Explosive returns: teaching event studies using hydrogen bomb development

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Event studies are ubiquitous in empirical finance, but absent from many undergraduate econometrics texts. We provide a case study drawing on Armen Alchian's inference of the use of lithium as the essential metal for use in hydrogen bombs testing. More rigorous tests validate Alchian's original finding, although the results are somewhat sensitive to the time period used to construct the model for normal returns. We provide two sample assignments; one for students with only an introduction to statistics, and one for students who have experience with linear regression.

Keywords: stock returns; Alchian, Armen; experiential learning; event study

Subject classification codes: A2, B41, G14

Introduction

More than 30 years ago, Eugene Fama declared that much of what we knew about the informational efficiency of financial markets came from the "growth industry" of event studies (Fama 1991). In addition to testing market efficiency, event studies have been used to identify the effects of macroeconomic announcements on bond prices (e.g., Balduzzi, Elton, and Green 2001) and detect pre-announcement informed trading (e.g., Kurov et al. 2019). They are also used outside of academia, such as in SEC disgorgement proceedings (Mitchell and Netter 1994) and by the Federal courts when evaluating securities fraud class action suits (Halliburton Co. v. Erica P. John Fund, Inc., 2014; Fisch, Gelbach, and Klick 2018).

We provide data for conducting a basic event study using an interesting antecedent to academic event studies such as Ball and Brown (1968) and Fama et al. (1969). In 1953, Armen Alchian inferred that lithium was the essential element for a newly developed hydrogen bomb months before the bomb was actually tested in the

Marshall Islands (Newhard 2014). He did so by noticing the stock price of Lithium Corp. of America was increasing in late 1953, relative to producers of other candidate minerals. Given the national security implications of his finding, his study was suppressed. In a retrospective interview, Alchian related the anecdote behind his stock market study (Alchian 1996)

> […] I like to brag that I did the first "event study" in corporate finance, back in the 1950s and 1960s. The year before the Hbomb was successfully created, we in the economics division at RAND were curious as to what the essential metal was- lithium, beryllium, thorium, or some other. The engineers and physicists wouldn't tell us economists, quite properly, given the security restrictions. So I told them I would find out. I read the U.S. Department of Commerce Year Book to see which firms made which of the possible ingredients. For the last six months of the year prior to the successful test of the bomb, I traced the stock prices of those firms. I used no inside information. Lo and behold! One firm's stock prices rose, as best I can recall, from about $2 or $3 per share in August to about $13 per share in December. It was the Lithium Corp. of America. In January, I wrote and circulated within RAND a memorandum titled "The Stock Market Speaks." Two days later I was told to withdraw it. The bomb was tested successfully in February, and thereafter the stock price stabilized.

Newhard (2014) summarizes the background of this incident and shows that the behavior of stock prices in early 1954 would have been consistent with Alchian's predictions, and the subsequent price increases were justified by growth in demand for lithium.

We provide the daily data and guidance for how to use this incident to introduce event studies to undergraduate students. The data are hand-collected from contemporary newspapers that Alchian could have used, and our illustrative example focuses on the period in late 1953 when he conducted his study. The example demonstrates the applicability of event studies beyond the classic examples of stock splits and earnings announcements, while still offering the opportunity to discuss those events in the context of the companies included in the dataset. Our example is small-scale enough to be implemented in a spreadsheet, but can also be coded in statistical software. Moreover, it is flexible. While our initial example illustrates Alchian's finding without the use of linear regression, we subsequently illustrate extensions to multi-factor models and incorporating a post-event sample which weaken the evidence for the (correct!) conclusion drawn from the simple model. These extensions highlight an opportunity to discuss the distinction between statistical and economic significance (Ziliak and McCloskey 2008).

This article contributes to the existing (but limited) pedagogical literature on "finance-style" event studies, particularly to undergraduate students who may want to design and carry out their own research projects.[1] Introducing this research methodology is useful for undergraduate students interested in topics in macroeconomics and financial economics broadly. The majority of recent research in macroeconomics relies on formal theory (such as dynamic stochastic general equilibrium models) (Glandon, et al. 2023). DSGE models in particular have a high barrier to entry and their utility in the undergraduate curriculum is, at best, controversial (see Colander (2018)). Event studies are, relatively speaking, easier to approach – they are more closely connected to the empirical approaches commonly taught in undergraduate statistics -- but much of the academic literature assumes familiarity with

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[1] The application of event studies (and use of the moniker) has broadened somewhat. For instance, Miller (2023) focuses on regression-based event studies with the use of panel data for studying treatment effects. At the undergraduate level, that type of event study is also discussed in (Wooldridge 2020). In this article, we focus on finance event studies in the tradition of Ball and Brown (1968) and Fama et al. (1969).

the methodology and attendant econometric issues. Existing reviews (for example, MacKinlay 1997; Kothari and Warner 2007; Corrado 2011) outline the methodology at the graduate level. There are a few other articles that offer suggestions for teaching with event studies (Fehrs 1990; Reese Jr. and Robins 2017; Martinez-Blasco et al. 2023). These focus on applying author-provided tools. Huntington-Klein (2022) illustrates an event study for a single firm and discusses some related tests.

In the next section, we provide some background on Alchian's original exercise and the construction of the data set. We subsequently explain and illustrate a simple formalization of Alchian's event study to illustrate the methodology and discuss extensions that instructors (or students) may want to explore. We conclude by suggesting some possible choices for instructors.

Background on the Alchian event study and data construction

Newhard (2014) discusses the background of hydrogen bomb testing in the United States and choices of possible metals used to develop hydrogen bombs in the early 1950s. He identifies four publicly traded firms as key manufacturers of candidate fuels that Alchian likely tracked (metals included in parentheses)

- Beryllium Corp. (Beryllium)
- American Smelting and Refining Corp. (ASRC) (Thallium)
- Metal Hydrides Inc. (MHI) (Thorium)
- Lithium Corp. of America (Lithium)

While other publicly traded firms were also involved in the production of these metals, many of them were more horizontally diversified firms, which could have made identifying the price impact of hydrogen bomb development more difficult for Alchian.

A salutary benefit of this sample of corporations for teaching purposes is that they present interesting data construction problems. Only ASRC was traded on the New York Stock Exchange in the 1950s; the remaining three were traded in over the counter markets. Bid and ask data for MHI was only reported weekly, while the other three are available daily. Beryllium Corp. underwent a stock split in 1953.

Constructing the data

We focus on the four firms listed above, the Dow Jones Industrial Average (DJIA), and the three-month Treasury bill rate as relevant time series for the event study. We construct time series of the bid prices for each security from the Wall Street Journal (WSJ) and New York Times (NYT).[2] Bid and ask prices for Beryllium Corp. and Lithium Corp. of America were listed in the WSJ's daily "Over the Counter Industrials" section of its financial reporting. MHI's bid and ask prices were published in the WSJ "Over the Counter Weekly List", usually published on the first trading day of the week for the previous Friday. ASRC, listed on the NYSE, had prices (including opening and closing prices) listed in both the WSJ and NYT.

For Treasury bill rates, we mainly use the monthly G.14 U.S. Government Security Yields and Prices reports, made available on the Federal Reserve Bank of St. Louis's FRASER library. FRASER is missing G.14 releases for the first two months of 1953, so for those data points we use reported yields in the WSJ and NYT for bills maturing in

[2] In practice we use microfilms for the WSJ. Newhard (2014) uses ProQuest scans of the WSJ, but we found that the quality of the scans often makes it difficult to read asks and bids. The NYT's online archive has very legible NYSE and Treasury bill data, but not the OTC stock data.

approximately three months. We use the reported closing DJIA from the WSJ.[3]

Equity price data, the DJIA, and the yield on 3-month T-Bills are shown in figure 1 over the period from 1953-54; analogous daily price returns are shown in figure 2. The vertical line indicates the date of the first lithium hydrogen bomb test ("Castle Bravo").   Asking students to examine the data in *levels* is pedagogically useful for a few reasons. First, it demonstrates how Alchian might have suspected that lithium was the key ingredient – the price of Lithium Corp. of America begins to rise several months prior to the Castle Bravo test. Second, it illustrates that several of the securities more or less follow random walks, and visually suggests why a model that adjusts for co-movement with the market might be warranted (given the positive comovement of several stocks with the market). Third, it makes certain empirical pitfalls -- Beryllium Corporation's stock split in early 1953, the mixed frequency of the equity data -- very apparent. Students who jump immediately to statistical analysis without plotting the data first may miss these features, which could affect inference later.

[3] The data, included as supplemental material, are also posted at https://github.com/ethans-carl/alchian_event_study

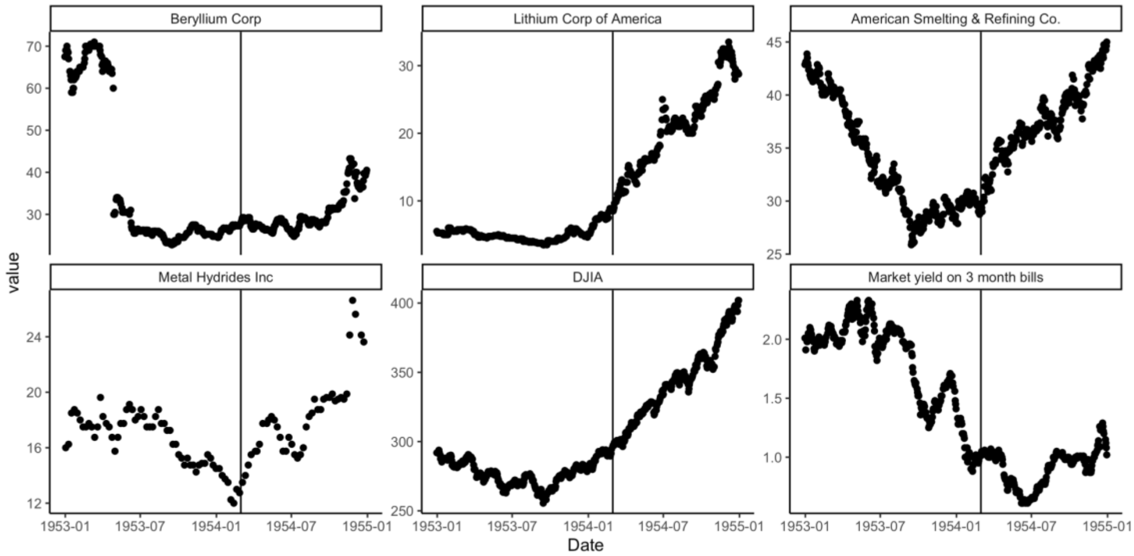


Figure 1: Stock prices for Beryllium Corp., Lithium Corp. of America, American Smelting and Refining Corporation and Metal Hydrides, Inc, Dow Jones Industrial Average, and Market Yield of 3-month Treasury Bill yield, 1953-1954. Vertical line indicates date of the Castle Bravo test.

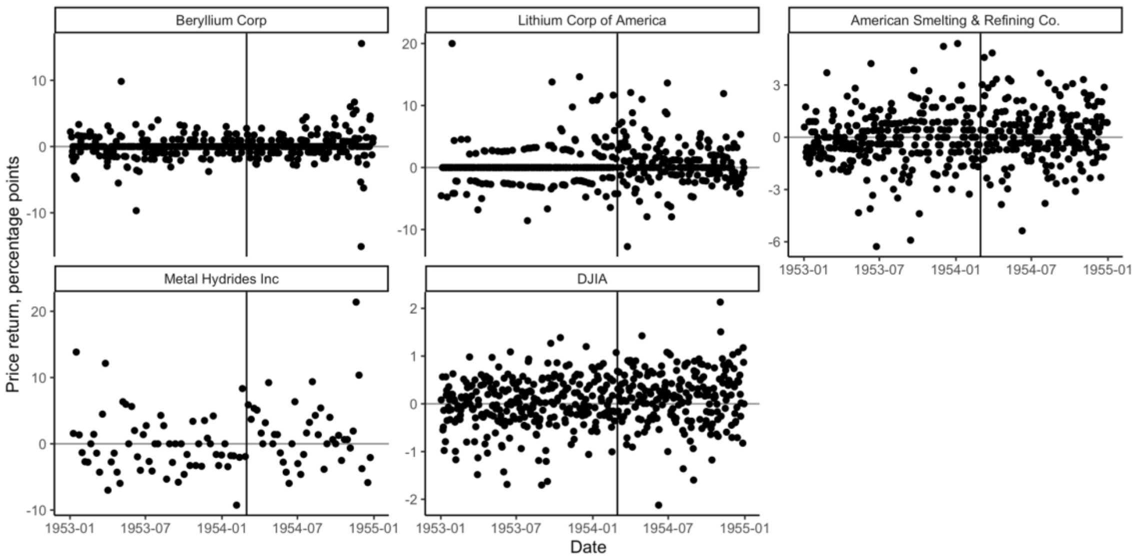


Figure 2: Daily price returns for Beryllium Corp., Lithium Corp. of America, American Smelting and Refining Corporation, and Dow Jones Industrial Average; Weekly price returns for Metal Hydrides, Inc 1953-1954. Vertical line indicates date of the Castle Bravo test.

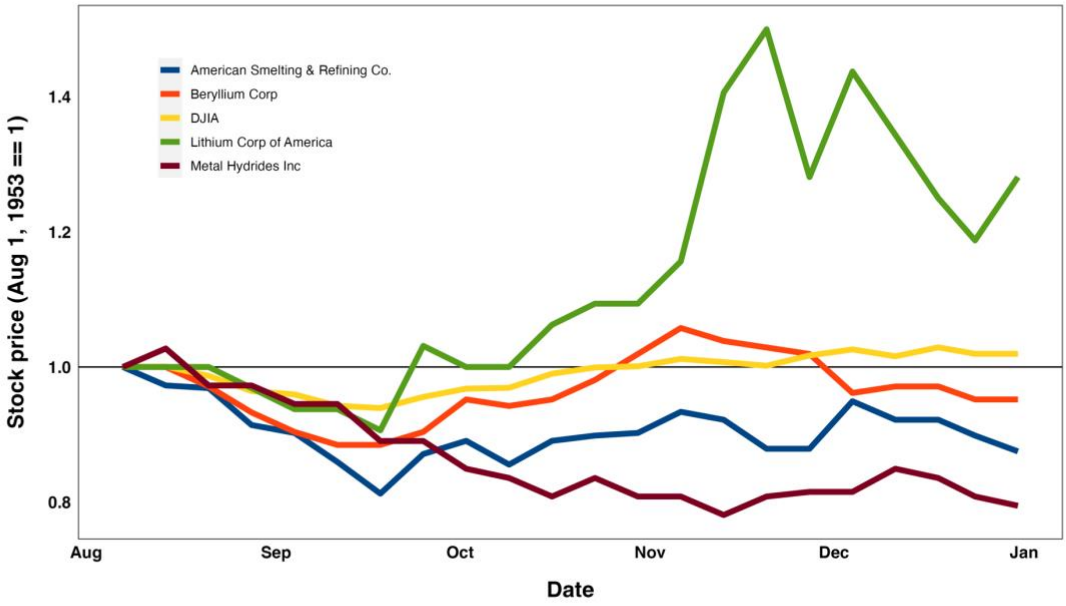


Figure 3: Prices for Beryllium Corp., Lithium Corp. of America, American Smelting and Refining Corporation, Metal Hydrides, Inc, and Dow Jones Industrial Average. Prices are normalized to equal 1 on August 1, 1953. Data is at a weekly frequency.

Figure 3 re-casts the price level data from figure 1 by normalizing the prices of each of the stocks to 1 on August 1, 1953 and plotting through the end of that year. It is clear from the figure how Alchian reached his conclusion that lithium was the key component in the hydrogen bomb before it was even tested – relatively speaking, the stock price of Lithium Corporation increased by more than 20% over the course of a few months. But the price level increase, while suggestive, does not place us on firm footing statistically. In the next section, we illustrate how to confirm Alchian's finding with a simple, formal event study.

Event study methodology: a simple illustration

The general procedure for short-horizon event studies outlined in Fama et al. (1969) is fairly straightforward:

1. Identify the event(s) (e.g., the day before, of, and after a set of announcements; the classic example is a stock split announcement)
2. Identify selection criteria for inclusion of firms
3. Select (and estimate) expected normal returns for a given security and then calculate *abnormal* returns – actual (ex-post) returns minus expected normal returns
4. (Optionally, but typically) aggregate abnormal returns at the firm level and/or in the cross section
5. Conduct inference on the (cumulative) abnormal returns using appropriate test statistics

Identifying the event and selection criteria for the inclusion of firms

Newhard (2014) provides a set of public and private events associated with the development of lithium-fueled hydrogen bombs, going back as early as 1948. The provided data, however, begins in 1953. Although instructors may invite students to test for abnormal returns after several different events – such as the actual Castle Bravo test – we focus on Alchian's description of his method of identifying the relevant metal through examining stock prices in late 1953.

Following the notation in MacKinlay (1997), call T_0 and T_1 the first and last day in the pre-event window, respectively, and T_2 the last day in the event window.

Table 1: Timing notation for event study

Symbol	Interpretation	Date used in our example

T_0	Beginning of estimation window/pre-event window	January 1, 1953
T_1	End of estimation window/pre-event window	July 31, 1953
T_2	End of event window	December 31, 1953

Calculating normal and abnormal returns

Alchian's description of his original study emphasized price levels. In practice, researchers usually examine excess or abnormal returns, which requires a choice about the appropriate counterfactual. This gives rise to the "joint hypothesis problem" – the fact that abnormal returns could both indicate market inefficiency or a poor choice of model for 'normal' returns. At a daily frequency, however, these risks to inference may be more limited (Fama 1991; Brown and Warner 1985).

Some guides for practitioners suggest focusing on statistical models such as a constant mean return model, a univariate regression on market returns, or a factor model (MacKinlay 1997). Depending on the instructor's pedagogical goals, students could be pointed towards a particular method, or asked to implement and compare different methods (as in the first assignment example included in appendix 2). We use this approach in our thesis seminar context to convey the message that the research process involves choices about appropriate design and, ideally, demonstrating robustness of results across those choices.

To fix notation, we index the four firms by i, and write R_{it} as the return (or excess return) for security i at date t. We regress (excess) returns in the pre-event window on a constant and a set of explanatory variables $\boldsymbol{X_{it}}$:

$$\mathrm{R_{it}} = \alpha + \boldsymbol{\beta}'\boldsymbol{X_{it}} + \varepsilon_{it}, \tag{1}$$
$$T_0 \leq t \leq T_1$$

For example, the constant mean return model would impose that $\boldsymbol{\beta}' = 0$; the market model would include the price return for a broader stock index as an explanatory variable; the 3-factor Fama-French model, $\boldsymbol{X_{it}}$ would contain the excess return for the market and the "high minus low" (HML) and "small minus big" (SMB) portfolio returns. As a side effect of the estimation, we obtain the standard error of the residuals, $\widehat{\sigma_{\varepsilon i}^2}$ used to estimate test statistics in the final step.

In the dataset included as supplemental material, we the daily time series of the DJIA and T-bill rates to facilitate implementing either a market model or a version of the Sharpe-Lintner CAPM. Kenneth French's web site includes estimates of portfolio factors for the Fama-French 3 factor model for this time period (Fama and French 1993). As an initial illustration, we focus on a mean return model, which can be calculated by hand in a spreadsheet quite easily; it merely uses the average price return in the pre-event window as the predicted price return during the event window.

Here, again, instructors could ask students to think how to account for the mixed-frequency nature of the data or Beryllium's stock split (treating it as a -50% return is both conceptually incorrect and dramatically affects the estimated market beta). In the results reported below, we drop that observation from the sample and focus on weekly returns for simplicity.

Given the choice of model for normal returns (and with estimated parameters in hand), we can calculate predicted returns during the event date, $\widehat{R_{it}}$:

$$\widehat{R_{i\tau}} = \hat{\alpha} + \widehat{\boldsymbol{\beta}}' \boldsymbol{X_{i\tau}}, \tag{2}$$

$$T_0 + 1 \leq \tau \leq T_2$$

And then abnormal returns are realized returns $\mathrm{R_{i\tau}}$ minus predicted returns

$$AR_{i\tau} = \mathrm{R_{i\tau}} - \widehat{R_{i\tau}} \tag{3}$$

Aggregation

In most event studies, there is temporal and/or cross-sectional aggregation of abnormal returns. The former makes sense when the market reaction over multiple days may be interesting. The latter is more relevant when we are interested in the average effect of an event across multiple firms (Kothari and Warner 2007). Here, we focus on the cumulative abnormal return, to understand the diffusion of information about the components of the hydrogen bomb tests. Formally, the cumulative return is just the sum of individual daily abnormal returns calculated over (a subset of) the window:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{4}$$

$$T_1 + 1 \leq \tau_1 < \tau_2 \leq T_2$$

Cross-sectional aggregates of (cumulative) abnormal returns are simple averages after summing across i.

Calculating test statistics

The typical approach in event studies of this type is to assume a null hypothesis that abnormal returns are strictly due to $i.i.d.$ forecast error of the model for normal returns.

An advantage of using higher frequency data is that differences between models of normal returns are often small enough as to not be consequential, minimizing the joint-hypothesis problem (Fama 1991). Under the null, abnormal returns have zero mean (conditional on the predictions of the model for normal returns).

In the first two or three decades following Ball and Brown (1968) and Fama et al. (1969), econometricians developing the theory of event studies spent considerable effort identifying and providing procedures to correct for a variety of issues – non-normality of returns, serial correlation, and issues caused non-synchronous trading. In practice, however, simulation studies suggested that these issues could often be ignored, or at least that the gains from alternative parametric estimation procedures were limited for daily data (Brown and Warner 1985).

The most common approach is to use the estimated standard deviation of abnormal returns during the estimation window (e.g., the variance of residuals from equation (1) to construct a t $-$statistic with degrees of freedom equal to the number of observations in the pre-event window minus the number of parameters estimated in equation (1).[4] This treats the abnormal returns as independent of one another, implying the variance of cumulated abnormal returns (CAR) between two dates is

$$\sigma^2\big(CAR(\tau_1,\tau_2)\big) = (\tau_2 - \tau_1 + 1)\widehat{\sigma_{\varepsilon i}^2} \tag{5}$$

Figure 4 plots the standardized CAR at the weekly frequency. These are the t $-$statistics for the test of significant cumulative abnormal returns. Treating the t-

[4] MacKinlay (1997) notes that the estimated abnormal return should contain a term that accounts for the sampling error from the estimated parameters for ordinary returns. As the length of the estimation window grows, this term approaches zero, justifying the practice of ignoring its contribution to the variance of abnormal returns.

statistics as (approximately) unit normal the dashed lines indicate approximate cutoffs for statistically significant CAR at the 95% level.[5]

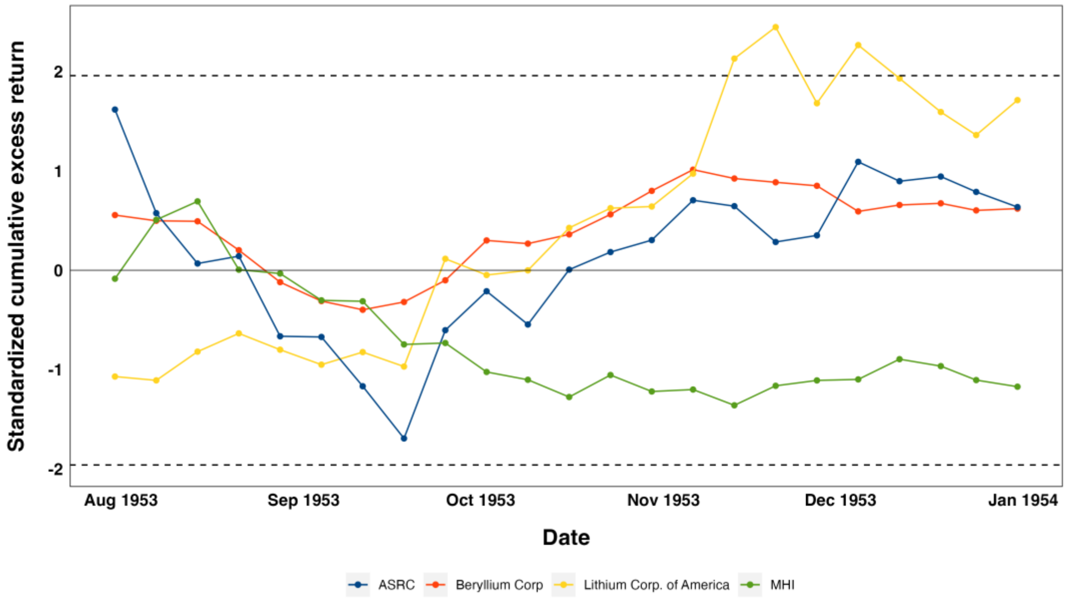


Figure 4: Standardized cumulative abnormal returns. Normal returns are the mean return in between January 2, 1953-July 31, 1953. Dashed lines indicate approximate cutoffs for significance of CAR at the 95% level.

Discussion of the results

The results suggest that Lithium Corp. of America began to earn statistically significant

[5] In the illustration, we focus on data at the weekly frequency to include each of the stocks. The conclusions are not different when we focus on the stocks available at a daily frequency, where the sample size is much larger and the test statistics are less likely to be misspecified. However, the statistical significance of the (weekly) CAR is sensitive to start date for the window; for instance, terminating the pre-sample at the end of June instead of July results in weekly CAR that are significant at the 10% level but not the 5% level. The reason for this is that the variance of normal returns is less precisely estimated (due to a smaller sample side) and the CAR variance is also larger (because it is cumulating over a larger window).

(cumulative) abnormal returns in mid-November, and that these returns were statistically significant (excluding a dip around the end-of-the-month) into mid-December. In other words, from the perspective of the simple model, Alchian's 'eyeball econometrics' were correct.

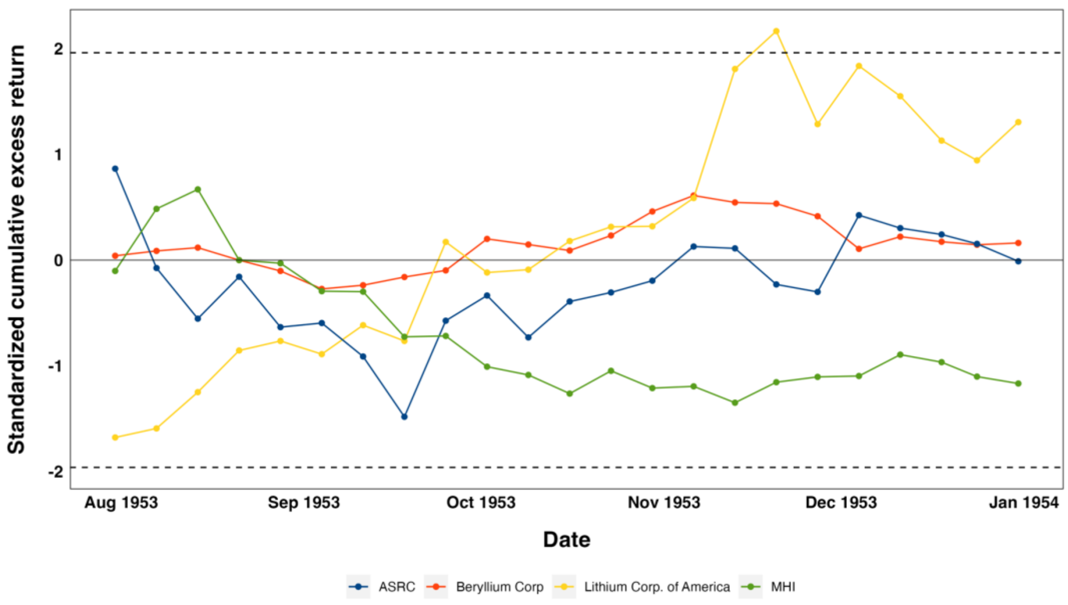
Interestingly, the statistically significant cumulative returns arrive somewhat prior to the November 30 earnings report by Lithium Corporation; the Wall Street Journal reported revenue per share for the first three quarters of the year eight times higher than the previous year (Newhard 2014). It is conceivable that abnormal returns were driven by informed trading prior to the release of the earnings report.

Fama's reviews of the market efficiency literature (Fama 1970; 1991) emphasize that event studies are suited for determining the 'semi-strong' form of the efficient markets hypothesis – the fact that publicly available information is reflected in prices. The lack of persistence in cumulative abnormal returns is essentially consistent with this theory. Since Lithium Corp. was an over-the-counter industrial stock, it is probably that a lack of liquidity impeded the ability of the stock price to reflect the available information about earnings immediately.

Sensitivity of Alchian's result

The previous subsection outlined Alchian's basic observation and showed that a simple event study provides some statistical evidence that rationalized his (correct!) conclusion about lithium's use in hydrogen bomb development in late 1953. We have already noted that this evidence is sensitive to window selection. In this section, we demonstrate that the result is not particularly sensitive the selection of the model for normal returns but is sensitive to the addition of a "post-event" window. While instructors seeking to illustrate the effects of world events on financial markets may skip some of these extensions, they may be useful for exploring more nuances of the research process and the distinction between statistical and economic significance.

Previously, we focused on a mean return model for normal returns. However, Fama et al (1969)'s early event study instead regressed returns on a measure of market returns (a "market model") to capture a component driven by ordinary market conditions. MacKinlay (1997) notes this reduces the variance of abnormal returns and increase the power of test statistics. Tables A.1 and A.2 in the appendix report the results of regressions of returns on the individual securities (at the daily and weekly frequency) against the price returns of the Dow Jones Industrial Average. Figure 5 plots CAR for the securities after adjusting for the component predicted by the market model. The top panel plots the weekly CAR, while the bottom panel plots the daily. Notably, the number of weeks Lithium Corporation had significant CAR drops to one, although at a daily frequency it had persistently significant CAR for much of late November and early December.



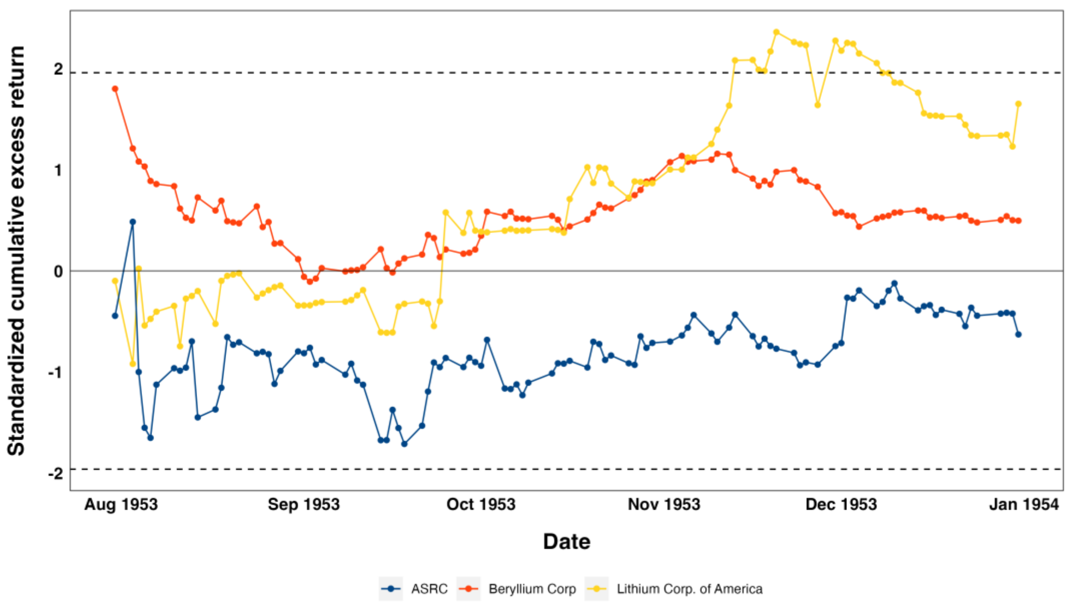


Figure 5: Standardized cumulative abnormal returns. Normal returns are the predicted value using a regression of individual firms' price returns on the price return of the Dow Jones Industrial Average for the period between January 2, 1953-July 31, 1953. Dashed lines indicate approximate cutoffs for significance of CAR at the 95% level.

Alternatively, we might use a factor model, such as the 3-factor Fama-French model to predict normal price returns. Coefficient estimates for the weekly and daily models are reported in appendix tables A.3 and A.4, respectively, and the related CAR estimates are in appendix figure A.1. The results are quite similar to the market model.

While the results are robust to alternative definitions of "normal returns," the results do change fairly dramatically if we include *post*-event data. A post-event window is sometimes included in event studies to improve the robustness of normal return estimates (MacKinlay 1997). Here, we extend the event window to include the first quarter of 1954 (incorporating the run-up to the Castle Bravo test and news reports of its aftermath); new dates are shown in table 2.

Table 2: Timing notation for event study with post sample

Symbol	Interpretation	Date used in our example
T_0	Beginning of pre-event window	January 1, 1953
T_1	End of pre-event window	July 31, 1953
T_2	End of event window	March 31, 1954
T_3	End of post-event window	December 31, 1954

Data from the remainder of 1954 is added to the sample used to calculate normal regressions. This more than doubles the available sample size. Coefficients from the weekly and daily regressions are reported in appendix tables A.5 and A.6, and CAR are plotted in appendix figure A.2. The salient feature of the graphs is that the CAR are generally insignificant until the end of March 1954, *after* news of the hydrogen bomb tests had taken place (although before news reports mentioned lithium as the key component). The reason for the difference is that in the data generating process appears to discretely change before and after the window. For example, in the daily market model regression, the market beta for Lithium Corp. of America is 0.42

and statistically insignificant using data from the pre-window sample, but its magnitude more than triples (to 1.42) and is significant at the 99% level in the post-window sample.

Of course, it is possible that the 'post' window is still capturing some effects of the event. For instance, if market participants gradually incorporated news about continued hydrogen testing throughout 1954 into the stock price of lithium-producing firms, that could imply that our post-window sample is estimating the effects of the event, rather than normal returns. But this interpretation – that the market caught on to the growth potential of lithium mining *after* the round of hydrogen bomb tests that kicked off in March 1954 -- is different from the conclusion we drew using a window that terminated at the end of 1953.

The difference demonstrates a useful lesson for students embarking on their own first research projects. We know, with certainty, that lithium was a key component of the Castle Bravo test. It is clear, from looking at the run-up in the price, how Alchian reached his conclusion. Although we may *fail to reject* the null of zero abnormal returns for certain specifications, that is not the same thing as *accepting* the null that Lithium Corporation had no excess returns. Substantively, the run-up in price (or cumulative 'abnormal' returns) is economically significant. The distinction between statistical and economically meaningful results is important for students to grasp, and instructors could use this result as an opportunity to discuss it, perhaps accompanied by additional reading (e.g., the classic polemic by Ziliak and McCloskey (2008)).

Suggestions for incorporating the Alchian event study in the classroom

In our context, the exercise is a lab or problem set in a research seminar that is the 'capstone' of the economics major.[6] Our senior seminars typically have 10-15 students who have already taken intermediate micro- and macro-economics, as well as as statistics and econometrics (with programming in the R programming language). In the context of the seminar, this assignment occurs early to remind students of skills they developed in their earlier econometrics courses (cleaning, transforming, and plotting data; estimating models via ordinary least squares and producing fitted values; reporting results in well-formatted tables and discussing them verbally), and additionally to introduce them the design and interpretation of event studies. The lab assignments (like this one) are intended to be a stepping stone for students to design their own original research projects. An example of the lab assignment is included in Appendix 2.

There are a number of possible other ways of implementing the Alchian exercise in an earlier class on financial markets or macroeconomics. The calculations are simple enough for students to execute in Excel or other spreadsheet software with only an understanding of *t*-tests; instructors need simply provide the data and appropriate formulas (or guide students through the calculations step-by-step). A sample assignment of this type is included as appendix 3.

At any level, instructors could ask students to first read Newhard's summary of Alchian's test. Newhard (2014) is not technical and provides historical context on Alchian's contribution (although it does spoil the punchline!). This could be used to give students some chance to select different event dates or windows, for instance. Alternatively, professors could provide data that obfuscates the particular companies

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[6] More details about the context of the senior seminar in our particular setting is given in Bourne and Grawe (2015).

and allow students to try to infer which firm was likely producing the materials used in the bomb tests.

Students with more background in econometrics or statistics may also be prepared to dig into the econometric issues more deeply. For instance, students could think about how to handle the missing and mixed-frequency data problems inherent in this incident; what are the tradeoffs between using weekly data or daily data? How should one deal with missing values? Furthermore, the literature has proposed different models for normal returns and students could be asked to assess the gains from factor models versus market or mean return models, or to assess their results for robustness to this choice (as in the sample lesson). Students could also implement nonparametric tests, such as rank tests ((Corrado 1989; 2011; Kolari and Pynnonen 2011), which make fewer assumptions about the underlying daily returns data, or to analyze the power of their tests.

Conclusion

Finance-style event studies are widely used in applied work and in legal and policy contexts. We provide the data and sample lesson plans for teaching students about this methodology by formalizing Armen Alchian's 1953 stock price study. We illustrate how different choices for models of normal return and sample composition may alter the conclusions of event studies.

Instructors who simply want to illustrate the information encoded in financial prices could use the example as a case study or in class demonstration. We hope the somewhat unusual nature of the example may inspire interest from students who are compelled by the classic illustrations using stock splits or changes to stock index composition. Labs based around Alchian's study gives students an opportunity to grapple with some of the messiness of real data and the challenges in designing and interpreting empirical research.

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Appendix 1: Additional tables and figures

Table A.1: Coefficients from weekly market model regressions, Jan. 2, 1953-July 31, 1953

	Beryllium Corp	Lithium Corp. of Am.	ASRC	MHI
alpha	-0.45	-0.48	-0.67**	0.42
	(0.69)	(0.75)	(0.30)	(0.90)
Market beta	1.06**	1.16	0.98***	0.04
	(0.49)	(0.76)	(0.30)	(0.53)
Num. Obs.	29	30	30	30
R2	0.064	0.085	0.180	0.000
R2 Adj.	0.029	0.052	0.151	-0.036
RMSE	4.58	4.41	2.41	4.74

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Newey-West standard errors in parentheses

Table A.2: Coefficients from daily market model regressions, Jan. 2, 1953-July 31, 1953

	Beryllium Corp	Lithium Corp. of Am.	ASRC
alpha	-0.12	-0.15	-0.11
	(0.17)	(0.16)	(0.09)
Market beta	1.01**	0.42	1.45***
	(0.44)	(0.27)	(0.26)
Num. Obs.	147	148	148
R2	0.084	0.008	0.333
R2 Adj.	0.078	0.001	0.328
RMSE	1.75	2.48	1.08

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Newey-West standard errors in parentheses

Table A.3: Coefficients from weekly 3-factor Fama-French model regressions, Jan. 2, 1953-July 31, 1953

	Beryllium Corp	Lithium Corp. of Am.	ASRC	MHI
alpha	-0.67	-0.76	-0.92***	0.65
	(0.64)	(0.75)	(0.23)	(0.75)
Broad stock return minus risk free rate (FF)	-0.03	-0.91	2.42*	-0.66
	(2.08)	(1.56)	(1.39)	(1.87)
SMB	-10.92*	-8.41	1.80	8.94
	(5.48)	(11.50)	(4.42)	(5.64)
HML	0.68	-2.73	1.17	6.64**
	(4.71)	(4.76)	(2.28)	(3.08)
Num. Obs.	29	30	30	30
R2	0.094	0.039	0.123	0.090
R2 Adj.	-0.015	-0.072	0.022	-0.015
RMSE	4.51	4.52	2.49	4.53

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Newey-West standard errors in parentheses.

Table A.4: Coefficients from daily 3-factor Fama-French model regressions, Jan. 2, 1953-July 31, 1953

	Beryllium Corp	Lithium Corp. of Am.	ASRC
alpha	-0.13	-0.15	-0.13
	(0.16)	(0.14)	(0.08)
Broad stock return minus risk free rate (FF)	1.51***	0.94**	1.61***
	(0.46)	(0.43)	(0.28)
SMB	1.37	1.06	0.39
	(0.92)	(0.70)	(0.35)
HML	-1.47***	-1.20	-0.35
	(0.54)	(0.87)	(0.47)
Num. Obs.	147	148	148
R2	0.149	0.034	0.356
R2 Adj.	0.131	0.014	0.343
RMSE	1.69	2.45	1.06

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Newey-West standard errors in parentheses.

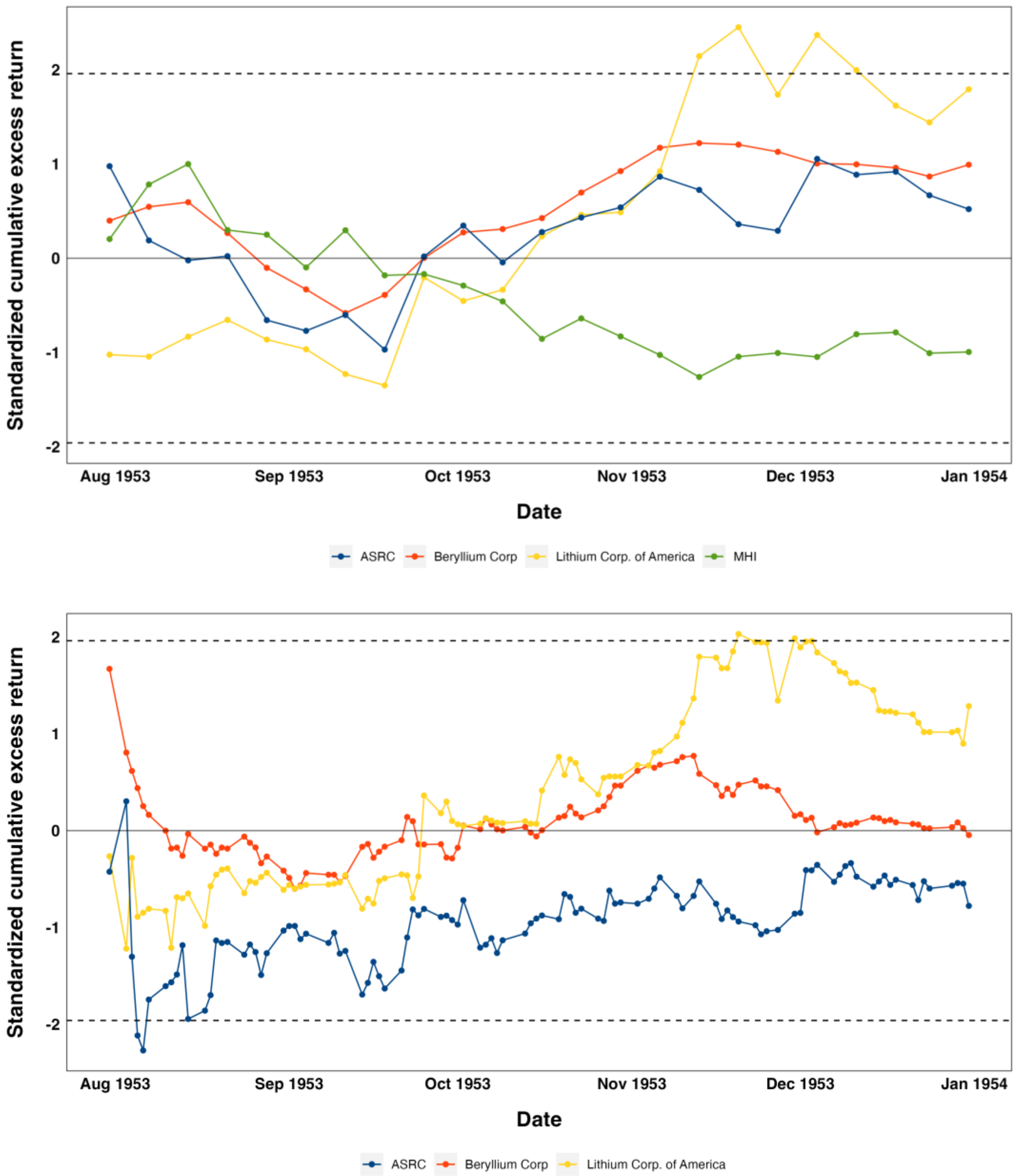

Figure A.1: Standardized cumulative abnormal returns. Normal returns are calculated as the predicted value of from a regression of price returns on the Fama-French market return, SMB, and HML factors from January 2, 1953-July 31, 1953. Dashed lines indicate approximate cutoffs for significance of CAR at the 95% level.

Table A.4: Coefficients from weekly regressions, combining pre- and post-window

Firm:	BC	LC	ASRC	MHI	BC	LC	ASRC	MHI
alpha	0.15	0.54	-0.29	0.80	0.16	0.94	-0.21	0.94
	(0.61)	(0.49)	(0.24)	(0.78)	(0.53)	(0.63)	(0.31)	(0.68)
Return on DJIA	0.58*	2.02***	1.41***	0.20				
	(0.31)	(0.27)	(0.20)	(0.32)				
Broad stock return minus risk free rate (FF)					-0.89	4.56**	3.22***	-0.76
					(1.54)	(1.92)	(1.00)	(1.67)
SMB					4.58	3.68	2.46	3.63
					(3.91)	(3.65)	(1.73)	(4.93)
HML					3.58	-5.55	-1.01	0.16
					(2.37)	(3.71)	(2.00)	(2.34)
Num. Obs.	67	68	68	68	67	68	68	68
R2	0.026	0.172	0.403	0.003	0.050	0.063	0.136	0.027
R2 Adj.	0.011	0.160	0.394	-0.012	0.005	0.019	0.095	-0.018
RMSE	4.94	6.12	2.38	4.96	4.88	6.51	2.86	4.90

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Newey-West standard errors in parentheses.

Pre-window runs from January 2, 1953-July 31, 1953. Post-window runs from April 1, 1954-December 30, 1954. BC indicates dependent variable is price return for Beryllium Corp.; LC indicates dependent variable is price return for Lithium Corp. of America; ASRC indicates dependent variable is price return for American Smelting and Refining Corp.; MHI indicates dependent variable is price return for Metal Hydrides, Inc.

Table A.5: Coefficients from daily regressions, combining pre- and post-window

Firm:	BC	LC	ASRC	BC	LC	ASRC
alpha	0.03	0.16	-0.04	-0.02	0.15	-0.06
	(0.12)	(0.15)	(0.06)	(0.13)	(0.16)	(0.06)
Return on DJIA	0.68**	1.10***	0.98***			
	(0.28)	(0.28)	(0.12)			
Broad stock return minus risk free rate (FF)				1.16***	1.34***	1.22***
				(0.38)	(0.36)	(0.17)
SMB				1.56**	0.22	0.42
				(0.73)	(0.68)	(0.30)
HML				-0.02	-0.37	-0.16
				(0.46)	(0.65)	(0.26)
Num. Obs.	336	337	337	336	337	337
R2	0.033	0.045	0.148	0.068	0.048	0.163
R2 Adj.	0.030	0.042	0.145	0.060	0.039	0.155
RMSE	2.07	2.83	1.32	2.03	2.82	1.31

* p < 0.1, ** p < 0.05, *** p < 0.01

Newey-West standard errors in parentheses.

Pre-window runs from January 2, 1953-July 31, 1953. Post-window runs from April 1, 1954-December 30, 1954. BC indicates dependent variable is price return for Beryllium Corp.; LC indicates dependent variable is price return for Lithium Corp. of America; ASRC indicates dependent variable is price return for American Smelting and Refining Corp.

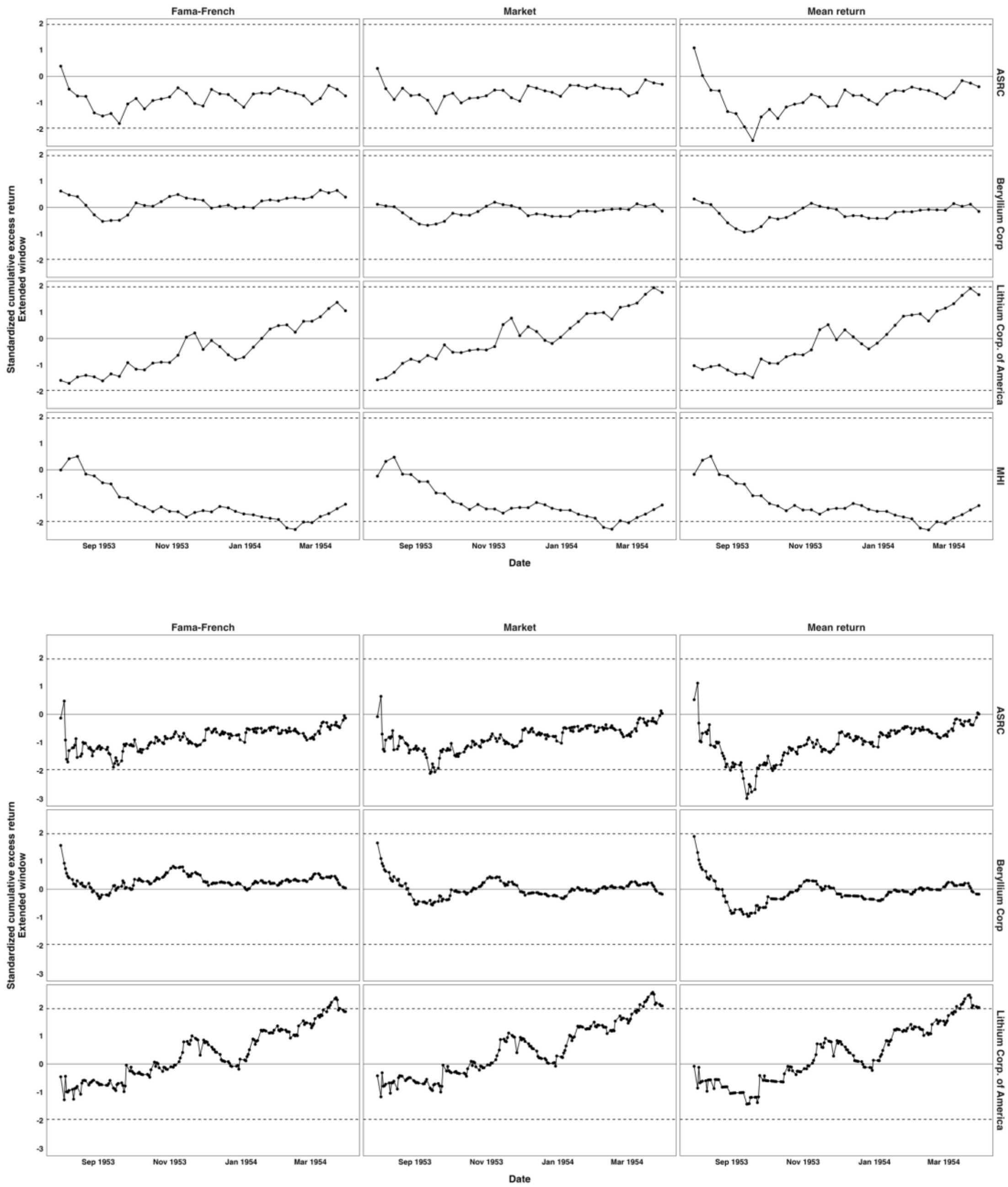

Figure A.2: Standardized cumulative abnormal returns for extended window. Dashed lines indicate approximate cutoffs for significance of CAR at the 95% level. Rows indicate firms, columns indicate model of normal returns. Normal return models are estimated using data from January 2, 1953-July 31, 1953 and April 1, 1954-December 30, 1954.

Table A.6: Coefficients of price returns of Lithium Corp, post-window

Frequency:	Weekly			Daily		
Normal return model:	Mean Return	Market	Fama-French	Mean Return	Market	Fama-French
alpha	2.75***	1.12	2.82**	0.54**	0.33	0.31
	(0.66)	(0.72)	(1.11)	(0.26)	(0.23)	(0.27)
Return on DJIA		2.15***			1.42***	
		(0.35)			(0.40)	
Broad stock return minus risk free rate (FF)			6.56**			1.62***
			(3.09)			(0.49)
SMB			4.67			0.04
			(5.05)			(0.92)
HML			-10.88**			-0.23
			(4.84)			(0.82)
Num. Obs.	38	38	38	189	189	189
R2	0.000	0.155	0.152	0.000	0.067	0.062
R2 Adj.	0.000	0.131	0.077	0.000	0.062	0.047
RMSE	7.68	7.06	7.07	3.14	3.03	3.04

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Newey-West standard errors in parentheses.

Estimation runs from April 1, 1954-December 30, 1954

Appendix 2: Sample lab assignment for an advanced class

Econometrics Lab: Event Studies

Instructions:

Before class: Read Newhard (2014) (posted on Moodle) and the handout out event studies.

This lab will walk you through the calculations for an event study using financial data. The particular application is a more formal version of the technique Alchian used to infer the materials used in the Castle Bravo hydrogen bomb tests (as described in Newhard).

You will be required to turn in two files:

Tables/figures/written answers to the questions (in pdf format)

Your R code. Your R code should be commented appropriately. It should also be written so that I can run it and obtain identical output to yours using the raw data – the same tables and figures, making only minimal changes (e.g., if I need to change a file path, that's fine, but any transformations of the data should be done in your R code, not "by hand" in a spreadsheet). You do *not* need to turn on your data separately for this lab.

If we don't finish the lab during class, you should finish your writeup and turn it in by Saturday at 12 noon.

Begin by importing the raw price data from Alchian_data.csv on Moodle. This is daily observations of reported stock prices for four stocks: Beryllium Corp (BC), Lithium Corp. of America (LCA), American Smelting and Refining Co (ASRC) and Metal Hydrides Inc. (MHI). There are also the daily Dow Jones Industrial average (DJIA), market yields on 3 month Treasury bills and the yield on newly issued 3-month Treasury bills.

1. **Plotting the raw data**

   (a) Generate a nice figure plotting the time series of the four stocks and the DJIA for the complete sample. (Assuming you are using the ggplot package, you may want to use geom_point instead of geom_line. Because the scales of prices are different, you probably want to use facet_wrap or something similar).

   (b) You should probably notice something unusual about the stock price of BC. BC underwent a 'stock split' where each outstanding share of stock became two shares. How was that reflected in the price of their stock?

   (c) You should also notice (if you haven't already) that MHI is available at a different frequency (only weekly), rather than daily. You need to make a choice about how to deal with that for your subsequent analysis, since the rest of your data is daily. Explain your choice.

2. **Calculating price returns** The price return is the simple percentage change in the price. Calculate this for each stock and for the DJIA.
   (a) Plot these price returns in a nice figure.
   (b) Comment on how BC's stock split is reflected in the price returns. You need to make a choice about how to deal with that observation; should you leave it "as-is," drop that observation, or otherwise modify how you will conduct the event study? State and justify the choice you make.
   (c) Similarly, MHI is only available at a weekly frequency. You need to make a choice about how do deal with that data series. State and justify the choice you make.

3. **Identifying the event**: We need to make a choice about what "event" we would like to test and what the window around that event will be.

   Call T_0 the beginning of the pre-event sample (the start of the sample period for your model of normal returns), T_1 the end of the pre-event sample, T_2 the end of the event window.

   Report your choices for T_0, T_1, T_2 .

4. **Calculating normal returns**. This is another choice you need to make!

   For the purposes of the lab, I'm going to ask you to calculate four common models and then choose one for the remainder of the analysis.

   1. Constant mean return model: The "normal return" is the average of the price return over the pre-event sample. You can estimate this as a regression:

   $$R_{it} = \alpha + \varepsilon_{it}$$

   2. Market return model: If R_{mt} is the price return of the DJIA, the normal return is the fitted value from a regression

   $$R_{it} = \alpha + \beta R_{mt} + \varepsilon_{it}$$

   3. A CAPM-style regression model: if R_t^f is the risk-free rate of return (in the dataset, use the 3-month Treasury bill rate) this is the fitted value of the following regression:

   $$R_{it} - R_t^f = \alpha + \beta(R_{mt} - R_t^f) + \varepsilon_{it}$$

Note that the risk-free rate in the data set is annualized, but your price return is not. Although in principle one needs to be careful about compounding, in practice a lot of people just divide by the number of periods in a year.

4. A Fama-French (FF) 3-factor model: The data needed for this regression is found at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/F-F_Research_Data_Factors_daily_CSV.zip

   The Fama-French 3 factor model predicts stock returns using variables which capture common factors affecting stock returns. One factor is "Mkt-RF" (similar to the CAPM; notice the values in the FF data will be different than what you calculated earlier, because they use a broader set of securities for the market return and the 1-month T-bill); "SMB" (the return of portfolios consisting of small market capitalization firms minus the return of portfolios of large firms) "HML" are the returns on portfolios of "value" stocks (those with low stock price relative to their "book value" – assets minus liabilities) minus "growth" stocks (firms with a high stock price relative to their book value):

$$R_{it} = \alpha + \beta_1(\text{Mkt-RF}) + \beta_2(\text{SMB}) + \beta_3(\text{HML}) + \varepsilon_{it}$$

(a) **For each security** report a 'nice' table comparing each of the four models (so you should have four tables, with four regressions each). Your tables should report the coefficient estimates, the R^2 and adjusted R^2 statistics for each model, and the estimated variance of the residuals, σ_{it}. Note that you will need the estimated variance of the residuals for later tests, and the residual degrees of freedom.

(b) After reporting the tables, choose the model you think is appropriate for calculating subsequent "normal" returns and explain why you chose it.

5. **Calculating (cumulative) abnormal returns**. Using the model you chose in the previous question, calculate expected returns (R_{it}) for each security over the event window, and then calculate abnormal returns

$$AR_{i\tau} = R_{i\tau} - \widehat{R_{i\tau}}$$

This is the prediction error for the model from the previous question, calculated "out of sample." You can use the predict function in R to generate the predicted returns and then use those predicted returns to calculate the AR. (Note that you may need to be careful about generating this object from your predictions depending on which model you picked in question (4))

Then, for each day within the window, calculate the cumulative abnormal returns ($CAR_{it}(\tau_1, \tau_2)$)

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$$

$$T_1 + 1 \leq \tau_1 < \tau_2 \leq T_2$$

cumsum is a good way to do this.

For each security, plot the daily abnormal return, and the cumulative abnormal return.

6. **Calculating test statistics**: There are a variety of ways to try to determine whether cumulative abnormal returns are significant. The simplest is to treat the abnormal returns on any given day as independent of one another. Under the null hypothesis of no abnormal returns in the event window, the variance of abnormal returns on any given day is the σ_{it} for your chosen model. Then the variance of the cumulative abnormal returns is

$$\mathrm{Var}\{CAR_i(\tau_1, \tau_2)\} = (\tau_2 - \tau_1 + 1)\ \sigma_{it}$$

   Calculate the variance of the CAR from the previous question for each security (so each day in the window, you should have the CAR and an estimate of the variance; the variance grows as the window size grows).

   (a) Calculate a standardized CAR for each security on each day:

$$\frac{CAR_i(\tau_1, \tau_2)}{\sqrt{\mathrm{Var}\{CAR_i(\tau_1, \tau_2)\}}}$$

   Under the null hypothesis of zero excess returns, this variable has a *t* distribution with the same degrees of freedom as the regression in the pre-sample.

   (b) Plot the standardized CAR for each security at each point in time

   (c) Calculating the $p{-}value$ of this test statistic takes a little finessing in R. If your standardized CAR is called Var1, you can use pval_sec = mutate(2*pt(abs(Var1), df = dof, lower.tail =FALSE) where dof is the degrees of freedom from the pre-estimation regression model. pval_sec is the p-value of the two-sided t-test here. Remember to change the names of your variables so that you don't accidentally overwrite your output. Which securities have significant cumulative abnormal returns during the window?

7. **Interpretation** In a 1991 review of research on the efficiency of capital markets, Eugene Fama noted that most studies found that public information was incorporated into prices within a day or so, although there were some "anomalies." Do you find evidence of significant abnormal returns that fades quickly, or is more persistent? Relate your findings to Fama's notion of "semi-strong" market efficiency.

Be prepared to discuss the choices you made and your interpretation of the results in class!

Appendix 3: Sample lab assignment for a class with only statistics as a pre-requisite

Lab: Event study

This lab will walk you through the basics of an event study. Event studies are a common statistical technique for identifying whether companies earned abnormal returns as a result of some event. This event study will focus on a small collection of industrial firms who produced metals potentially useful in creating hydrogen bombs in the early 1950s. Your goal is to identify which of the following firms produced the metal used in hydrogen bomb production using stock prices alone

Beryllium Corp. (Beryllium)

American Smelting and Refining Corp. (ASRC) (Thallium)

Metal Hydrides Inc. (MHI) (Thorium)

Lithium Corp. of America (Lithium)

To do this, you will use the provided spreadsheet. It contains end of week stock prices and weekly price returns (the percentage change in the stock price) for each of these firms, as well as the weekly return for the Dow Jones Industrial Average (DJIA), for each week in 1953 and 1954. (This is data is actual data, and an economist named Armen Alchian claimed he worked out the right firm using this data while he was working at the RAND Corporation in 1953).

Event studies work by coming up with a model of "normal" returns using data prior to the event, and then calculating the difference between the actual returns and normal returns *during* a period of time around an event. This period of time is usually called the “event window”. For this lab, you will use all of the weeks from January 1953-July 1953 as your “pre-sample” and the “event window” will be August 1953-December 1953. (This roughly corresponds with when Alchian was doing his study; note the actual bomb was not tested until March 1954).

(1) Create a line graph comparing stock prices each firm over the years 1953-54.

(2) A theory of stock prices is that they generally follow random walks – the best prediction of tomorrow’s price is today’s price. Does this seem true for the stocks in this dataset?

    Do any firms stand out to you as being very different from the price index?

(3) We need to come up with a set of predicted price returns during the event. For this, we’ll use the average price return prior to the event. Calculate the mean price return for each of the four stocks and the DJIA for the first week of January through the last week of July. This is our prediction of *normal returns.* We also need a measure of the variability of normal returns. For this, we can use the variance of returns for the same January-July period we calculated the mean for. (Use the VAR.S function in Excel to calculate this, to adjust for the finite sample size). Call this variance σ_i^2 for each stock *i*.

(4) Next, calculate *abnormal returns* (AR) for each stock. Abnormal returns are just the actual price return minus the normal return – basically, the part of the return we wouldn’t have predicted using our model for normal returns. In a new set of 5 columns, calculate this for each week for each of the stocks and the DJIA for the period, starting from the beginning of August 1953 and ending at the end of December 1953. Report the mean abnormal return for each of the individual stocks.

(5) Then, calculate *cumulative abnormal returns* (CAR). This is basically the return you would get if you bought the stock the last week of July and held it throughout the window. It grows throughout the window because you're adding (accumulating) more and more weeks. An example of how to calculate this is shown in the table below:

Week	Abnormal return for stock i	CAR_i
1	.1	=**.1**
2	.25	=**.1**+.25 = **.35**
3	-.05	=.**35** + (-.05) = .3

(6) Finally, we can test the statistical significance of our cumulative abnormal returns. The null hypothesis is that abnormal returns are zero and independent across weeks. This means that the CAR should also be mean zero, with variance equal to the number of weeks of AR you're adding up (so for the first week, the variance is σ_i^2, for the second week it's $2\sigma_i^2$, the third week it's $3\sigma_i^2$, and so on.

(7) For each stock (and the DJIA) calculate the *standardized CAR*:

$$Standardized\ CAR_i = \frac{CAR_i}{\sqrt{Var(CAR_i)}}$$

Then plot the standardized CAR for each stock.

(8) The standardized CAR is a t-statistic with degrees of freedom equal to the number of weeks in the pre-sample window minus 1. We can calculate statistical significance by using a t-table or Excel's built in functions. To do the latter, create 5 new columns showing the p-value of the standardized CAR.

(9) For which stock(s) are there significant CAR? Which firm do you think Alchian identified as the producer of the essential metal for hydrogen bomb development?

(10) The (semi-strong) expectations hypothesis suggests that public information should not help investors earn returns. Do your results contradict this prediction?