Federal Reserve Bank of Dallas

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

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Working Paper 2314 September 2023 (Revised March 2024)

Research Department

https://doi.org/10.24149/wp2314r1

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

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September 22, 2023
Revised: March 8, 2024

Abstract

A large number of companies operating in the EV and battery supply chain have listed on a U.S. stock exchange in recent years. I compile a unique data set of high-frequency stock returns for those companies and investigate the extent to which an "industry" factor specific to the EV and battery supply chain (an "EV" factor) can explain their returns. Those returns are decomposed into systematic and idiosyncratic components, with the former given by a set of latent factors extracted from a large panel of stock returns using high-frequency principal components. It is found that a market factor and a factor associated with tech stocks have good explanatory power for the stocks of interest. I identify an "EV" factor as the first principal component of the idiosyncratic returns and find it has relatively good explanatory power for EV and battery stocks, often exceeding that of the tech factor. There is also evidence for a lithium factor that plays an important role in the returns of lithium companies.

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

JEL Classifications: G10; Q40; C55

*The views expressed in this paper are my own and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. I thank Alex Chudik, Junting Duan, Markus Pelger and participants at the USAEE 2022 and 2023 conferences, the EMEE 2023 workshop and the 2023 Federal Reserve System Energy Meeting for many helpful comments. I also thank Jessica Rindels, Kenya Schott and Sona Shah for excellent research assistance. All errors are my own.

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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]

Investors can now invest in the EV and battery space by holding stocks of these companies or investing in one of several exchange-traded funds that hold them. While a large literature has examined the properties and determinants of the returns of clean energy stocks and indexes, much less work has been done that focuses specifically on the stock returns of companies in the EV and battery supply chain, particularly those that have listed recently. This paper begins to fill this knowledge gap by investigating the relationships that exist between the returns of these companies with one another and with the broader market.

More specifically, this paper asks a set of related questions whose answers jointly shed light on those relationships: How much variation in the returns of these companies is due to systematic factors that explain common variation in stocks more generally? Are there specific patterns in terms of which factors matter? Do those patterns resemble other sectors in the economy? To what extent can the returns of EV and battery companies be explained by an "industry" factor specific to the EV and battery supply chain (hereafter referred to as an "EV" factor)?

As a first step towards addressing these questions, I compile a unique data set of intradaily stock returns for more than 70 companies 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

[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.

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. Hereafter, this set of stocks is referred to generically as EV stocks, with the understanding that the term covers the entire supply chain. One challenge is that most of these companies have gone public in just the past few years, so data is limited. The use of intradaily stock price data helps overcome this issue by significantly expanding the sample size and allowing the use of recently developed methods for applying principal components analysis (PCA) to high-frequency data sets (Pelger, 2019 and Pelger, 2020).

The EV stock returns are decomposed into systematic and idiosyncratic components by regressing them against a small set of risk factors. In this paper, those risk factors are given by a set of latent factors extracted from a large panel of stocks on the S&P 500 and Nasdaq 100 using high-frequency principal components. This approach follows recent work in Pelger (2020) which has shown that latent factors such as these can help explain stock returns.[3]

The decomposition is first used to explore whether the latent factors have any explanatory power for the returns of EV stocks. The answer to this question is not clear a priori. The latent factors are designed to explain the returns of a large cross-section of stocks and should, therefore, be useful for explaining stock returns more generally. With that said, the EV and battery supply chain is niche and many EV and battery companies have characteristics that may differ from the typical stock. The analysis shows, however, that these latent factors do indeed have explanatory power for most EV stocks, generally explaining between 20 to 40 percent of their variation.

Interestingly, the analysis shows that most of the explanatory power is due to just two of the latent factors. One is a "market" factor that reflects common variation in the returns of all stocks. The other is, for lack of a better word, a "cyclical" or "tech" factor that loads positively on tech, consumer discretionary and communication stocks and negatively on utilities and consumer staples. EV stocks generally have less exposure to the market factor than other stocks but above-average exposure to the tech factor. The beta (regression coefficient) of the tech factor on EV stocks is the

[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).

same sign as the loading of that factor on tech stocks, pointing to an underlying risk factor that generates positive comovement between the two groups of stocks. It is shown that these findings do not extend to more "traditional" battery and auto companies that are not primarily focused on the EV space.

The idiosyncratic returns, the residual after one has controlled for the influence of the systematic risk factors, are found to be an important component of all EV stock returns. The final part of the paper uses these returns to investigate whether there is any evidence for an industry factor that broadly affects companies operating in the EV and battery supply chain but which is unique to those firms. This type of analysis is, to the best of my knowledge, novel in the clean energy literature.

I identify an "EV" factor as the first principal component of the idiosyncratic returns and find that it loads positively on all of those returns. The explanatory power of this EV factor is high for many of the stocks, rivaling or exceeding that of the tech factor in many cases. This points to EV stocks having three primary sources of comovement among themselves: a market factor, which also leads to comovement with all other stocks; the tech factor, which also creates comovement with tech stocks; and the EV factor. It is also shown that lithium companies are exposed to their own specific risk-factor as the second principal component of the idiosyncratic returns loads heavily on those companies and has relatively high explanatory power for their returns.

Finally, analysis using smaller, non-overlapping sub-samples shows important variation in the explanatory power of some of the factors over time. In particular, the ability of systematic factors to explain the returns of EV and battery companies is significantly less in 2023 than in prior years. On the other hand, the explanatory power of both the EV and lithium factors is relatively good regardless of the sample period.

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.[4]

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, such as the Nasdaq OMX Green Economy Index or the WilderHill Clean Energy Index.[5] 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

[4]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.

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

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 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).[6] 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.

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

2 DATA AND METHODOLOGY

2.1 DATA Intradaily stock price data is sourced from Polygon.io, 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). I have price observations at 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 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.

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.[7] I identify 78 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 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

[7] 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.

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 "battery materials" group contains three companies that produce inputs used in the production of battery cells.

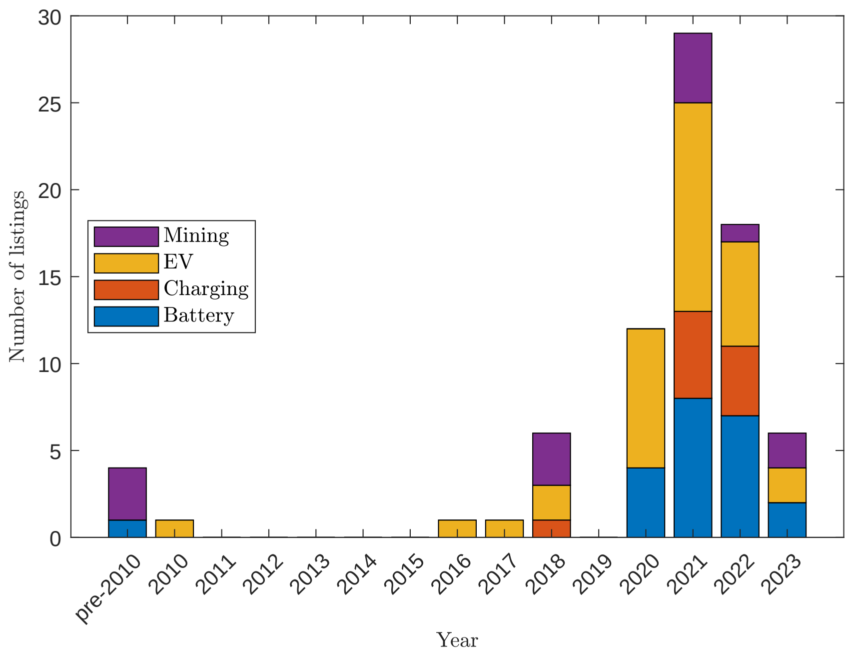
Among the EV group, I categorize firms into original equipment manufacturers (OEM) or other. Three Chinese OEMs are listed on an American exchange but sell predominantly in the Chinese market. Only three firms are grouped in the other category. One, JZXN, is a Chinese company that focuses on selling 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 2023. 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 include Albemarle (ALB), a lithium company; CBAK Energy (CBAT), a Chinese lithium-ion battery company that produces batteries used in consumer applications; SQM, a lithium company; and Westwater Resources (WWR), a graphite mining company.

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

Figure 1: Listings per year for EV and battery companies



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 liquid, have many fewer trades and often have data quality issues.[8]

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 de-meaned and then standardized to have unit variance. Λ and F are not uniquely identified so the

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

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,

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

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 regression is done individually for each company i. The systematic return for company i is given by $\sum_{j=1}^{\hat{K}} \beta_{ij} f_{jt}$ while the idiosyncratic return is given by the residual.

This model provides useful information both with respect to how the factor loads on the return (the signs of the betas) and how much variance each factor can explain. That information can then be used to see if any patterns hold across groups of stocks. It is also important to point out that no specific assumptions are made about the correlation structure of the idiosyncratic returns. A key part of the paper is to uncover what the data tell us about those correlations.

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. With this in mind, the paper's baseline results are based on a sample that includes data from 2022 to 2023. I also report results for a longer sample that starts in 2021 (with many fewer firms) and for sub-sample analysis using just 2022 and 2023. In all cases, companies are dropped if they do not have a full set of data for the sample.

A frequency also needs to be selected for constructing 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 in the EV stocks 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. However, the test statistics for a handful of companies are extremely large, suggesting the presence of significant noise. Those stocks are

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

	Test statistic	R^2
Factor 1	4.23	.32
Factor 2	1.47	.06
Factor 3	1.39	.04
Factor 4	1.11	.02
Factor 5	1.19	.02
Factor 6	1.01	.01

removed from the sample for the baseline results.[9]

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 2022-2023 sample, the X panel has a total of 544 companies while there are 38 companies in the panel of EV and battery companies. Of those, there are 8 mining companies, 9 battery companies, 17 EV companies; and 4 EV charging companies. Each company has $T = 12883$ returns.

Even given the tests, one might remain concerned about the presence of 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 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 2022-2023 sample. The

[9] In general, the intradaily returns of these stocks provide little insight into the questions of interest because their returns are not explained by the latent factors to any important degree, nor are their idiosyncratic returns generally correlated with the idiosyncratic returns of other companies.

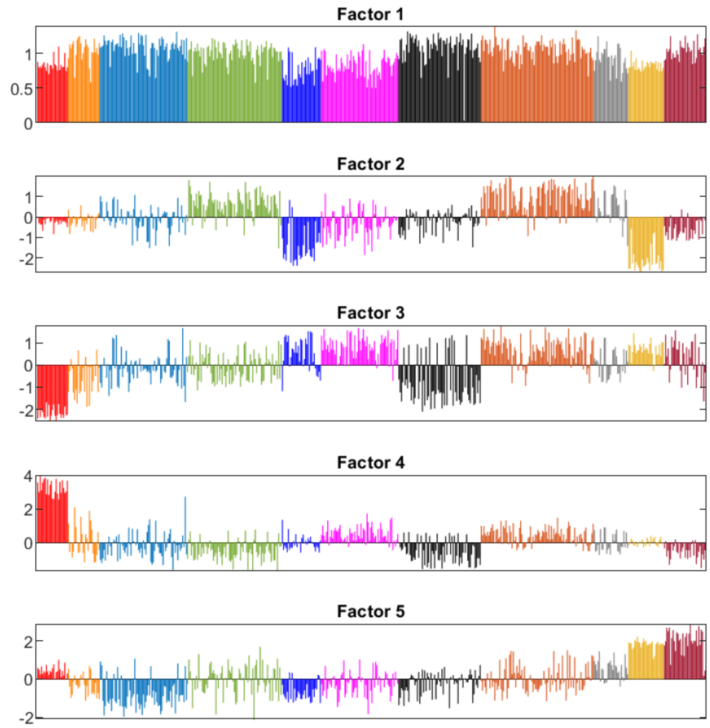


Figure 2: Loadings of the five systematic factors. Stocks are sorted by their two-digit GICS code. In order these are energy (red); materials (orange); industrials (light blue); consumer discretionary (green); consumer staples (dark blue); health care (pink); financials (black); tech (dark organge);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

variance explained by each factor is reported in the third column of table. The first factor explains about 32 percent, the second 6 percent, the third about 4 percent and the fourth and fifth about 2 percent each. In total, the first five factors explain roughly 52 percent of the variation of the panel.

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. 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). The two-digit codes are color-coded in the figure.

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	0.21	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**

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.[10]

A slightly different approach is 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 the sum of the individual contributions to the R^2 is exactly

[10]Despite the differences in samples and data sets, the systematic factors 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 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, whether there are any specific patterns that emerge about which factors are important, and whether those patterns resemble other sectors in the economy.

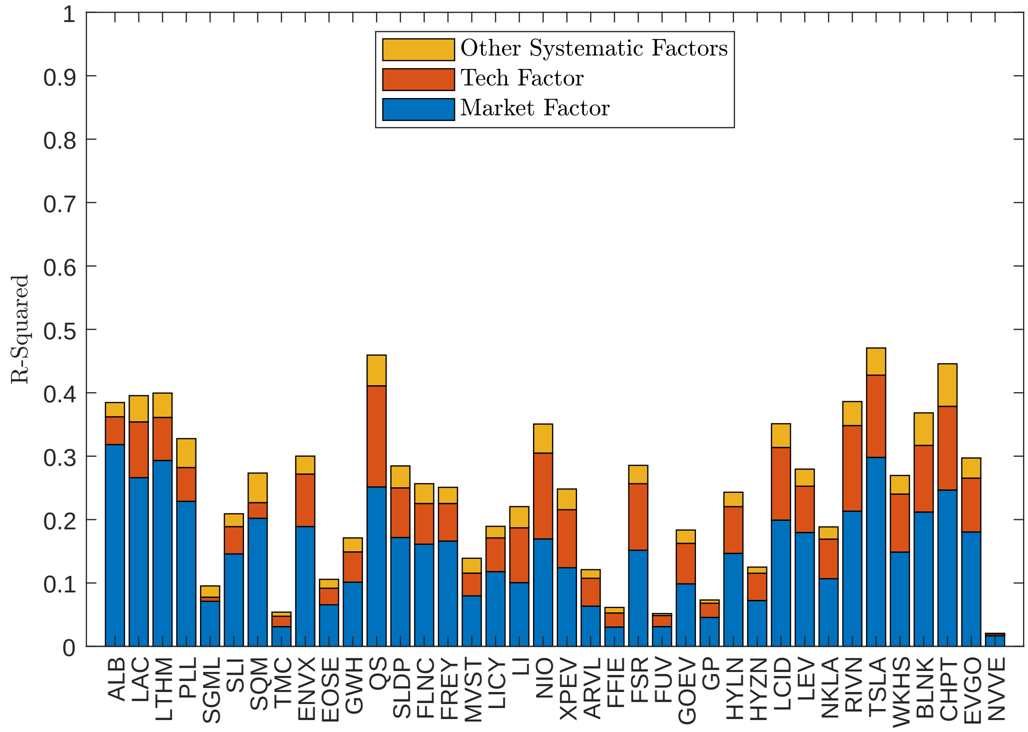
To answer these questions, the returns are regressed on a constant and the factors, one-at-a-time, to produce R^2 values for each factor and each firm. Figure 3 shows the explanatory power of each factor for each stock. The contribution of the market factor is shown by the blue bar, the tech factor by red, and the remaining three systematic factors in yellow.

The systematic factors have explanatory power for most of the stocks and exceeds 30 percent in some cases. A general pattern that emerges from Figure 3 is that the market and tech factors are the ones with good explanatory power. The explanatory power of the remaining three factors is modest at best.

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 off all groups, although to varying degrees. The tech factor is also important, with the median R^2 generally exceeding that of most industries. Its importance is found to be somewhat less for the mining group.

Table 2 does not provide any guidance as to which direction the tech factor loads onto the

Figure 3: Explanatory power of systematic factors for individual stocks

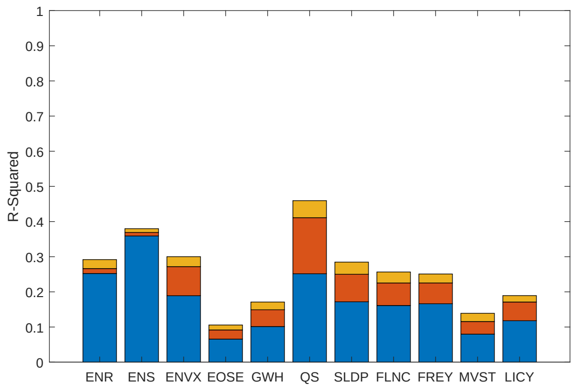


returns. This is important to know because that factor loads on cyclical and defensive sectors in opposite directions.[11] The betas from the regressions were investigated and found to be of the same sign as the loadings of the factor on tech stocks. As such, the returns of EV stocks respond to the tech factor in the same direction as tech and consumer discretionary stocks.

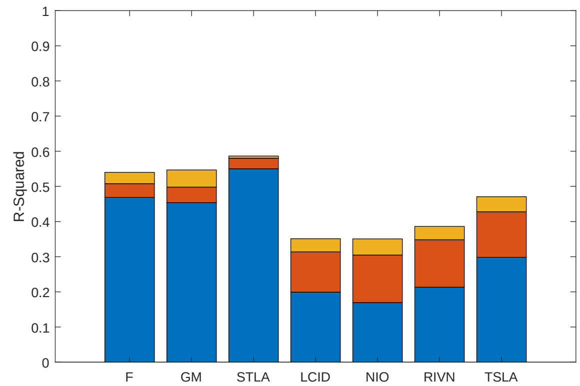
One useful exercise is to compare these profiles with those of more "traditional" companies. Figure 4a does this for battery companies by comparing two major battery companies, Energizer (ENR) and EnerSys (ENS), with the companies in the advanced and lithium-ion battery groups, as well as Li-Cycle (LICY), a startup battery recycling company in the battery materials group. For both ENR and ENS, the market factor plays a key role in explaining their returns while the cyclical factor plays essentially no role.

Similar results are found when comparing auto companies. Figure 4b compares Ford (F), GM, and Stellantis (STLA) on the one hand, with Lucid, Nio, Rivian and Tesla, as examples. The tech

[11]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 comovement in the opposite direction.



(a) Battery Companies



(b) Auto Companies

Figure 4: Comparing return profiles for traditional vs. EV-focused companies. The blue bar is for the market factor; red for the tech factor; yellow for the other three systematic factors.

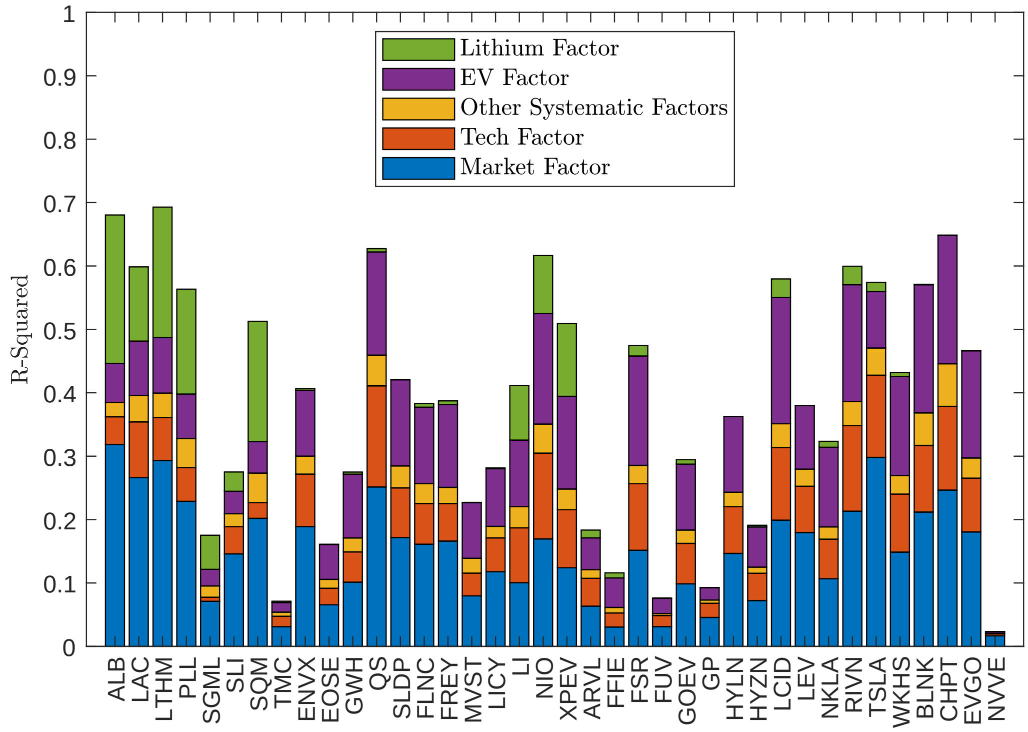
factor plays an important role in the EV companies but only a minor role for the traditional auto companies. For the latter, the market factor is the dominating factor in explaining their returns.[12]

With respect to the relationship between the returns and the latent factors, the results show that EV stocks most closely resemble tech stocks (and other cyclicals). *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 also 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 the returns of tech indexes as an observed risk factor. My results are somewhat different in nature from these previous findings in two regards. The first difference relates to the focus here on EV and battery companies, as earlier works generally considered other parts of the clean energy space. The second difference is that my results suggest it is not so much that tech stocks help explain EV and battery returns as it is that EV and battery stocks ARE tech stocks, at least in terms of how their returns are affected by the systematic risk

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

Figure 5: Explanatory power of all factors for individual stocks



factors used in this paper.

3.3 IDIOSYNCRATIC RETURNS This section investigates the properties of the idiosyncratic returns, which Figure 3 implies are an important part of the overall returns. I first investigate the correlation structure of the idiosyncratic returns, then test for the presence of cross-sectional dependence, and finally apply principal components to extract an "EV" factor from them.

A cursory investigation shows the idiosyncratic returns are not highly correlated with each other. With 38 stocks in Y, there are 703 unique pairwise correlations. The mean correlation across all pairs is just 0.11 while the median is 0.09. The correlations are found to be stronger for particular sub-groups, though, in particular for lithium companies, three Chinese EV companies and for EV charging firms.[13]

Next, the CD* test of Pesaran and Xie (2022) is used to test for the presence of cross-sectional

[13]Figure 11 of the appendix shows the correlation matrix itself, with correlations greater than the average value highlighted in red and those more than twice the average highlighted in green.

dependence in the idiosyncratic returns. 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. The test statistic is -42.2 and so strongly rejects the null of no cross-sectional dependence.[14]

Finally, principal components is applied to the idiosyncratic returns to provide further information on common movements among them. The first principal component loads on all companies and can explain 15 percent of the variation in idiosyncratic returns. Given the loadings, I refer to this as an "EV" factor. The second principal component loads heavily on lithium companies and for that is reason is hereafter referred to as a "lithium" factor. The remaining components appear to be picking up variation that essentially idiosyncratic in nature and are not discussed further here.

How much variation in the individual stock returns can the EV and lithium factors explain? Figure 5 shows the explanatory power for both factors along with the systematic factors. It can be seen that the relative importance of the EV factor is fairly high: its explanatory power typically exceeds that of the tech factor, although in most cases it is less important than the market factor. The lithium factor is less important for most stocks but plays an outsized role for lithium companies, which are apparently exposed to a very specific risk factor.[15]

These results point to three primary sources of comovement among EV stocks: the market factor, which also leads to comovement with all stocks; the tech factor, which generates comovement with tech stocks and other cyclicals; and the EV factor, representing comovement among themselves. Lithium companies also have a fourth source of comovement. Despite these common drivers, though, for many EV stocks a large fraction of the returns remains purely idiosyncratic and unexplained by any of the factors.

[14] The null was also rejected at a one percent level using the cross-sectional dependence test of Juodis and Reese (2021).

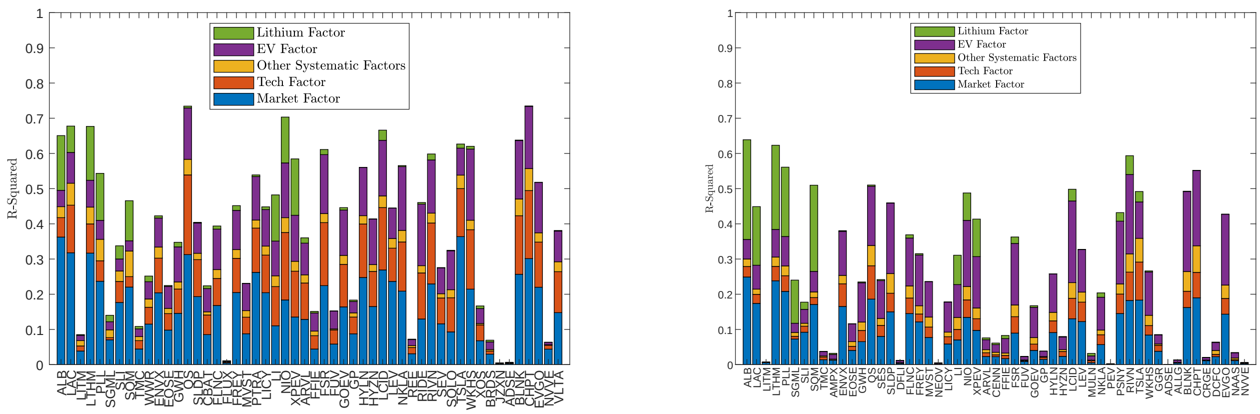
[15] It seems plausible this risk factor is tied somehow to lithium prices. I leave this question for future research.

4 ADDITIONAL RESULTS

4.1 SUB-SAMPLE ANALYSIS One important question is whether there have been shifts in the relative importance of the factors over time. The use of high frequency data allows for estimation of the factors over smaller, non-overlapping samples of data. This is done using a 2022 sub-sample and a 2023 sub-sample. For reach sample, I use all companies with a full set of data but remove stocks which are heavily contaminated with noise. This gives 52 stocks in 2022 and 53 stocks in 2023.

Figures 6a and 6b show the results. The key insights from this exercise are as follow. First, the explanatory power of the tech factor declined significantly in 2023 compared to 2022, when it played a major role in driving EV stock returns. While EV stocks rode the tech boom and bust in earlier parts of the sample they appear to have become less connected with tech returns since the end of the bust. More generally, the overall ability of the systematic risk factors to explain EV stock returns diminished in 2023 as the explanatory power the market factor also declined. Finally, the sub-sample analysis shows that the EV factor played a strong role regardless of the sample, although the explanatory power of the EV factor was typically larger in 2023 than in 2022. It is also found that the lithium factor played an extremely strong role in driving lithium stocks in 2023, less so in 2022.

4.2 LONGER SAMPLE It is possible to extend the sample to the beginning of 2021 and repeat the analysis for 22 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 on tech, consumer discretionary and communications stocks, and continues to play an important role in explaining the stock returns of the EV and battery companies. Both the EV and lithium factors have good explanatory power over this longer sample.



(a) 2022 Sample **(b)** 2023 Sample

Figure 6: Explanatory power of factors across sub-samples.

4.3 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, results were produced using daily stock return data from the CRSP database. This provides a check on whether my results are sensitive to the choice of the frequency and also provides a check on the quality of the returns data. The online appendix contains details for the baseline sample period. I find the 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, as do the EV and lithium factors. The results for the sub-sample analysis are also quite similar when using daily return data.

5 CONCLUSION

This paper has investigated how the stock returns of companies operating in the EV and battery supply chain are related both to themselves and to the broader market. It is found that there are three main drivers of comovement among EV stocks. One is a market factor, which also generates comovement with the broader market. A second is a factor that leads to comovement with tech stocks and other cyclicals. Finally, EV stocks are also exposed to a risk factor unique to those firms.

Both of the systematic factors have good explanatory power for many EV stocks, as does the EV factor itself. There is also evidence for a lithium factor that primarily affects lithium companies. Sub-sample analysis shows there is important time variation in the ability of the systematic factors to explain EV stock returns: the explanatory power of both the market and tech factors declined significantly in 2023 relative to earlier years.

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. There are also several other avenues for potential future research. In ongoing work, I am investigating whether the relationships uncovered here hold more broadly for other clean energy companies, such as solar and wind companies. Another important question is to what extent the returns of clean energy companies are related more broadly speaking to the returns of green stocks.

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

Company	Ticker	Exchange	Category	Sub-category
Albemarle	ALB	NYSE	Mining	Lithium
American Lithium	AMLI	Nasdaq	Mining	Lithium
Atlas Lithium	ATLX	Nasdaq	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
Standard Lithium	SLI	NYSE	Mining	Lithium
SQM	SQM	NYSE	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
Electrovaya	ELVA	Nasdaq	Battery	Lithium-ion
Fluence	FLNC	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
ABTC	ABAT	Nasdaq	Battery	Materials
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
Next.e.Go	EGOX	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
Hyzon	HYZN	Nasdaq	EV	OEM (hydrogen)
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
REE Automotive	REE	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
Vinfast	VFS	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
Allego	ALLG	NYSE	Charging	Services
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

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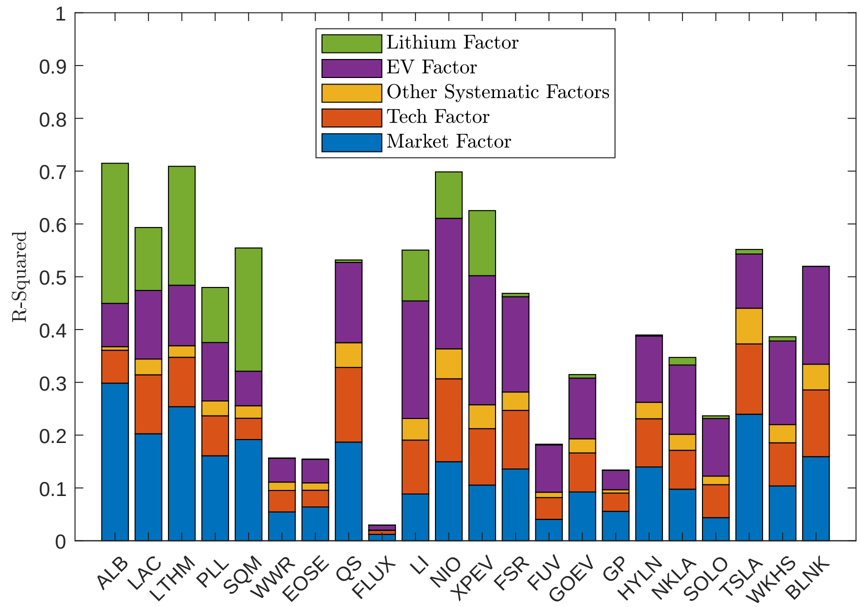
NOT FOR PUBLICATION APPENDIX

A 2021 TO 2023 SAMPLE

This section includes results for the longer sample that includes data from the start of 2021 to the end of 2023. Figure 7 shows the explanatory power of each factor for the stocks which have a full sample available over the entire sample. Figure 8 shows the loadings on the factors.

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



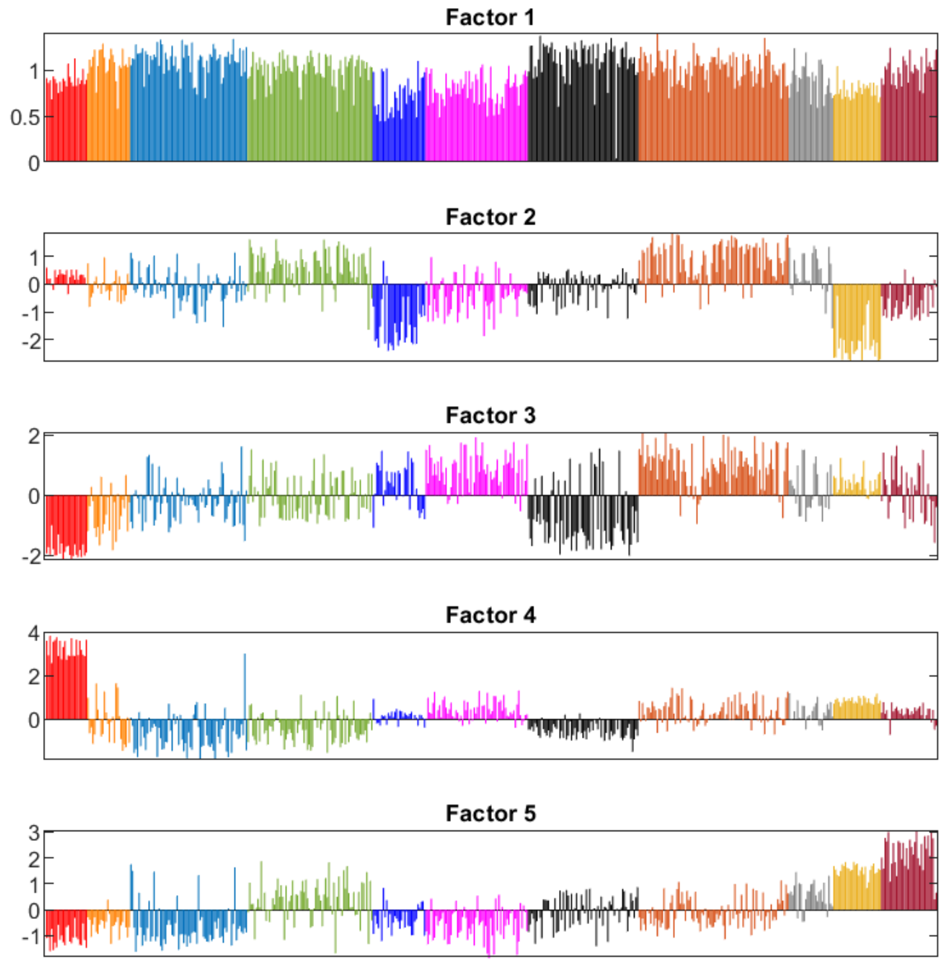
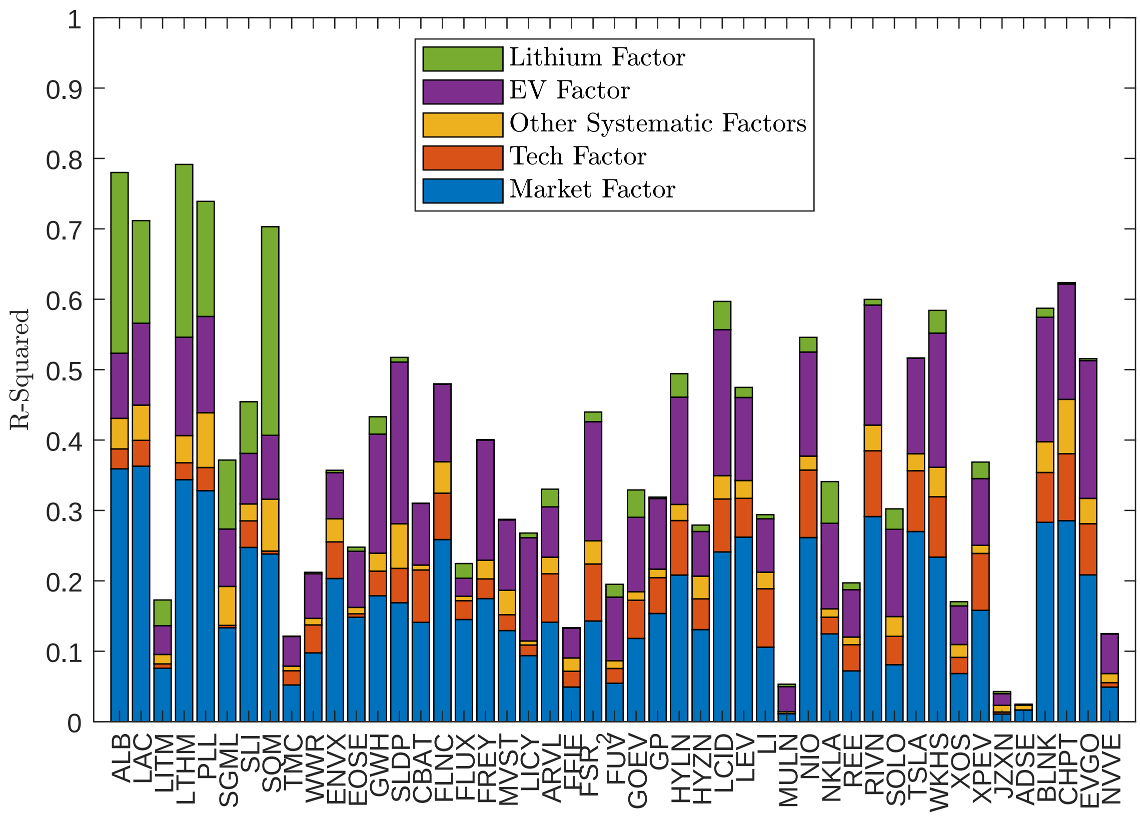


Figure 8: Loadings of the five systematic factors. Stocks are sorted by their two-digit GICS code. In order these are energy (red); materials (orange); industrials (light blue); consumer discretionary (green); consumer staples (dark blue); health care (pink); financials (black); tech (dark organge); communications (gray); utilities (yellow); real estate (maroon).

B DAILY DATA

This section includes results for using daily data for the 2022-2023 sample. Overall, these results are broadly similar to the results using the high-frequency data. Figure 9 shows the explanatory power of each factor for the stocks which have a full sample available over the entire sample. Figure 10 shows the loadings on the factors.

Figure 9: Breakdown of explanatory of systematic factors for individual stocks



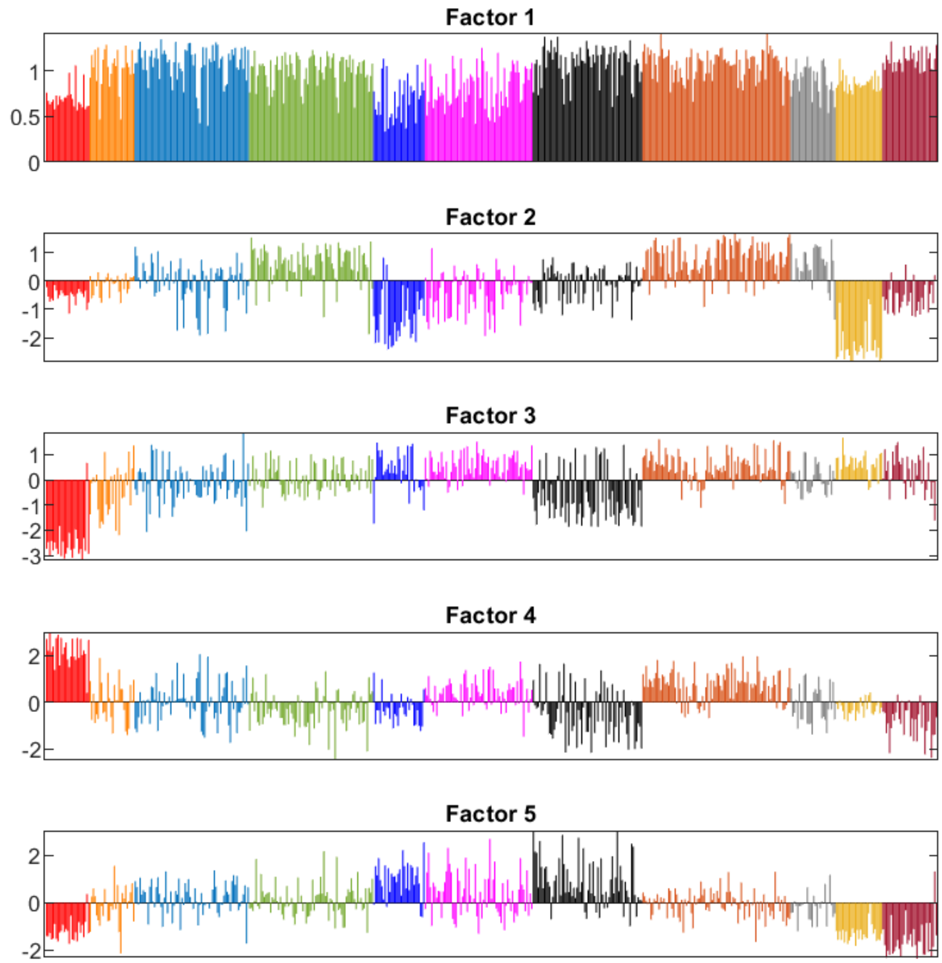


Figure 10: Loadings of the five systematic factors. Stocks are sorted by their two-digit GICS code. In order these are energy (red); materials (orange); industrials (light blue); consumer discretionary (green); consumer staples (dark blue); health care (pink); financials (black); tech (dark organge); communications (gray); utilities (yellow); real estate (maroon).

B.1 CORRELATION MATRIX Figure 11 shows the correlation matrix for the idiosyncratic returns based on the 2022-2023 sample. Any correlation greater than the average is highlighted in red. Any correlation twice the size of the average is highlighted in green.

Row	ALB	LAC	LTHM	PLL	SGML	SLI	SQM	TMC	ENVX	EOSE	GWH	QS	SLDP	FLNC	FREY	MVST	LICY	LI	NIO	XPEV	ARVL	FFIE	FSR	FUV	GOEV	GP	HYLN	HYZN	LCID	LEV	NKLA	RIVN	TSLA	WKHS	BLNK	CHPT	EVGO	NVVE
ALB	1.00	0.30	0.53	0.29	0.12	0.10	0.41	0.03	0.11	0.05	0.07	0.08	0.09	0.11	0.11	0.05	0.07	0.07	0.07	0.06	0.00	0.02	0.08	0.05	0.05	0.03	0.06	0.01	0.08	0.06	0.06	0.09	0.08	0.07	0.14	0.14	0.08	-0.01
LAC	0.30	1.00	0.36	0.32	0.15	0.16	0.23	0.07	0.09	0.07	0.11	0.14	0.10	0.12	0.11	0.07	0.10	0.11	0.13	0.10	0.04	0.07	0.11	0.05	0.09	0.04	0.13	0.07	0.13	0.09	0.08	0.13	0.11	0.12	0.15	0.17	0.12	0.02
LTHM	0.53	0.36	1.00	0.30	0.14	0.12	0.34	0.04	0.12	0.06	0.09	0.13	0.11	0.14	0.15	0.06	0.10	0.08	0.11	0.07	0.03	0.02	0.12	0.05	0.07	0.04	0.08	0.03	0.12	0.08	0.07	0.13	0.11	0.10	0.17	0.19	0.12	0.01
PLL	0.29	0.32	0.30	1.00	0.15	0.14	0.25	0.06	0.10	0.05	0.11	0.12	0.12	0.13	0.13	0.08	0.09	0.03	0.05	0.04	0.04	0.05	0.08	0.04	0.07	0.04	0.09	0.06	0.09	0.08	0.07	0.08	0.08	0.09	0.15	0.15	0.12	0.01
SGML	0.12	0.15	0.14	0.15	1.00	0.08	0.11	0.02	0.06	0.03	0.05	0.06	0.03	0.07	0.06	0.02	0.03	0.05	0.05	0.04	0.01	0.02	0.03	0.04	0.04	0.01	0.05	0.03	0.05	0.04	0.05	0.05	0.03	0.04	0.08	0.08	0.05	-0.01
SLI	0.10	0.16	0.12	0.14	0.08	1.00	0.09	0.05	0.06	0.04	0.07	0.08	0.09	0.09	0.07	0.04	0.09	0.04	0.06	0.05	0.05	0.05	0.07	0.02	0.04	0.01	0.06	0.07	0.07	0.07	0.05	0.05	0.03	0.08	0.09	0.08	0.09	0.01
SQM	0.41	0.23	0.34	0.25	0.11	0.09	1.00	0.03	0.07	0.03	0.06	0.05	0.07	0.08	0.09	0.05	0.07	0.08	0.07	0.05	0.00	0.05	0.06	0.03	0.06	0.02	0.04	0.02	0.07	0.04	0.05	0.08	0.08	0.07	0.10	0.09	0.06	0.01
TMC	0.03	0.07	0.04	0.06	0.02	0.05	0.03	1.00	0.05	0.05	0.04	0.04	0.05	0.04	0.03	0.03	0.05	0.01	0.05	0.02	0.04	0.02	0.05	0.02	0.05	0.03	0.06	0.02	0.03	0.05	0.04	0.07	0.04	0.05	0.05	0.04	0.03	0.02
ENVX	0.11	0.09	0.12	0.10	0.06	0.06	0.07	0.05	1.00	0.12	0.15	0.20	0.15	0.22	0.20	0.14	0.14	0.08	0.12	0.10	0.07	0.04	0.14	0.04	0.11	0.05	0.13	0.10	0.14	0.13	0.12	0.15	0.09	0.13	0.21	0.24	0.16	0.00
EOSE	0.05	0.07	0.06	0.05	0.03	0.04	0.03	0.05	0.12	1.00	0.11	0.12	0.09	0.12	0.12	0.06	0.08	0.05	0.08	0.05	0.04	0.02	0.10	0.04	0.08	0.04	0.09	0.05	0.08	0.11	0.07	0.09	0.06	0.09	0.14	0.15	0.12	0.02
GWH	0.07	0.11	0.09	0.11	0.05	0.07	0.06	0.04	0.15	0.11	1.00	0.16	0.16	0.16	0.15	0.12	0.13	0.04	0.10	0.07	0.05	0.04	0.14	0.04	0.09	0.06	0.14	0.10	0.13	0.15	0.12	0.10	0.07	0.14	0.20	0.21	0.17	0.05
QS	0.08	0.14	0.13	0.12	0.06	0.08	0.05	0.04	0.20	0.12	0.16	1.00	0.28	0.16	0.21	0.16	0.16	0.13	0.20	0.17	0.15	0.11	0.27	0.06	0.16	0.06	0.19	0.11	0.32	0.18	0.18	0.31	0.19	0.22	0.30	0.34	0.25	0.02
SLDP	0.09	0.10	0.11	0.12	0.03	0.09	0.07	0.05	0.15	0.09	0.16	0.28	1.00	0.12	0.17	0.15	0.15	0.06	0.14	0.09	0.10	0.10	0.20	0.04	0.13	0.06	0.16	0.11	0.21	0.16	0.13	0.22	0.15	0.17	0.22	0.22	0.22	0.02
FLNC	0.11	0.12	0.14	0.13	0.07	0.09	0.08	0.04	0.22	0.12	0.16	0.16	0.12	1.00	0.22	0.12	0.14	0.10	0.15	0.10	0.06	0.05	0.11	0.05	0.11	0.06	0.13	0.10	0.14	0.13	0.10	0.16	0.11	0.16	0.24	0.26	0.19	0.04
FREY	0.11	0.11	0.15	0.13	0.06	0.07	0.09	0.03	0.20	0.12	0.15	0.21	0.17	0.22	1.00	0.14	0.17	0.06	0.13	0.09	0.07	0.07	0.16	0.06	0.12	0.05	0.13	0.10	0.16	0.14	0.12	0.15	0.10	0.16	0.23	0.27	0.19	0.02
MVST	0.05	0.07	0.06	0.08	0.02	0.04	0.05	0.03	0.14	0.06	0.12	0.16	0.15	0.12	0.14	1.00	0.13	0.07	0.10	0.08	0.08	0.07	0.13	0.02	0.10	0.04	0.12	0.09	0.11	0.13	0.12	0.12	0.10	0.14	0.17	0.19	0.14	0.01
LICY	0.07	0.10	0.10	0.09	0.03	0.09	0.07	0.05	0.14	0.08	0.13	0.16	0.15	0.14	0.17	0.13	1.00	0.07	0.12	0.08	0.06	0.07	0.13	0.01	0.09	0.05	0.11	0.10	0.12	0.13	0.11	0.13	0.08	0.13	0.17	0.18	0.16	0.03
LI	0.07	0.11	0.08	0.03	0.05	0.04	0.08	0.01	0.08	0.05	0.04	0.13	0.06	0.10	0.06	0.07	0.07	1.00	0.54	0.57	0.08	0.10	0.14	0.05	0.10	0.01	0.04	0.05	0.18	0.07	0.10	0.19	0.16	0.11	0.11	0.11	0.09	0.01
NIO	0.07	0.13	0.11	0.05	0.05	0.06	0.07	0.05	0.12	0.08	0.10	0.20	0.14	0.15	0.13	0.10	0.12	0.54	1.00	0.64	0.10	0.11	0.22	0.10	0.15	0.04	0.12	0.09	0.28	0.10	0.17	0.32	0.27	0.20	0.20	0.23	0.15	0.02
XPEV	0.06	0.10	0.07	0.04	0.04	0.05	0.05	0.02	0.10	0.05	0.07	0.17	0.09	0.10	0.09	0.08	0.08	0.57	0.64	1.00	0.09	0.11	0.18	0.07	0.13	0.02	0.08	0.07	0.23	0.10	0.15	0.25	0.22	0.16	0.16	0.16	0.12	0.01
ARVL	0.00	0.04	0.03	0.04	0.01	0.05	0.00	0.04	0.07	0.04	0.05	0.15	0.10	0.06	0.07	0.08	0.06	0.08	0.10	0.09	1.00	0.07	0.11	0.05	0.11	0.07	0.09	0.08	0.13	0.09	0.08	0.11	0.07	0.13	0.09	0.11	0.09	0.02
FFIE	0.02	0.07	0.02	0.05	0.02	0.05	0.05	0.02	0.04	0.02	0.04	0.11	0.10	0.05	0.07	0.07	0.07	0.10	0.11	0.11	0.07	1.00	0.11	0.02	0.09	0.05	0.07	0.08	0.12	0.08	0.06	0.11	0.08	0.10	0.08	0.09	0.09	0.02
FSR	0.08	0.11	0.12	0.08	0.03	0.07	0.06	0.05	0.14	0.10	0.14	0.27	0.20	0.11	0.16	0.13	0.13	0.14	0.22	0.18	0.11	0.11	1.00	0.04	0.17	0.05	0.18	0.11	0.35	0.15	0.18	0.30	0.21	0.21	0.21	0.25	0.21	-0.01
FUV	0.05	0.05	0.05	0.04	0.04	0.02	0.03	0.02	0.04	0.04	0.04	0.06	0.04	0.05	0.06	0.02	0.01	0.05	0.10	0.07	0.05	0.02	0.04	1.00	0.06	0.06	0.03	0.05	0.09	0.05	0.03	0.09	0.06	0.06	0.07	0.07	0.07	0.00
GOEV	0.05	0.09	0.07	0.07	0.04	0.04	0.06	0.05	0.11	0.08	0.09	0.16	0.13	0.11	0.12	0.10	0.09	0.10	0.15	0.13	0.11	0.09	0.17	0.06	1.00	0.07	0.12	0.09	0.19	0.11	0.13	0.19	0.14	0.19	0.16	0.16	0.15	0.02
GP	0.03	0.04	0.04	0.04	0.01	0.01	0.02	0.03	0.05	0.04	0.06	0.06	0.06	0.06	0.05	0.04	0.05	0.01	0.04	0.02	0.07	0.05	0.05	0.06	0.07	1.00	0.04	0.07	0.06	0.09	0.05	0.05	0.03	0.06	0.07	0.07	0.06	0.02
HYLN	0.06	0.13	0.08	0.09	0.05	0.06	0.04	0.06	0.13	0.09	0.14	0.19	0.16	0.13	0.13	0.12	0.11	0.04	0.12	0.08	0.09	0.07	0.18	0.03	0.12	0.04	1.00	0.12	0.17	0.17	0.24	0.17	0.10	0.20	0.22	0.26	0.19	0.03
HYZN	0.01	0.07	0.03	0.06	0.03	0.07	0.02	0.02	0.10	0.05	0.10	0.11	0.11	0.10	0.10	0.09	0.10	0.05	0.09	0.07	0.08	0.08	0.11	0.05	0.09	0.07	0.12	1.00	0.10	0.13	0.18	0.08	0.08	0.12	0.12	0.14	0.13	0.05
LCID	0.08	0.13	0.12	0.09	0.05	0.07	0.07	0.03	0.14	0.08	0.13	0.32	0.21	0.14	0.16	0.11	0.12	0.18	0.28	0.23	0.13	0.12	0.35	0.09	0.19	0.06	0.17	0.10	1.00	0.14	0.19	0.47	0.28	0.23	0.25	0.28	0.24	0.02
LEV	0.06	0.09	0.08	0.08	0.04	0.07	0.04	0.05	0.13	0.11	0.15	0.18	0.16	0.13	0.14	0.13	0.13	0.07	0.10	0.10	0.09	0.08	0.15	0.05	0.11	0.09	0.17	0.13	0.14	1.00	0.16	0.14	0.11	0.19	0.21	0.20	0.17	0.02
NKLA	0.06	0.08	0.07	0.07	0.05	0.05	0.05	0.04	0.12	0.07	0.12	0.18	0.13	0.10	0.12	0.12	0.11	0.10	0.17	0.15	0.08	0.06	0.18	0.03	0.13	0.05	0.24	0.18	0.19	0.16	1.00	0.18	0.14	0.19	0.19	0.22	0.17	-0.01
RIVN	0.09	0.13	0.13	0.08	0.05	0.05	0.08	0.07	0.15	0.09	0.10	0.31	0.22	0.16	0.15	0.12	0.13	0.19	0.32	0.25	0.11	0.11	0.30	0.09	0.19	0.05	0.17	0.08	0.47	0.14	0.18	1.00	0.31	0.22	0.22	0.24	0.21	0.02
TSLA	0.08	0.11	0.11	0.08	0.03	0.03	0.08	0.04	0.09	0.06	0.07	0.19	0.15	0.11	0.10	0.10	0.08	0.16	0.27	0.22	0.07	0.08	0.21	0.06	0.14	0.03	0.10	0.08	0.28	0.11	0.14	0.31	1.00	0.18	0.16	0.16	0.13	0.02
WKHS	0.07	0.12	0.10	0.09	0.04	0.08	0.07	0.05	0.13	0.09	0.14	0.22	0.17	0.16	0.16	0.14	0.13	0.11	0.20	0.16	0.13	0.10	0.21	0.06	0.19	0.06	0.20	0.12	0.23	0.19	0.19	0.22	0.18	1.00	0.24	0.21	0.20	0.03
BLNK	0.14	0.15	0.17	0.15	0.08	0.09	0.10	0.05	0.21	0.14	0.20	0.30	0.22	0.24	0.23	0.17	0.17	0.11	0.20	0.16	0.09	0.08	0.21	0.07	0.16	0.07	0.22	0.12	0.25	0.21	0.19	0.22	0.16	0.24	1.00	0.45	0.31	0.02
CHPT	0.14	0.17	0.19	0.15	0.08	0.08	0.09	0.04	0.24	0.15	0.21	0.34	0.22	0.26	0.27	0.19	0.18	0.11	0.23	0.16	0.11	0.09	0.25	0.07	0.16	0.07	0.26	0.14	0.28	0.20	0.22	0.24	0.16	0.21	0.45	1.00	0.37	0.04
EVGO	0.08	0.12	0.12	0.12	0.05	0.09	0.06	0.03	0.16	0.12	0.17	0.25	0.22	0.19	0.19	0.14	0.16	0.09	0.15	0.12	0.09	0.09	0.21	0.07	0.15	0.06	0.19	0.13	0.24	0.17	0.17	0.21	0.13	0.20	0.31	0.37	1.00	0.02
NVVE	-0.01	0.02	0.01	0.01	-0.01	0.01	0.01	0.02	0.00	0.02	0.05	0.02	0.02	0.04	0.02	0.01	0.03	0.01	0.02	0.01	0.02	0.02	-0.01	0.00	0.02	0.02	0.03	0.05	0.02	0.02	-0.01	0.02	0.02	0.03	0.02	0.04	0.02	1.00

Figure 11: Correlations of idiosyncratic returns of EV and battery companies for 2022-2023 sample.