F500: Empirical Finance
Lecture 4: Event Study Analysis

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Outline

1. Basic structure of an event study
2. Measuring normal return
3. Measuring abnormal return
4. Extensions and refinements
5. Alternative methodology
    1. Differences in Differences
    2. Matcing approach
6. Stock Splits

Reading: Linton (2019), Chapter 6. Classic studies: Fama, Fisher, Jensen and Roll (1969) and Brown and Warner (1980, JFE).

- Try to measure the impact of an event on an outcome variable Y. Compare with theoretical prediction.
- Specifically we may compare

$$Y_{after} - Y_{before}$$

  but this may be biased because there may be many things happening at the same time as the event
- Use a control group against which to measure the change in outcomes. Thus we divide into treated and control and compute the "diff in diffs"

$$\left(Y_{after}^{treated} - Y_{before}^{treated}\right) - \left(Y_{after}^{control} - Y_{before}^{control}\right)$$

- This is a general principle applied in many fields from Labor economics to medicine etc.
- The questions that need to be addressed are: how to measure Y, what is the treatment and control group, and what is before and after.

- Financial Applications. Example of firm specific events like:
  - stock splits
  - reverse splits
  - share repurchase
  - mergers and acquisitions
  - earnings announcements
  - seasoned equity offering
  - inclusion in stock index
  - insider trading
  - Short selling restrictions
  - single stock circuit breakers
- Market wide events
  - macroeconomic announcements
  - Regulatory changes such as Dodd-Frank
- Main target is the effect on the valuation of firms, but also interested in other outcome variables like volatility and bid-ask spreads.

Classic Examples of an Event Study

Stock Splits

- A firm splits stock 2:1 means that it doubles the number of shares (allocating them pro rata to original owners) and halfs the price level.
- According to present value calculations this should have no effect on the valuation of the firm and on the return (which is percentage change in price) on holding the stock.
- Various other theories as to why stock splits may be beneficial

Earning announcements

- Under strong-form efficiency: earnings announcement have no effect on the firm's stock price. Under semi-strong, the anticipated earnings have no effect, but the unanticipated part should have an immediate and "permanent" effect on prices. Some practical definitions

Definition

Earnings surprise = announced earnings minus the previous day's Institutional Brokers' Estimate System(I/B/E/S) mean forecast
"good news" if earnings surprise $>$ .025 x I/B/E/S mean
"bad news" if earnings surprise $<$ -.025 x I/B/E/S mean

http://thomsonreuters.com/products_services/financial/financial_products/a-z/ibes/

Seven Steps in an Event Study:

1. Event Definition
2. Selection Criteria
3. Normal and Abnormal Returns
4. Estimation Procedure
5. Testing Procedure
6. Empirical Results
7. Interpretation and Conclusion

Event Definition and Alternative Hypothesis

- Types of adjustment of outcomes to an event
  - Immediate and permanent effect (including no effect) (Efficient markets)
  - Underreaction: gradual adjustment to new level
  - Overreaction: rapid adjustment that overshoots the new level and then returns to it.
- In practice, "immediate" and "permanent" must be defined with some "flexibility"
- Studies may try to allow for these possible adjustment mechanisms in the null hypothesis or may treat them as part of the alternative.
- Short term versus long term.

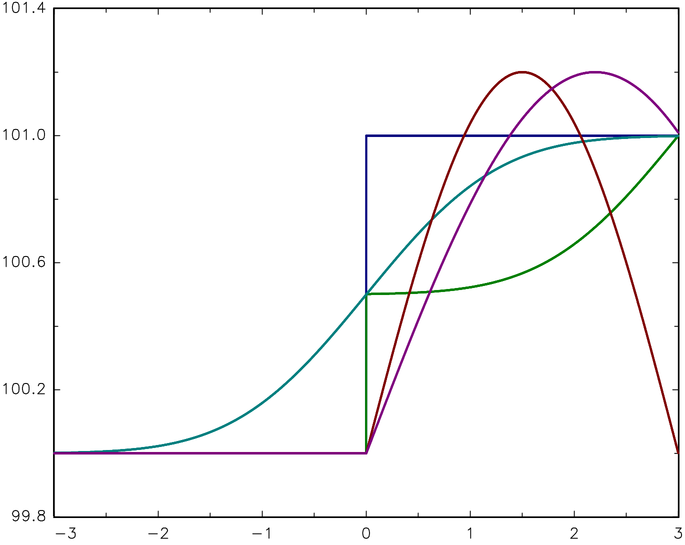


Figure: Shows examples of price trajectories around event at time 0.

Example

Dubow and Monterio (2006) develop a measure of ‘market cleanliness’. The measure of market cleanliness was based on the extent to which ‘informed price movements’ were observed ahead of ‘significant’ (i.e. price-sensitive) regulatory announcements made by issuers to the market. These price movements could indicate insider trading. In that case they were looking for movements of prices before the announcement date 0.

Normal Return Definition

Definition

(Market Model) Suppose that

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it},$$

$$E\left(\varepsilon_{it} | r_{m1}, \ldots, r_{mT}\right) = 0, \;\; E(\varepsilon_{it}\varepsilon_{js} | r_{m1}, \ldots, r_{mT}) = \begin{cases} \sigma^2_{\varepsilon i} & \text{if } i = j, t = s \\ 0 & \text{else} \end{cases}$$

- In some cases with limited data, e.g., IPO's, set $\alpha_i = 0$ and $\beta_i = 1$ i.e., just use the market return.
- Economic models restrict α_i rather than estimating it empirically, e.g. $\alpha_i = 0$ under the CAPM. For short event windows, this adds little value since volatilities dominate unconditional means over short sample intervals. For long event windows, the CAPM is subject to known anomalies, which can bias the findings
- Latest research uses multiple factors with $\alpha_i \neq 0$

Measuring Abnormal Return

- The sample of firms are typically chosen all to have been subject to the same type of event. *sampling interval:* typically daily, weekly, or monthly. Suppose event occurs at calendar time t_i for firm i.
- The estimation window (denoted $\mathcal{E}$) consists of $t = t_i - k - T, \ldots, t_i - k$. Typically take as long as possible without being too long; add some "quarantine" period k. For example, estimation window might be -250,...,-21 days
- The event window (denoted $\mathcal{S}$) consists of $t = t_i - l, \ldots, t_i + T_i^*$. Depends on the purpose of the study. e.g., -1,0,+1 days or ± 30 months in the Fama et al study. Short horizon versus long horizon.
- For notational simplicity we assume that the estimation window for all firms is $t = 1, \ldots, T$ and the event window is $T + 1, \ldots, T + T^*$. We assume that the data are generated (under the null hypothesis of no effect) from the market model for all $t = 1, \ldots, T + T^*$

Without Estimation Error

- Suppose that we observed the event window errors (also called Abnormal Returns) without estimation error

$$AR_{it} = \varepsilon^*_{it} = \overbrace{r_{it}}^{treated} - \overbrace{(\alpha_i + \beta_i r_{mt})}^{control}, \quad t = T+1, \ldots, T+T^*$$

for ($t \in \mathcal{S}$).

- Suppose also that ε^*_{it} is normally distributed. Then under the null hypothesis of no effect (ε^*_{it} has mean zero and variance $\sigma^2_{\varepsilon_i}$)
  - The standardized abnormal return

$$SAR_{it} = z_{it} = \frac{\varepsilon^*_{it}}{\sigma_{\varepsilon_i}} \sim N(0,1), \quad t = T+1, \ldots, T+T^*$$

Compare $|SAR_{it}|$ with $z_{\alpha/2}$ for two sided α-level test

  - The cumulated abnormal return over the event window

$$CAR_i(\tau) = \sum_{t=T+1}^{T+\tau} \varepsilon^*_{it} \sim N(0, \tau\sigma^2_{\varepsilon_i}), \quad SCAR_i(\tau) = \frac{CAR_i(\tau)}{\sqrt{\tau\sigma^2_{\varepsilon_i}}} \sim N(0,1),$$

Compare $|SCAR_i(\tau)|$ with $z_{\alpha/2}$ for two sided α-level test

Alternative Hypothesis

- Suppose that ε_{it}^* has mean μ_{it},
  - The SAR test statistic is $N(\mu_{it}/\sigma_{\varepsilon_i}, 1)$ and the test has power that increases with $|\mu_{it}|/\sigma_{\varepsilon_i}$
  - The SCAR test statistic is $N(\sum_{t=T+1}^{T+\tau} \mu_{it}/\sqrt{\tau\sigma_{\varepsilon_i}^2}, 1)$ and the test has power that increases with $|\sum_{t=T+1}^{T+\tau} \mu_{it}|/\sqrt{\tau\sigma_{\varepsilon_i}^2}$.
    - ★ If $\mu_{it} = \mu_i$, then power increases with square root of τ
    - ★ If μ_{it} changes with time, then can have $\sum_{t=T+1}^{T+\tau} \mu_{it} = 0$ even though $\sum_{t=T+1}^{T+\tau} |\mu_{it}| > 0$. For example, if first overreaction followed by reversal, the total effect in the window may be zero.

- One could alternatively look at

$$\sum_{t=T+1}^{T+\tau} SAR_{it}^2,$$

which would be $\chi^2(\tau)$ under the null hypothesis. Has power against case $\sum_{t=T+1}^{T+\tau} \mu_{it} = 0$ provided $\sum_{t=T+1}^{T+\tau} \mu_{it}^2 > 0$

Estimation of Parameters

- In practice we dont know α_i, β_i. We can write the estimation window data in matrix form (R_i is $(T \times 1)$)

$$R_i = X_i \theta_i + \varepsilon_i$$

$$R_i = \begin{pmatrix} r_{i1} \\ \vdots \\ r_{iT} \end{pmatrix} \; ; \; X_i = \begin{pmatrix} 1 & r_{m1} \\ \vdots & \vdots \\ 1 & r_{mT} \end{pmatrix} \; ; \; \theta_i = \begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix}$$

- The OLS estimator of the market model, its residuals and estimated error variance are:

$$\widehat{\theta}_i = \left(X_i^{\intercal} X_i \right)^{-1} X_i^{\intercal} R_i$$

$$\widehat{\sigma}^2_{\varepsilon_i} = \frac{\widehat{\varepsilon}_i^{\intercal} \widehat{\varepsilon}_i}{T-2} \quad ; \quad \widehat{\varepsilon}_i = R_i - X_i \, \widehat{\theta}_i$$

Then compute the residuals over the event window using the event window data R_i^* $(T^* \times 1), X_i^*$ $(T^* \times 2)$

$$X_i^* = \begin{pmatrix} 1 & r_{m,T+1} \\ \vdots & \vdots \\ 1 & r_{m,T+T^*} \end{pmatrix}$$

$$\widehat{\varepsilon}_i^* = R_i^* - X_i^* \, \widehat{\theta}_i$$

$$\widehat{\varepsilon}_{it}^* = r_{it}^* - \widehat{\alpha}_i - \widehat{\beta}_i r_{mt}^*$$

These are called the abnormal returns, otherwise denoted $\widehat{AR}_{it}$ and collected in a vector

$$\widehat{AR}_i = (\widehat{AR}_{i,T+1}, \ldots, \widehat{AR}_{i,T+T^*})^\intercal.$$

Contain estimation error

- The abnormal returns/residuals in vector form are

$$\widehat{\varepsilon}_i^* = R_i^* - X_i^*\ \theta_i - X_i^*\ (\widehat{\theta}_i - \theta_i) = \varepsilon_i^* - X_i^*(X_i^{\intercal} X_i)^{-1} X_i^{\intercal} \varepsilon_i \in \mathbb{R}^{T^*}$$

- We have under the null hypothesis of no effect (i.e., that the return model assumptions remain valid in the event window)

$$E\left[\widehat{\varepsilon}_i^*\ \mid X_i^*, X_i\right] = E[\varepsilon_i^* \mid X_i^*, X_i] - X_i^*(X_i^{\intercal} X_i)^{-1} X_i^{\intercal} E[\varepsilon_i \mid X_i^*, X_i] = 0$$

$$E\left[\widehat{\varepsilon}_i^*\ \widehat{\varepsilon}_i^{*\intercal} \mid X_i^*, X_i\right] = \sigma_{\varepsilon_i}^2 (I_{T^*} + X_i^* \left(X_i^{\intercal} X_i\right)^{-1} X_i^{*\intercal}) = V_i = (V_{i;ts})_{t,s=1}^{T^*}$$

- Under normality assumption, we have

$$\widehat{\varepsilon}_i^* \sim N\left(0, V_i\right)$$

Normality Based Theory

Define the cumulated abnormal returns and the standardized quantity by

$$\widehat{CAR}_i(\tau) = \sum_{t=T+1}^{T+\tau} \widehat{\varepsilon}_{it}^*, \quad \widehat{SCAR}_i(\tau) = \frac{\widehat{CAR}_i(\tau)}{\widehat{\sigma}_i(\tau)}, \; \tau = 1, \ldots, T^*$$

$$\widehat{\sigma}_i^2(\tau) = c^\intercal \widehat{V}_i c = \widehat{\sigma}_{\varepsilon_i}^2 c^\intercal (I + \; X_i^* \left(X_i^\intercal X_i \right)^{-1} X_i^{*\intercal}) c$$

where c is a $T^* \times 1$ vector whose first τ elements are one and the rest zero

Theorem

Suppose that $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon_i}^2)$. *Then*

$$\widehat{SCAR}_i(\tau) \sim t\,(T-2) \overset{T \to \infty}{\Longrightarrow} N(0,1)$$

This requires normality of ε. If normality is not there, we can say nothing about the distribution of $\widehat{SCAR}_i(\tau)$ because the event window is assumed to be fixed in size.

Aggregating Abnormal Returns for Statistical Power and absence of normality

- We now consider tests obtained by aggregating over firms subject to the same event or type of event
- When there are a large number of firms this gives consistent tests without assuming normality.
- We can aggregate across firms different ways. Which method is preferable depends upon the implicit alternative hypothesis (or hypotheses).

- Assume no overlap in event windows or at least no cross sectional correlation in $\widehat{\varepsilon}^*_{i,t}$ (as in our market model assumption above)
- Re-order time so that all date zeros are synchronous (keep notation simple). Let n be the number of firms with event. Define the $nT^* \times 1$ vector of abnormal returns and its exact covariance matrix

$$\widehat{\varepsilon}^* = \begin{pmatrix} \widehat{\varepsilon}^*_{1,T+1} \\ \vdots \\ \widehat{\varepsilon}^*_{1,T+T^*} \\ \widehat{\varepsilon}^*_{2,T+1} \\ \vdots \\ \widehat{\varepsilon}^*_{n,T+T^*} \end{pmatrix} \quad ; \quad V = \begin{bmatrix} V_1 & 0 & \cdots & 0 \\ 0 & \ddots & & \\ \vdots & & \ddots & \\ 0 & \cdots & & V_n \end{bmatrix}$$

- The $nT^* \times 1$ abnormal return vector $\widehat{\varepsilon}^*$ should be mean zero and has $nT^* \times nT^*$ covariance matrix V under the null

- For $\tau = 1, \ldots, T^*$ let

$$\widehat{ACAR}(\tau) = \frac{1}{n} \sum_{i=1}^{n} \sum_{t=T+1}^{T+\tau} \widehat{\varepsilon}_{it}^{*}$$

be the average cumulated abnormal return.

- If n is large, because of the law of large numbers and central limit theorem $(n, T \to \infty,\ T^*$ fixed$)$, we have under the null hypothesis that

$$\widehat{SACAR}(\tau) = \frac{\widehat{ACAR}(\tau)}{\widehat{\sigma}(\tau)} = \frac{\frac{1}{n} \sum_{i=1}^{n} \sum_{t=T+1}^{T+\tau} \widehat{\varepsilon}_{is}^{*}}{\sqrt{\frac{1}{n^2} \sum_{i=1}^{n} c^{\intercal} \widehat{V}_i c}} \Longrightarrow N(0,1),$$

where c is as before the $T^* \times 1$ vector whose first τ elements are one and the remaining are zero.

- We can test the null hypothesis comparing $|\widehat{SCAR}(\tau)|$ with $z_{\alpha/2}$ or compare $\widehat{ACAR}(\tau)$ with the confidence bands

$$\pm z_{\alpha/2} \sqrt{\frac{1}{n^2} \sum_{i=1}^{n} c^{\intercal} \widehat{V}_i c}$$

- For $\tau = 1, \ldots, T^*$ let

$$\widehat{ASCAR}(\tau) = \sqrt{n}\frac{1}{n}\sum_{i=1}^{n}\widehat{SCAR}_i(\tau) = \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\frac{\sum_{t=T+1}^{T+\tau}\widehat{\varepsilon}_{it}^*}{\widehat{\sigma}_i(\tau)}$$

be the average standardized cumulated abnormal return.

- If n is large, because of the law of large numbers and central limit theorem $(n, T \to \infty, \ T^* \text{ fixed})$, we have under the null hypothesis that

$$\widehat{ASCAR}(\tau) \Longrightarrow N(0,1),$$

- We can test the null hypothesis comparing $|\widehat{ASCAR}(\tau)|$ with $z_{\alpha/2}$

Cross-sectional Regression Tests/Description

- Cross-sectional models relate the size of the abnormal return to observed cross-sectional characteristics.
  - Is there a sensible relationship?
- Fit a linear regression of the n CAR's on the covariates. Need to use heteroskedasticity-adjusted standard errors since this is a cross-sectional regression.

Example

Abnormal return due to a new stock offering is linearly related to the size of the offering (as a % of total equity): $Y =$ cross-section of CAR's, $X =$ cross-section of offering sizes

Difference in Differences

- We next consider the **fixed effect** model, which is the mainstay of Angrist and Pischke (2009). We suppose that for outcome y_{it}

$$y_{it} = \alpha_i + \gamma_t + \delta D_{it} + \varepsilon_{it}, \qquad E(\varepsilon_{it} | D_{it}) = 0.$$

  where $D_{it} = 1$ if unit i received a treatment in period t and $D_{it} = 0$ otherwise.
  - The α_i and γ_t are firm specific and time specific variables that are not observed and are **nuisance parameters**.
  - The parameter δ measures the treatment effect

- The model is non-nested with the market model because the time effect γ_t is not restricted to be related to the return or excess return on the market portfolio, but on the other hand the model has a homogeneous effect δ of the treatment on the outcome

- For any i, j, t, s we have

$$\begin{aligned}\Delta\Delta y_{it;js} &= (y_{it} - y_{is}) - (y_{jt} - y_{js}) \\ &= y_{it} + y_{js} - y_{is} - y_{jt} \\ &= \alpha_i + \gamma_t + \delta D_{it} + \varepsilon_{it} + \alpha_j + \gamma_s + \delta D_{js} + \varepsilon_{js} \\ &- \alpha_i - \gamma_s - \delta D_{is} - \varepsilon_{is} - \alpha_j - \gamma_t - \delta D_{jt} - \varepsilon_{jt} \\ &= \delta (D_{it} + D_{js} - D_{is} - D_{jt}) + \varepsilon_{it} + \varepsilon_{js} - \varepsilon_{is} - \varepsilon_{jt}.\end{aligned}$$

The double differencing has eliminated the nuisance parameters α_i, γ_t.

- Suppose that $D_{it} + D_{js} - D_{is} - D_{js} = 1$: for example $D_{it} = 1$ (firm i received the treatment in period t) and $D_{js} = D_{is} = D_{js} = 0$ (firm j did not receive the treatment in t or s and i did not receive treatment in period s). Then

$$\Delta\Delta y_{it;js} = \delta + \varepsilon_{it} + \varepsilon_{js} - \varepsilon_{is} - \varepsilon_{jt},$$

and $\Delta\Delta y_{it;js}$ is an unbiased estimator of δ. Average over all such; if take $\{(i, j, t, s)$ distinct$\}$ then standard t-test.

Example

Jovanovic and Menkveld (2012) conducted an empirical study of the entry of a HFT liquidity provider into the market for Euronext Amsterdam listed Dutch index stocks on the Chi-X stock exchange in London in 2007/2008. A simple before and after analysis would be confounded because 2007/2008 was the beginning of the macro financial crisis. Therefore, they compare the Dutch stocks with Belgian stocks that had no such HFT entry but were affected similarly by the macro financial crisis. Specifically, they compute

$$\left(Dutch_{after} - Dutch_{before}\right) - \left(Belgian_{after} - Belgian_{before}\right),$$

where $Dutch_j, Belgian_j$ are Dutch and Belgian outcomes (such as bid ask spreads) respectively averaged over the time period $j \in \{before, after\}$. Their results show *improved* market quality metrics, *reduced* adverse selection components, and *more* trading due to the treatment.

Matching approach

- For a sample of firms E that have an event, find firms M that did not have event but match those according to some observed characteristics C.
- That is, for each $i \in E$ find the firm j that solves

$$j(i) = \arg\min_{j \in M} ||C_i - C_j||,$$

where $||.||$ is some norm. For example C could be market capitalization, prior earnings growth etc.

- Compare average changes in outcomes for the matched firms (control) with the event firms (treated) over the event window relative to the estimation window

$$\sum_{i \in E} \Delta Y_i - \sum_{i \in E} \Delta Y_{j(i)}$$

- This can be particularly advantageous when the outcome of interest is not returns but for example trading volume or bid ask spreads.

Can do t-test of difference in means. **Wilcoxon signed rank test** is a nonparametric test that median outcomes in the treatment and control groups are the same. Assumption of iid

1. Let $X_i = \Delta Y_i$ and $Y_i = \Delta Y_{j(i)}$. Test whether the median returns of X and Y are the same
2. Calculate $|X_i - Y_i|$ and $\mathrm{sign}(X_i - Y_i)$, $i = 1, \ldots, n$. Let

$$W = \left| \sum_{i=1}^{n} \mathrm{sign}(X_i - Y_i) \mathrm{Rank}(|X_i - Y_i|) \right|$$

   where $\mathrm{Rank}(Z_i)$ means the rank of Z_i in the sample $Z_1, \ldots, Z_n$.
3. Compare z with standard normal where

$$z = \frac{W - 0.5}{\sqrt{n(n+1)(2n+1)/6}}$$

Barber and Lyon (1997) argue that for long term event studies one should use buy and hold returns relative to a matched control firm instead of the CAR.

- The use of the market model has three biases
  - New listing bias (sampled firms have longer history than firms included in the index)
  - Rebalancing bias (index frequently rebalances whereas individual stock does not)
  - Skewness bias (long run AR has a positive skewness
- BL suggest instead for firms $i, j(i)$ compute the buy and hold returns

$$\mathcal{R}_{i,T+1:T^*} = \frac{P_{i,T+T^*}}{P_{i,T+1}} \quad ; \quad \mathcal{R}_{j(i),T+1:T^*} = \frac{P_{j(i),T+T^*}}{P_{j(i),T+1}}.$$

Then perhaps average over i the difference and do a t-test or Wilcoxon

Some further issues

- Key assumption for all statistical analysis
  - *The event occurrence is exogenous to earlier stock price changes*
- This makes the event a "natural experiment" that can be used to identify its effect on firm value.
- Suppose events (or announcements) are voluntary, i.e., endogenous. The fact that the firm chooses to announce at a particular time conveys information. Presumably, they are going to announce only at a time most favorable. This introduces a bias.
- When events are modeled accounting for the firm's choice to announce some event, the resulting specifications are typically nonlinear cross-sectional regressions, not the simple linear specifications typically used.

Stock Splits

- The Announcement day (when the split is announced) is on average 52 days prior to the Ex-date (when the split is made, which is during non trading hours)
- Event window typically may start with the announcement day and end after the split day. Or may be just around the split day.
- Most splits are 2:1; Berkshire Hathaway in Jan 2010 did a 50:1 split. Effect may vary with size of split.
- Empirically, stock splits are procyclical - many stock splits at the end of a bull market

Most traders view stock splits as high potential trading opportunities. They consider splits a positive progression in value and goodwill for companies and their investors. Corporate executives use stock splits as marketing and investor relation tools. They know that stock splits make shareholders feel better and engender a sense of greater wealth. Others have a different view.

Berkshire Hathaway (Warren Buffet's company) stock prices soars above \$200,000 (Financial times, 15/08/14)

> *Shareholder eugenics might appear to be a hopeless undertaking. However, were we to split the stock or take other actions focussing on stock price rather than business value, we would attract an entering class of buyers inferior to the existing class of sellers (WB, Letter to shareholders 1983)*

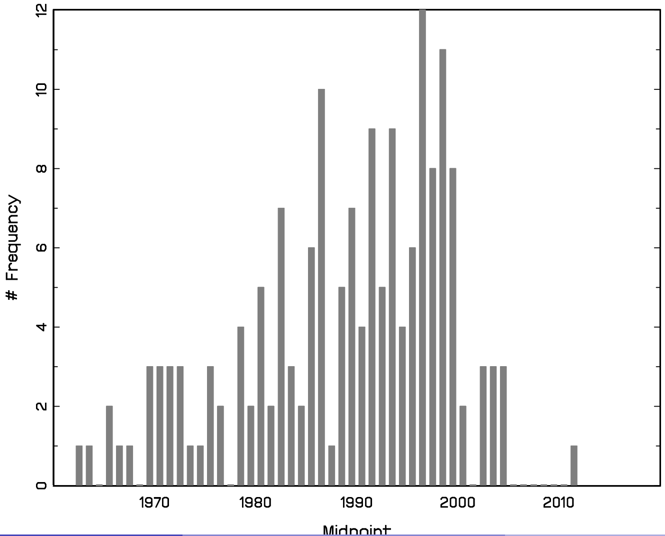
A hard to trade stock encourages investors to take a long term view and locks out those more likely to trade on emotion

- Dolley (1933) studies splits between 1921-1931 and found price increases at the time of split. Short windows
- Fama et al. (1969) study. Argues that Dolley did not control for price appreciation trend established prior to split. CARs, simple market model, monthly data, Key point is large window around the split date, ± 30 months. 940 splits between 1927-1959. They find:
  - CAR increased linearly up to split date and then stayed constant. That is, abnormal returns prior to the split date but not after
  - Argue that results are consistent with the semi strong form of efficiency. Most of the effect occurs a long time before the actual split date. Sample selection: firms that split tend to have had a period of high price appreciation prior to split decision. Splits tend to happen more during bull markets than bear markets.
  - They argue that split announcement signals that dividends may increase in future. Provides some evidence on this by dividing into high dividend after ex group and low dividend after ex group. Found that the high group had positive ARs after ex date, while the low group has negative ARs upto a year after the ex date.

- Other studies have found significant short term/long term effects and questioned the Fama et al. methodology
  - Ikenberry, Rankine and Stice (1996) found a significant post-split excess returns of 7.93 percent in the first year and 12.15 percent in the first three years for a sample of 1,275 two-for-one stock splits. These excess returns followed an announcement return of 3.38 percent, indicating that the market underreacts to split announcements.
  - Ohlson and Penman (1985) examine stock return volatilities prior to and subsequent to the ex-dates of stock splits. They find an increase of approximately 30% in the return standard deviations following the ex-date. This hold for daily and weekly returns and persists for a long while.

Dow Splits

Total of 167 splits for Dow stocks (for the samples we obtained from Yahoo, which in some cases go back to 1960). When did Dow splits occur?

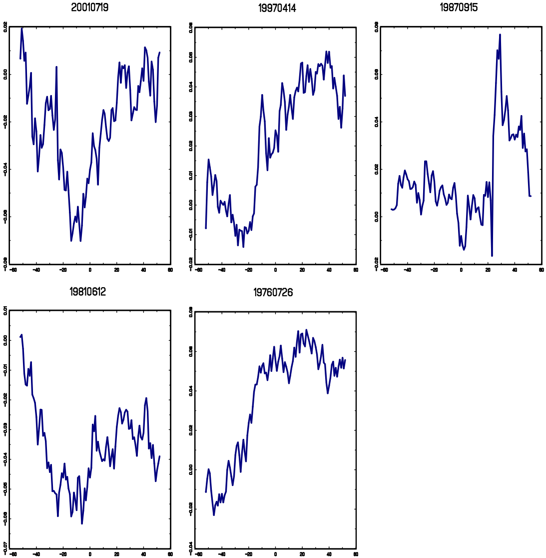


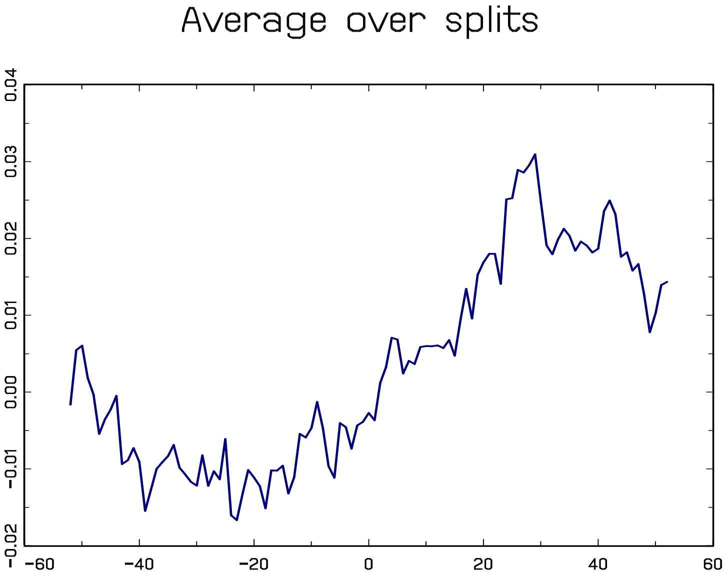
What is the typical size?

Size	Number
$<$1.5	3
1.5	30
2	119
3	12
4	3

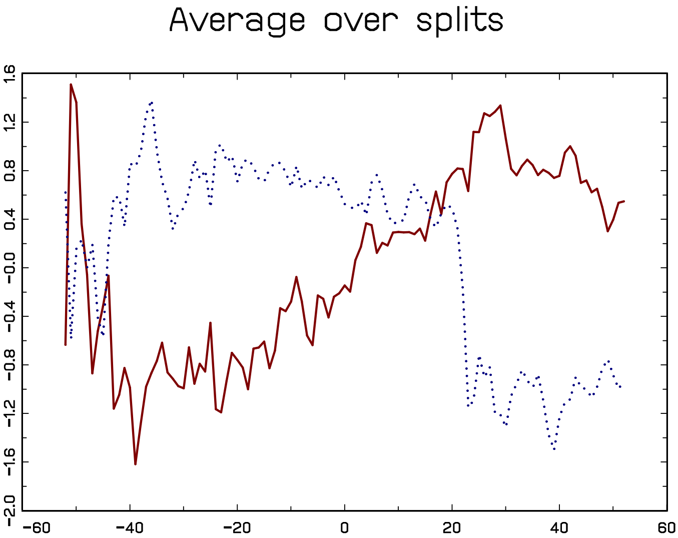
Could use as regressor in cross sectional regression of CAR

For Exxon, there were 5 splits during the sample period. Below shows the ± 52 day CAR for each one

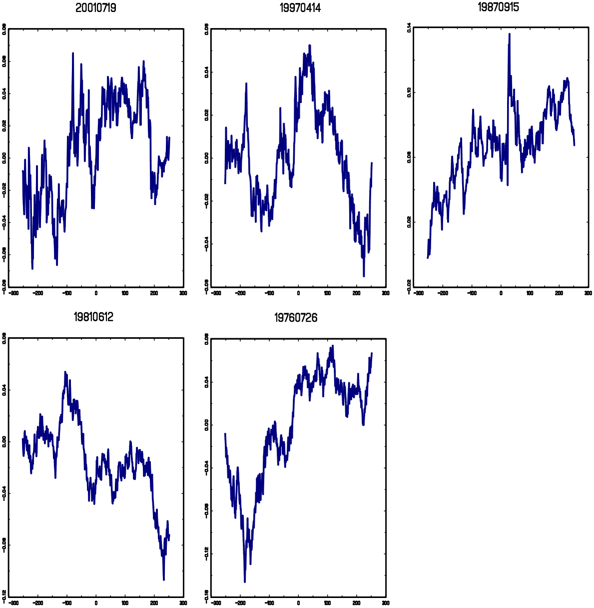



Average over splits
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-60
-40
-20
0
20
40
60

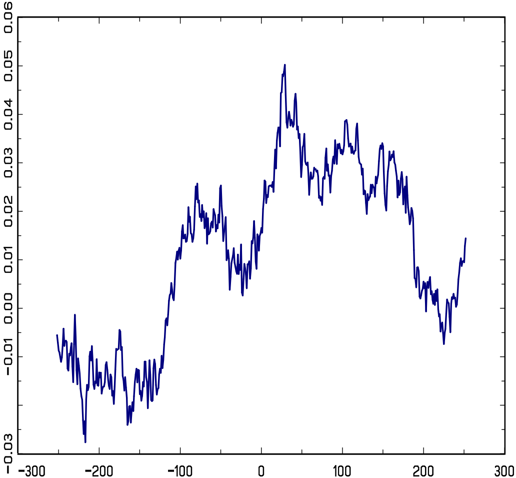
In statistical scale



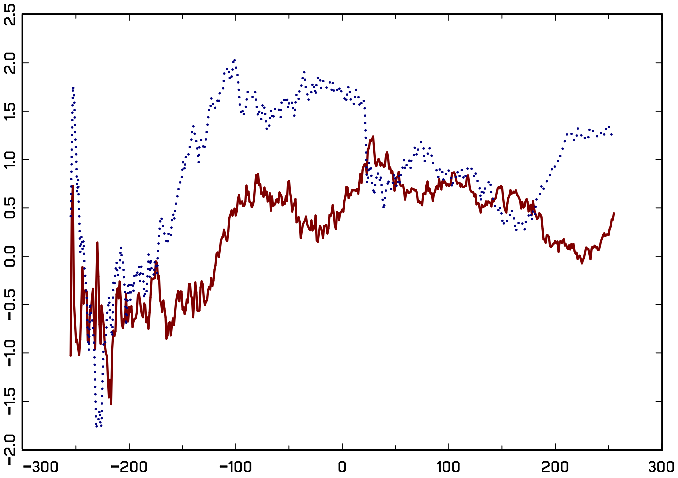
±252 days



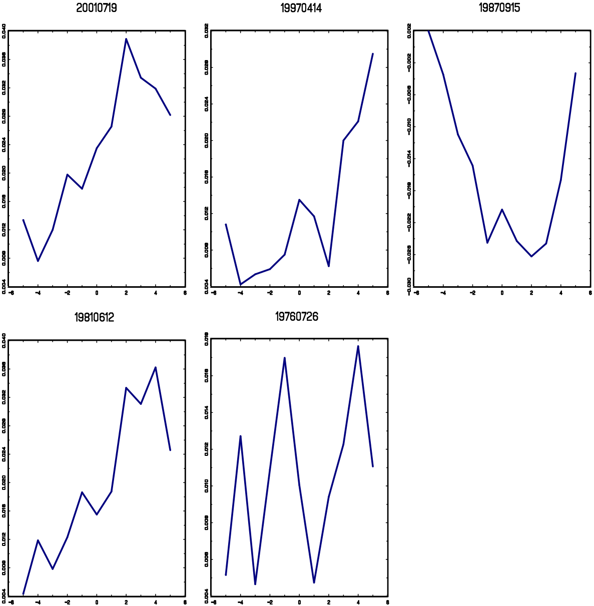
Average over splits



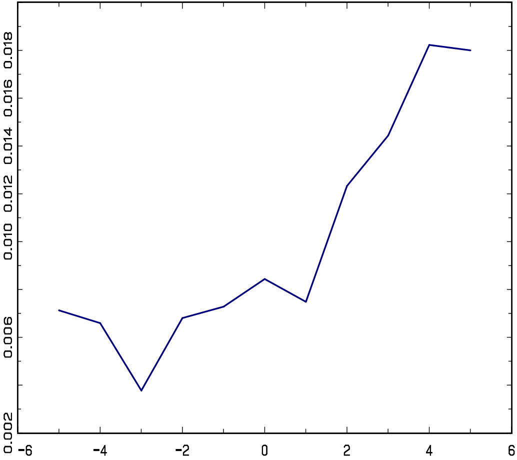
Average over splits



± 5 days



Average over splits



Some Economic Arguments why firms split their stock

1. Achieving an optimal trading range. When price level too high it is harder for retail investor participation (so improves liquidity). Some evidence for this in terms of the average price level of US stocks: it has kept pretty much in the range $30-40 since the 1930's despite massive increase in the level of stock indexes say.
2. Achieving an optimal effective tick size. The bid ask spread is bounded from below by the tick size but what really matters for traders is the relative tick size (and hence the relative bid ask spread), which is determined largely by the price level. Too small a tick size discourages liquidity provision, too large a tick size is costly for retail investors especially.
3. Brokers promote stocks with lower prices more than stocks with higher prices (relative commissions higher).
4. Some institutional investors are prohibited from investing in stocks whose price is too low
5. Signalling that managers expect future sustainable improvements in earnings and dividends

The Nominal Share Price Puzzle William C. Weld, Roni Michaely, Richard H. Thaler, and Shlomo Benartzi (Journal of Economic Perspectives, 2009) WMTB record the "facts":

1. US share prices have remained constant since great depression (so lots of stock splits), however, general price level has increased more than 10 times, so that real stock price level has decreased ten fold
2. Initial Public Offering share prices have also remained constant in nominal terms
3. Maintaining constant stock prices increases trading costs (because real bid-ask spreads)
4. Large firms tend to have higher share prices than small firms
5. The pattern of share prices varies dramatically across countries

WMTB present evidence against all the standard hypotheses that explain stock splits

1. The long term decline in real stock price levels is not justified by the marketability hypothesis. Also not consistent with the increase in institutional ownership (pension funds)
2. Optimal effective tick size hypothesis fails because it predicts that if tick sizes fall (as they have since 1999), then prices should also fall (they didn't).
3. Signaling hypothesis predicts that when the cost of the signal changes, the intensity of the signal should change. Should have seen a decline in the nominal share price
4. WMTB falls back on "tradition" as the only explanation consistent with the data!!!

Further Examples

See the examples at
http://web.mit.edu/doncram/www/eventstudy.html
http://xa.yimg.com/kq/groups/22100777/1232924180/name/CH1-%25EE%2580%2580EventS%25EE%2580%2581tudies.pdf
Recent examples of interest

- ITG study of Citigroup reverse split. Considers a variety of outcomes not just returns
  http://www.itg.com/news_events/papers/CitiSplit2.pdf
- Fernando, May, and Megginson (2012, JF) Examine the question of whether firms derive value from investment bank relationships by studying how the Lehman collapse affected industrial firms that received underwriting, advisory, analyst, and market-making services from Lehman. Equity underwriting clients experienced an abnormal return of around –5%, on average, in the 7 days surrounding Lehman's bankruptcy, amounting to $23 billion in aggregate risk-adjusted losses.