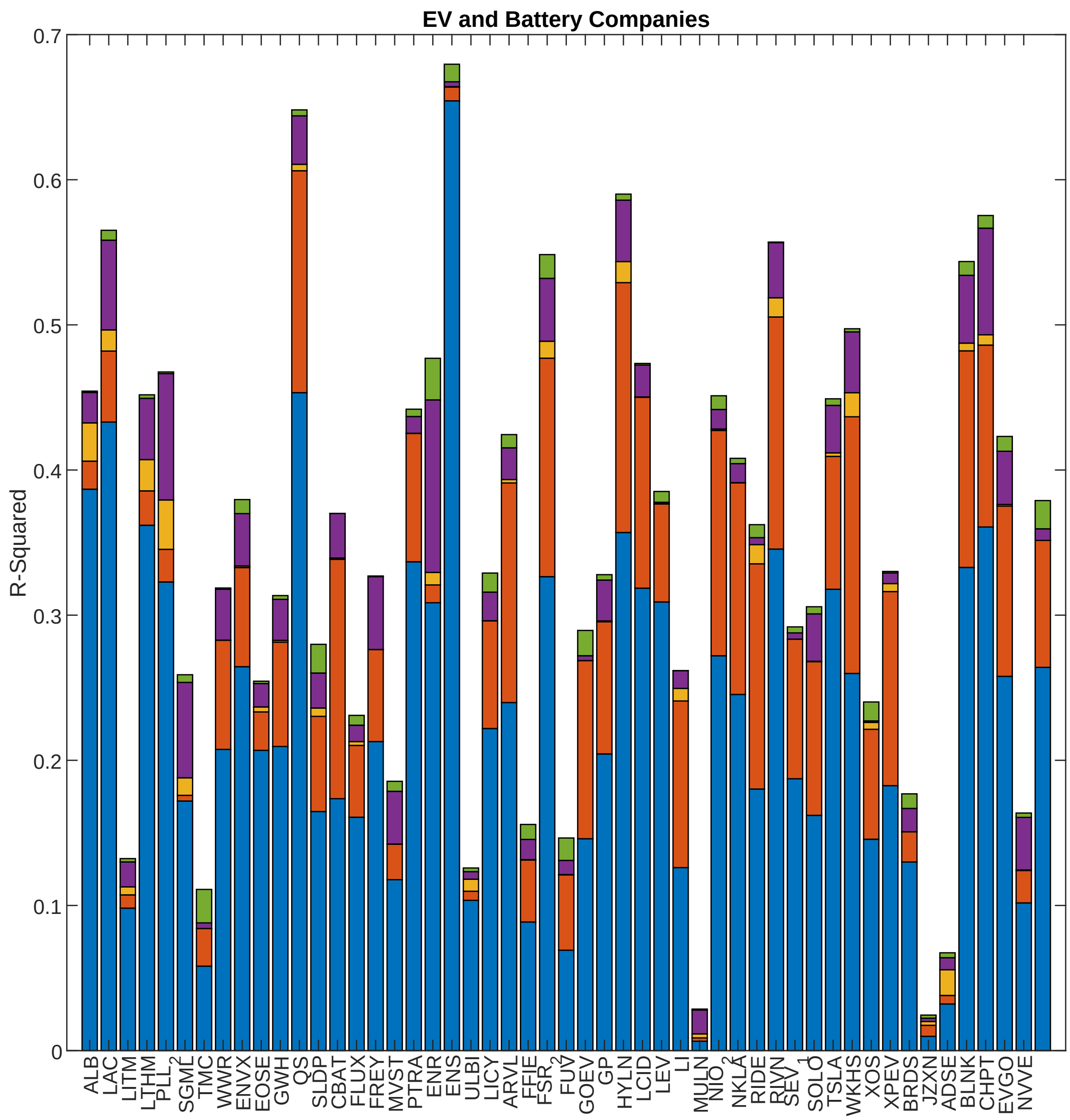


Figure 11: Comparing return profiles for traditional vs. EV-focused companies