Financial Econometrics, 2ST119

Lecture 3. Asset Return Predictability and Market Efficiency

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"An economist accompanied by a companion strolls down the street when they come upon a $100 bill lying on the ground.

As the companion reaches down to pick it up, the economist says: 'Don't bother – if it were a real $100 bill, someone would have already picked it up."

Definitions of Market Efficiency

intrinsic value = true price of the stock (includes all information, so changes immed. after every decision)

- Fama (1970): "A market in which prices always fully reflect available information is called efficient."
- Malkiel (1992): "A capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. Formally, the market is said to be efficient with respect to some information set [...] if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to an information set implies that it is impossible to make economic profits by trading on the basis of that information set." (Source: Campbell/Lo/MacKinlay p.20ff.)

How to Test for Capital Market Efficiency?

- Problems:
  - How to measure whether prices fully reflect available information?
  - What is the relevant information set? And how to observe?
- Solutions:
  - Malkiel's third sentence: by measuring the profits that can be made by trading on information.
  - This is the foundation of almost all the empirical work on ME.
  - We can measure the profits earned by market professionals, e.g. mutual fund managers.
  - Disadvantage: no direct observation of the information used in the trading strategies.
  - Another solution is to use the information and test the forecastability of the abnormal return.

Testability of the EMH

- General idea: Testing market efficiency by analyzing whether it is possible to earn abnormal returns (excess returns) by using the information.
- Classification of information sets (Roberts, 1967):
  - *Weak-form efficiency*: The information set includes only the history of prices or returns themselves.
    (*)Evaluate predictions of future returns on the basis of the history of past returns.
  - *Semistrong-form efficiency*: The information set includes all information known to all market participants (public information).
    (*)Difficult to test.
  - *Strong-form efficiency*: The information set includes all information known to any market participants (private information).
    (*)Basically not testable.
- Abnormal return: difference between the return and its normal return.
- ME implies that abnormal return is not forecastable in the sense "random".

Implications of the EMH

- Implications for the predictability of price changes?
- Perfect market efficiency realistic?
  - What is about information and transaction costs?
  - What is about risk?
- General Problem:
  - What is the correct benchmark, i.e. what is the correct equilibrium model?
  - Joint hypothesis problem.

$\longrightarrow$ Is the EMH testable at all?

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Testing Random Walk Hypotheses

- What is about the predictability of future prices using past prices?
- Martingale and random walk processes describe situations in which

$$\mathrm{Cov}[f(r_t), g(r_{t+k})] = 0, \quad \text{for } t, k \neq 0 \tag{1}$$

payoff functions from my side

where $f(\cdot)$ and $g(\cdot)$ are specific functions.

- The martingale model

$$\mathrm{E}[p_{t+1} | p_t, p_{t-1}, ...] = p_t$$

$$\mathrm{E}[p_{t+1} - p_t | p_t, p_{t-1}, ...] = 0 \quad \text{martingale difference}$$

Testing Random Walk Hypotheses

the longer the time horizon, the more difficult to make money from the market even if prices are sticky and there is some autocorrelation (?)

- The random walk model

$$\begin{aligned} p_t &= \mu + p_{t-1} + \varepsilon_t \\ r_t &= p_t - p_{t-1} \end{aligned} \tag{2}$$

insider information is NOT random walk

  - Type 1 random walk (RW1):
    (2) with $\varepsilon_t \sim IID(0, \sigma^2)$ and hence $r_t \sim IID(\mu, \sigma^2)$.
  - Type 2 random walk (RW2):
    (2) with $\varepsilon_t \sim INID(0, \sigma_t^2)$ and hence $r_t \sim INID(\mu, \sigma_t^2)$.
  - Type 3 random walk (RW3):
    (2) with $\mathrm{E}[\varepsilon_t] = 0$, $\mathrm{V}[\varepsilon_t] = \sigma_t^2$ and $\mathrm{Cov}[\varepsilon_t, \varepsilon_{t-k}] = 0$, for $k \neq 0$.

Testing the Random Walk Type 1 Hypothesis

not so important cause lack of power

- The Cowles-Jones Test
  - Idea: Comparing the frequencies of sequences (consecutive returns of the same sign) and reversals (consecutive returns of different signs) in a time series of returns and tabulating them against its sampling distribution under the RW hypothesis.
- The Runs Test
  - Run: Number of sequences of consecutive positive and negative returns.
  - Idea: Computing the number of runs (number of sequences of consecutive positive and negative returns) and tabulate them against its sampling distribution under the RW hypothesis.

Testing the Random Walk Type 2 Hypothesis

- Problem: Under a RW2 process, the returns are not necessarily identically distributed. However, constructing statistical tests for the RW2 hypothesis is extremely difficult without making any assumptions how the marginal distributions of the data can vary through time.

- In financial practice the use of technical analysis is an interesting alternative.

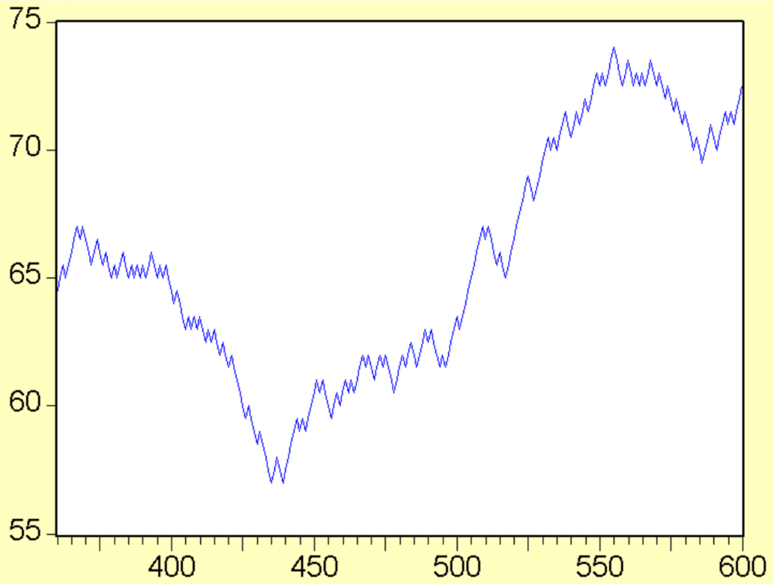
- Technical analysis: Method of predicting the appropriate time to buy (sell) a stock by analyzing stock charts (charting methods).
  - Detecting trends in the price series.
  - Detecting a momentum in the price series.
  - Detecting predictable patterns in the price series.

The Rationale

- The rationale for charting methods:
  - Traders believe in the "castle-in-the-air theory".
  - Trends tend to perpetuate themselves. overshooting or the other way around
  - Resistance and support areas tend to perpetuate themselves.

    on top in the bottom
- The rationale against charting methods:
  - Chartists often "miss the boat".
  - Technical trading strategies must ultimately self-defeating.
  - Anticipation of technical signals possible?
  - Misinterpretation of the randomness in stock prices.

Trends or absolute randomness?



The View from Academia

"Obviously, I'm biased against the chartist. This is not only a personal predilection but a professional one as well. Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) after paying transaction costs, the method does not do better than a buy-and-hold-strategy for investors, and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: It's your money we are trying to save."

Burton G. Malkiel, "A Random Walk Down Wall Street" (1999), p. 140.

Some Elaborate Technical Trading Rules

read LeBaron

- Filter rules:
  - Buy an asset when its price increases by x% and (short) sell it when its price drops by x% (x% filter).
  - Idea: Filtering out all movements smaller than a specified size (noise).
- Moving average rules:
  - Buy (short sell) when the short-period moving average rises above (falls below) the long-period moving average.
  - Idea: Detecting the end of a long term trend.
- Trading range breaks:
  - Buy (sell) when the price rises above (below) the local maximum (minimum) (the so-called resistance level).
  - Idea: People have the habit of remembering what they paid for a stock or what they wish they had paid.

Testing the Random Walk Type 3 Hypothesis

- Testing for autocorrelation in returns:
  - Empirical autocorrelation:

ACP ACF in R

$$\hat{\rho}_j = \frac{\hat{\gamma}_j}{\hat{\gamma}_0} = \frac{\sum_{t=j+1}^{T}(r_t - \bar{r})(r_{t-j} - \bar{r})}{\sum_{t=1}^{T}(r_t - \bar{r})^2}$$

  - Box-Pierce and Ljung Box statistics:

find it in the FE package

$$Q_{BP}(k) = T\sum_{j=1}^{k}\hat{\rho}_j^2 \overset{a}{\sim} \chi^2(k)$$

$$Q_{LB}(k) = T(T+2)\sum_{j=1}^{k}\frac{\hat{\rho}_j^2}{T-j} \overset{a}{\sim} \chi^2(k)$$

- Variance ratio tests as a tool to test for the predictability in asset returns have been proposed by Lo and MacKinlay (1988).
- Basic property of random walk processes: Under all three random walk hypotheses, the variance of random walk increments must be a linear function of the time interval over which the returns are measured.
- Idea of the variance ratio test: Comparing the variances of differently aggregated returns.
- Define $r_t(q) = r_t + r_{t-1} + ... + r_{t-q+1}$ as an q-period aggregated return. Then, the variance ratio is computed as

if it's a random walk, it should be 1

$$VR(q) = \frac{V[r_t(q)]}{qV[r_t]} = 1 + 2\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\rho_k \tag{3}$$

problem: the returns may be autocorrelated but as some of them pos and some neg. so can make their sum = 0

where ρ_k denotes the autocorrelation of order k.

The Variance Ratio Test under the IID Assumption

- Rewrite the sample range as $T = mq + 1$, where $q > 1$ is an integer variable. Then, the sequence of log prices are indexed by $p_0, p_1, ..., p_{mq}$.
- The sample mean and sample variance of the log returns are given by

$$\hat{\mu} = \frac{1}{mq}\sum_{k=1}^{mq}(p_k - p_{k-1}) = \frac{1}{mq}(p_{mq} - p_0) \quad (4)$$

$$\hat{\sigma}_a^2 = \frac{1}{mq}\sum_{k=1}^{mq}(p_k - p_{k-1} - \hat{\mu})^2 \quad (5)$$

- Moreover, an alternative estimator for σ^2 on the basis of q-period returns is given by

not overlapping

$$\hat{\sigma}_b^2 = \frac{1}{mq}\sum_{k=1}^{m}(p_{qk} - p_{qk-q} - q\hat{\mu})^2 \quad (6)$$

The Variance Ratio Test under RW1

- Then, under RW1, the (estimated) variance difference $\widehat{VD}(q) = \hat{\sigma}_b^2 - \hat{\sigma}_a^2$ is asymptotically normally distributed with

$$\sqrt{mq}\widehat{VD}(q) \overset{a}{\sim} N(0, 2(q-1)\sigma^4) \tag{7}$$

- Similarly, for the variance ratio $\widehat{VR}(q) = \hat{\sigma}_b^2 / \hat{\sigma}_a^2$, it can be shown that

$$\sqrt{mq}(\widehat{VR}(q) - 1) \overset{a}{\sim} N(0, 2(q-1)) \tag{8}$$

- Two refinements:
  - using overlapping q-period returns,
  - correcting the (small sample) bias:

here: overlapping, we prefer that because sample size can be large

$$\bar{\sigma}_c^2 = \frac{1}{q(mq-q+1)(1-q/(mq))} \sum_{k=q}^{mq} (p_k - p_{k-q} - q\hat{\mu})^2 \tag{9}$$

$$\bar{\sigma}_a^2 = \frac{1}{mq-1} \sum_{k=1}^{mq} (p_k - p_{k-1} - \hat{\mu})^2 \tag{10}$$

The Variance Ratio Test under RW1

- Then, under the RW1 hypothesis, the statistics

$$\overline{VD}(q) = \bar{\sigma}_c^2 - \bar{\sigma}_a^2, \quad \overline{VR}(q) = \bar{\sigma}_c^2 / \bar{\sigma}_a^2 \tag{11}$$

and asymptotically distributed as

$$\sqrt{mq}\,\overline{VD}(q) \;\overset{a}{\sim}\; N\left(0, \frac{2(2q-1)(q-1)}{3q}\sigma^4\right) \tag{12}$$

the two tests produce the same results (not value)

$$\sqrt{mq}(\overline{VR}(q) - 1) \;\overset{a}{\sim}\; N\left(0, \frac{2(2q-1)(q-1)}{3q}\right) \tag{13}$$

- If σ^4 is estimated by $\bar{\sigma}_a^4$, we have

$$\frac{\sqrt{mq}\,\overline{VD}(q)}{\sqrt{\bar{\sigma}_a^4}} \left(\frac{2(2q-1)(q-1)}{3q}\right)^{-1/2} \;\overset{a}{\sim}\; N(0,1) \tag{14}$$

The Variance Ratio Test under RW3

diff to previous one: they also estimate the variance of this

- Under the RW3 hypothesis returns can reveal (conditional) heteroscedasticity. Then, the asymptotic variance of the variance ratios will depend on the type and degree of heteroscedasticity.
- Lo and MacKinlay (1988) derive an heteroscedasticity-consistent variance ratio test.
- Under general forms of heteroscedasticity, the following equality holds asymptotically:

$$\overline{VR}(q) \stackrel{a}{=} 1 + 2 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right) \hat{\rho}_k \tag{15}$$

The Variance Ratio Test under RW3

- Since the estimators $\hat{\rho}_k$, $k = 1, 2, \ldots$ are asymptotically uncorrelated, we obtain an estimator of $\hat{\mathrm{V}}[\widehat{VR}(q)]$ by

$$\hat{\theta}(q) = \hat{\mathrm{V}}[\widehat{VR}(q)] = 4 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right)^2 \hat{\delta}_k \tag{16}$$

where $\delta_k = \mathrm{V}[\hat{\rho}_k]$.

- It can be shown that a heteroscedastic-consistent estimator of δ_k is given by

$$\hat{\delta}_k = \frac{\sum_{j=k+1}^{mq} (p_j - p_{j-1} - \hat{\mu})^2 (p_{j-k} - p_{j-k-1} - \hat{\mu})^2}{\left[\sum_{j=1}^{mq} (p_j - p_{j-1} - \hat{\mu})^2\right]^2} \tag{17}$$

- Plugging in these estimators, the variance ratio test statistic has the form

$$\frac{\sqrt{mq}(\widehat{VR}(q) - 1)}{\sqrt{\hat{\theta}(q)}} \overset{a}{\sim} N(0, 1) \tag{18}$$

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Testing for Asset Return Predictability

- The question whether asset returns are predictable is a highly disputed question in empirical finance.
- Some important studies in this area:
  - Fama (1965)
  - Fisher (1966)
  - French and Roll (1986)
  - De Bondt and Thaler (1985, 1987)
  - Fama and French (1988)
  - Lo and MacKinlay (1988, 1990)
  - Campbell, Lo and MacKinlay (1997)

The study in Campbell/Lo/MacKinlay (1997)

- Data source: Center for Research in Securities Prices (CRSP) 1962-1994, stock data from NYSE and AMEX, 1962-1994.
- Empirical analysis for
  - value-weighted indexes
  - equal-weighted indexes
  - size-sorted portfolios
  - individual securities

Autocorrelations in daily, weekly, and monthly stock index returns

compare at the diff. measures for diff. aggreg. levels

u can do this for Swedish market

Sample Period	Sample Size	Mean	SD	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_3$	$\hat{\rho}_4$	$\hat{Q}_5$	$\hat{Q}_{10}$
A. Daily Returns									
CRSP Value-Weighted Index									
62:07:03–94:12:30	8,179	0.041	0.824	17.6	−0.7	0.1	−0.8	263.3	269.5
62:07:03–78:10:27	4,090	0.028	0.738	27.8	1.2	4.6	3.3	329.4	343.5
78:10:30–94:12:30	4,089	0.054	0.901	10.8	−2.2	−2.9	−3.5	69.5	72.1
CRSP Equal-Weighted Index									
62:07:03–94:12:30	8,179	0.070	0.764	35.0	9.3	8.5	9.9	1,301.9	1,369.5
62:07:03–78:10:27	4,090	0.063	0.771	43.1	13.0	15.3	15.2	1,062.2	1,110.2
78:10:30–94:12:30	4,089	0.078	0.756	26.2	4.9	2.0	4.9	348.9	379.5
B. Weekly Returns									
CRSP Value-Weighted Index									
62:07:10–94:12:27	1,695	0.196	2.093	1.5	−2.5	3.5	−0.7	8.8	36.7
62:07:10–78:10:03	848	0.144	1.994	5.6	−3.7	5.8	1.6	9.0	21.5
78:10:10–94:12:27	847	0.248	2.188	−2.0	−1.5	1.6	−3.3	5.3	25.2
CRSP Equal-Weighted Index									
62:07:10–94:12:27	1,695	0.339	2.321	20.3	6.1	9.1	4.8	94.3	109.3
62:07:10–78:10:03	848	0.324	2.460	21.8	7.5	11.9	6.1	60.4	68.5
78:10:10–94:12:27	847	0.354	2.174	18.4	4.3	5.5	2.2	33.7	51.3
C. Monthly Returns									
CRSP Value-Weighted Index									
62:07:31–94:12:30	390	0.861	4.336	4.3	−5.3	−1.3	−0.4	6.8	12.5
62:07:31–78:09:29	195	0.646	4.219	6.4	−3.8	7.3	6.2	3.9	9.7
78:10:31–94:12:30	195	1.076	4.450	1.3	−6.3	−8.3	−7.7	7.5	14.0
CRSP Equal-Weighted Index									
62:07:31–94:12:30	390	1.077	5.749	17.1	−3.4	−3.3	−1.6	12.8	21.3
62:07:31–78:09:29	195	1.049	6.148	18.4	−2.5	4.4	2.4	7.5	12.6
78:10:31–94:12:30	195	1.105	5.336	15.0	−1.6	−12.4	−7.4	8.9	14.2

compute this yourself: how to treat holidays, split into two (before and after covid) variance ration test here is more forgiving

Variance ratios for weekly stock index returns

Sample period	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. CRSP Equal-Weighted Index					
62:07:10–94:12:27	1,695	1.20	1.42	1.65	1.74
		(4.53)*	(5.30)*	(5.84)*	(4.85)*
62:07:10–78:10:03	848	1.22	1.47	1.74	1.90
		(3.47)*	(4.44)*	(4.87)*	(4.24)*
78:10:10–94:12:27	847	1.19	1.35	1.48	1.54
		(2.96)*	(2.96)*	(3.00)*	(2.55)*
B. CRSP Value-Weighted Index weighted= acc. to the size of the company					
62:07:10–94:12:27	1,695	1.02	1.02	1.04	1.02
		(0.51)	(0.30)	(0.41)	(0.14)
62:07:10–78:10:03	848	1.06	1.08	1.14	1.19
		(1.11)	(0.89)	(1.05)	(0.95)
78:10:10–94:12:27	847	0.98	0.97	0.93	0.88
		(-0.45)	(-0.40)	(-0.50)	(–0.64)

Variance ratios for weekly size-sorted portfolio returns

Time period	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. Portfolio of firms with market values in smallest CRSP quintile					
62:07:10–94:12:27	1,695	1.35	1.77	2.24	2.46
		(7.15)*	(9.42)*	(10.74)*	(9.33)*
62:07:10–78:10:03	848	1.34	1.76	2.22	2.46
		(5.47)*	(7.33)*	(8.03)*	(6.97)*
78:10:10–94:12:27	847	1.37	1.79	2.22	2.49
		(4.67)*	(5.91)*	(6.89)*	(6.60)*
B. Portfolio of firms with market values in central CRSP quintile					
62:07:10–94:12:27	1,695	1.20	1.39	1.59	1.65
		(4.25)*	(4.85)*	(5.16)*	(4.17)*
62:07:10–78:10:03	848	1.21	1.43	1.66	1.79
		(3.25)*	(4.03)*	(4.27)*	(3.67)*
78:10:10–94:12:27	847	1.19	1.33	1.44	1.47
		(2.79)*	(2.74)*	(2.63)*	(2.14)*
C. Portfolio of firms with market values in largest CRSP quintile					
62:07:10–94:12:27	1,695	1.06	1.10	1.14	1.11
		(1.71)	(1.46)	(1.38)	(0.76)
62:07:10–78:10:03	848	1.11	1.21	1.30	1.32
		(2.05)*	(2.15)*	(2.12)*	(1.59)
78:10:10–94:12:27	847	1.01	1.00	0.98	0.92
		(0.29)*	(0.05)	(-0.13)	(-0.41)

you can't make money compared to small companies (if they survive)

Empirical Evidence for Daily and Weekly Portfolio Returns

- For equal-weighted indexes based on daily and weekly data:
  - Clear evidence against the random walk hypothesis.
  - Significantly positive autocorrelations.
  - Variance ratios greater than one.
  - However: Degree of predictability seems to decline through time. $\rightarrow$ Increasing market efficiency through time?

- For value-weighted indexes:
  - The random walk hypothesis cannot be rejected for any aggregation level q.
  - No significant evidence for asset return predictability.

Variance ratios for weekly individual security returns

Sample	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. Averages of variance ratios over individual securities					
All stocks (411 stocks)	1,695	0.96 (0.04)	0.92 (0.07)	0.89 (0.11)	0.85 (0.14)
Small stocks (100 stocks)	1,695	0.95 (0.06)	0.90 (0.09)	0.88 (0.12)	0.85 (0.15)
Medium stocks (100 stocks)	1,695	0.96 (0.04)	0.93 (0.07)	0.90 (0.09)	0.85 (0.13)
Large stocks (100 stocks)	1,695	0.95 (0.03)	0.91 (0.06)	0.89 (0.11)	0.86 (0.15)
B. Variance ratios of equal- and value-weighted portfolios of all stocks					
Equal-weighted portfolio (411 stocks)	1,695	1.11 (2.75)*	1.20 (2.83)*	1.30 (2.88)*	1.29 (1.99)*
Value-weighted portfolio (411 stocks)	1,695	0.99 (-0.26)	0.97 (-0.43)	0.96 (-0.42)	0.93 (−0.53)

heteroskedastic robust version

Cross-autocorrelation matrices for size-sorted portfolios

$$\hat{\Upsilon}_0 = \begin{array}{cc} & \begin{array}{ccccc} R_{1t} & R_{2t} & R_{3t} & R_{4t} & R_{5t} \end{array} \\ \begin{array}{c} R_{1t} \\ R_{2t} \\ R_{3t} \\ R_{4t} \\ R_{5t} \end{array} & \begin{pmatrix} 1.000 & 0.938 & 0.892 & 0.839 & 0.728 \\ 0.938 & 1.000 & 0.976 & 0.944 & 0.856 \\ 0.892 & 0.976 & 1.000 & 0.979 & 0.914 \\ 0.839 & 0.944 & 0.979 & 1.000 & 0.961 \\ 0.728 & 0.856 & 0.914 & 0.961 & 1.000 \end{pmatrix} \end{array}$$

contemporaneous autocorr. betw. the portfol.

$$\hat{\Upsilon}_1 = \begin{array}{cc} & \begin{array}{ccccc} R_{1t} & R_{2t} & R_{3t} & R_{4t} & R_{5t} \end{array} \\ \begin{array}{c} R_{1t-1} \\ R_{2t-1} \\ R_{3t-1} \\ R_{4t-1} \\ R_{5t-1} \end{array} & \begin{pmatrix} 0.352 & 0.226 & 0.171 & 0.115 & 0.024 \\ 0.330 & 0.232 & 0.182 & 0.129 & 0.037 \\ 0.324 & 0.244 & 0.197 & 0.147 & 0.053 \\ 0.310 & 0.242 & 0.201 & 0.153 & 0.059 \\ 0.265 & 0.223 & 0.187 & 0.147 & 0.057 \end{pmatrix} \end{array}$$

$$\hat{\Upsilon}_2 = \begin{array}{cc} & \begin{array}{ccccc} R_{1t} & R_{2t} & R_{3t} & R_{4t} & R_{5t} \end{array} \\ \begin{array}{c} R_{1t-2} \\ R_{2t-2} \\ R_{3t-2} \\ R_{4t-2} \\ R_{5t-2} \end{array} & \begin{pmatrix} 0.163 & 0.089 & 0.057 & 0.032 & -0.010 \\ 0.141 & 0.078 & 0.051 & 0.029 & -0.010 \\ 0.135 & 0.079 & 0.051 & 0.032 & -0.005 \\ 0.121 & 0.071 & 0.046 & 0.028 & -0.006 \\ 0.084 & 0.045 & 0.025 & 0.012 & -0.016 \end{pmatrix} \end{array}$$

$$\hat{\Upsilon}_3 = \begin{array}{cc} & \begin{array}{ccccc} R_{1t} & R_{2t} & R_{3t} & R_{4t} & R_{5t} \end{array} \\ \begin{array}{c} R_{1t-3} \\ R_{2t-3} \\ R_{3t-3} \\ R_{4t-3} \\ R_{5t-3} \end{array} & \begin{pmatrix} 0.155 & 0.106 & 0.074 & 0.050 & 0.027 \\ 0.141 & 0.100 & 0.071 & 0.050 & 0.031 \\ 0.143 & 0.105 & 0.077 & 0.058 & 0.039 \\ 0.137 & 0.104 & 0.079 & 0.061 & 0.044 \\ 0.120 & 0.093 & 0.074 & 0.061 & 0.047 \end{pmatrix} \end{array}$$

$$\hat{\Upsilon}_4 = \begin{array}{cc} & \begin{array}{ccccc} R_{1t} & R_{2t} & R_{3t} & R_{4t} & R_{5t} \end{array} \\ \begin{array}{c} R_{1t-4} \\ R_{2t-4} \\ R_{3t-4} \\ R_{4t-4} \\ R_{5t-4} \end{array} & \begin{pmatrix} 0.104 & 0.063 & 0.036 & 0.016 & -0.007 \\ 0.097 & 0.062 & 0.036 & 0.017 & -0.006 \\ 0.095 & 0.060 & 0.033 & 0.015 & -0.011 \\ 0.100 & 0.067 & 0.039 & 0.023 & -0.004 \\ 0.094 & 0.064 & 0.038 & 0.025 & -0.001 \end{pmatrix} \end{array}$$

Asymmetry of cross-autocorrelation matrices

$$\widehat{\Upsilon}(1)-\widehat{\Upsilon}'(1) = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ R_5 \end{array} \begin{array}{c} \begin{array}{ccccc} R_1 & R_2 & R_3 & R_4 & R_5 \end{array} \\ \begin{pmatrix} 0.000 & -0.104 & -0.153 & -0.195 & -0.241 \\ 0.104 & 0.000 & -0.061 & -0.113 & -0.181 \\ 0.153 & 0.061 & 0.000 & -0.054 & -0.134 \\ 0.195 & 0.113 & 0.054 & 0.000 & -0.088 \\ 0.241 & 0.181 & 0.134 & 0.088 & 0.000 \end{pmatrix} \end{array}$$

$$\widehat{\Upsilon}(2)-\widehat{\Upsilon}'(2) = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ R_5 \end{array} \begin{array}{c} \begin{array}{ccccc} R_1 & R_2 & R_3 & R_4 & R_5 \end{array} \\ \begin{pmatrix} 0.000 & -0.052 & -0.079 & -0.089 & -0.094 \\ 0.052 & 0.000 & -0.029 & -0.042 & -0.055 \\ 0.079 & 0.029 & 0.000 & -0.014 & -0.029 \\ 0.089 & 0.042 & 0.014 & 0.000 & -0.018 \\ 0.094 & 0.055 & 0.029 & 0.018 & 0.000 \end{pmatrix} \end{array}$$

$$\widehat{\Upsilon}(3)-\widehat{\Upsilon}'(3) = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ R_5 \end{array} \begin{array}{c} \begin{array}{ccccc} R_1 & R_2 & R_3 & R_4 & R_5 \end{array} \\ \begin{pmatrix} 0.000 & -0.035 & -0.069 & -0.087 & -0.093 \\ 0.035 & 0.000 & -0.024 & -0.054 & -0.062 \\ 0.069 & 0.034 & 0.000 & -0.022 & -0.035 \\ 0.087 & 0.054 & 0.022 & 0.000 & -0.018 \\ 0.093 & 0.062 & 0.035 & 0.018 & 0.000 \end{pmatrix} \end{array}$$

$$\widehat{\Upsilon}(4)-\widehat{\Upsilon}'(4) = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ R_5 \end{array} \begin{array}{c} \begin{array}{ccccc} R_1 & R_2 & R_3 & R_4 & R_5 \end{array} \\ \begin{pmatrix} 0.000 & -0.033 & -0.059 & -0.084 & -0.102 \\ 0.033 & 0.000 & -0.024 & -0.050 & -0.070 \\ 0.059 & 0.024 & 0.000 & -0.023 & -0.049 \\ 0.084 & 0.050 & 0.023 & 0.000 & -0.030 \\ 0.102 & 0.070 & 0.049 & 0.030 & 0.000 \end{pmatrix} \end{array}$$

Summarizing the Results

- For equal-weighted indexes: Significantly positive autocorrelations.
- For value-weighted indexes: No significant autocorrelations.
- For portfolios of small-size companies: Significantly positive autocorrelations.
- For portfolios of large-size companies: No significant autocorrelations.
- Individual securities:
  - Weak, significantly negative autocorrelations.
  - Large, significantly positive cross-autocorrelations across individual securities across time.
  - Larger capitalization stocks lead smaller capitalization stocks lag.

The Performance of Technical Trading Rules

can we make money on technical trading rules? if yes, market not so efficient

- Brock, Lakonishok and LeBaron (1992)
- Data: Dow Jones Industrial Average (DJIA) on a daily basis. Sample range: 1897-1986.
- Analyzed trading rules:
  - variable-length moving average (VMA),
  - fixed-length moving average (FMA),
  - trading range break-out (TRB),
  - combination with one percent band (filter).
- Analyzed returns: daily returns during buy and sell periods.
- Benchmark return: unconditional mean return over the complete period.

Test results for VMA rules

avg return, signif.

short run (1 day)
long run (50 days)

Period	Test	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Panel A: Full Sample								
1897–1986	(1, 50, 0)	14240	10531	0.00047	−0.00027	0.5387	0.4972	0.00075
				(2.68473)	(−3.54645)			(5.39746)
	(1, 50, 0.01)	11671	8114	0.00062	−0.00032	0.5428	0.4942	0.00094
				(3.73161)	(−3.56230)			(6.04189)
	(1, 150, 0)	14866	9806	0.00040	−0.00022	0.5373	0.4962	0.00062
				(2.04927)	(−3.01836)			(4.39500)
	(1, 150, 0.01)	13556	8534	0.00042	−0.00027	0.5402	0.4943	0.00070
				(2.20929)	(−3.28154)			(4.68162)
	(5, 150, 0)	14858	9814	0.00037	−0.00017	0.5368	0.4970	0.00053
				(1.74706)	(−2.61793)			(3.78784)
	(5, 150, 0.01)	13491	8523	0.00040	−0.00021	0.5382	0.4942	0.00061
				(1.97876)	(−2.78835)			(4.05457)
	(1, 200, 0)	15182	9440	0.00039	−0.00024	0.5358	0.4962	0.00062
				(1.93865)	(−3.12526)			(4.40125)
	(1, 200, 0.01)	14105	8450	0.00040	−0.00030	0.5384	0.4924	0.00070
				(2.01907)	(−3.48278)			(4.73045)
	(2, 200, 0)	15194	9428	0.00038	−0.00023	0.5351	0.4971	0.00060
				(1.87057)	(−3.03587)			(4.26535)
	(2, 200, 0.01)	14090	8442	0.00038	−0.00024	0.5368	0.4949	0.00062
				(1.81771)	(−3.03843)			(4.16935)
	Average			0.00042	−0.00025			0.00067
Panel B: Subperiods								
1897–1914	(1, 150, 0)	2925	2170	0.00039	−0.00025	0.5323	0.4959	0.00065
				(1.19348)	(−1.48213)			(2.30664)
1915–1938	(1, 150, 0)	4092	2884	0.00048	−0.00045	0.5503	0.4941	0.00092
				(1.16041)	(−1.82639)			(2.59189)
1939–1962	(1, 150, 0)	4170	2122	0.00036	−0.00004	0.5422	0.5151	0.00040
				(1.06310)	(−1.26932)			(1.98384)
1962–1986	(1, 150, 0)	3581	2424	0.00037	−0.00012	0.5205	0.4777	0.00049
				(0.94029)	(−1.49333)			(2.11283)

Empirical Findings for VMA Rules

- Significantly positive excess returns after buy signals: Average one-day return of 0.042% ($\approx$ 12% p.a.) over different trading rules for buys (unconditional mean return 0.017%).
- Significantly negative excess returns after sell signals: Average one-day return of -0.025% ($\approx$ 7% p.a.) for sells.
- Fraction of positive returns
  - in buy periods: $\approx$ 53.8%,
  - in sell periods: $\approx$ 49.42%.
- Application of a 1% filter leads to even higher (excess) returns.
- Average difference between buy and sell returns: 0.067%.
- Stable results over different subperiods.

always hold for e.g. 10 days, fixed

performs a bit better

Test results for FMA rules

Test	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
(1, 50, 0)	340	344	0.0029	−0.0044	0.5882	0.4622	0.0072
			(0.5796)	(−3.0021)			(2.6955)
(1, 50, 0.01)	313	316	0.0052	−0.0046	0.6230	0.4589	0.0098
			(1.6809)	(−3.0096)			(3.5168)
(1, 150, 0)	157	188	0.0066	−0.0013	0.5987	0.5691	0.0079
			(1.7090)	(−1.1127)			(2.0789)
(1, 150, 0.01)	170	161	0.0071	−0.0039	0.6529	0.5528	0.0110
			(1.9321)	(−1.9759)			(2.8534)
(5, 150, 0)	133	140	0.0074	−0.0006	0.6241	0.5786	0.0080
			(1.8397)	(−0.7466)			(1.8875)
(5, 150, 0.01)	127	125	0.0062	−0.0033	0.6614	0.5520	0.0095
			(1.4151)	(−1.5536)			(2.1518)
(1, 200, 0)	114	156	0.0050	−0.0019	0.6228	0.5513	0.0069
			(0.9862)	(−1.2316)			(1.5913)
(1, 200, 0.01)	130	127	0.0058	−0.0077	0.6385	0.4724	0.0135
			(1.2855)	(−2.9452)			(3.0740)
(2, 200, 0)	109	140	0.0050	−0.0035	0.6330	0.5500	0.0086
			(0.9690)	(−1.7164)			(1.9092)
(2, 200, 0.01)	117	116	0.0018	−0.0088	0.5556	0.4397	0.0106
			(0.0377)	(−3.1449)			(2.3069)
Average			0.0053	−0.0040			0.0093

more realistic

Empirical Findings for FMA Rules

- The returns are computed based on 10-day holding period after buy/sell signals.
- Average difference with (without) an 1%-filter is 1.09% (0.77%) whereas the unconditional 10-day mean return is 0.17%.
- On average, we find a return of 0.53% (-0.40%) for buys (sells).
- Performance of a trading strategy:
  - Borrowing and doubling the investment in the index upon a buys signal. Selling all shares and investing in a risk-free asset upon a sell signal.
  - Under a 1-50 FMA rule with 1% filter: On average about 3.5 buy/sell signals per year.
  - Gained return: 1.8% (1.6%) on the buy (sell) side.

  $\Longrightarrow$ Extra return of 3.4% before transaction costs.

Test results for TBR rules

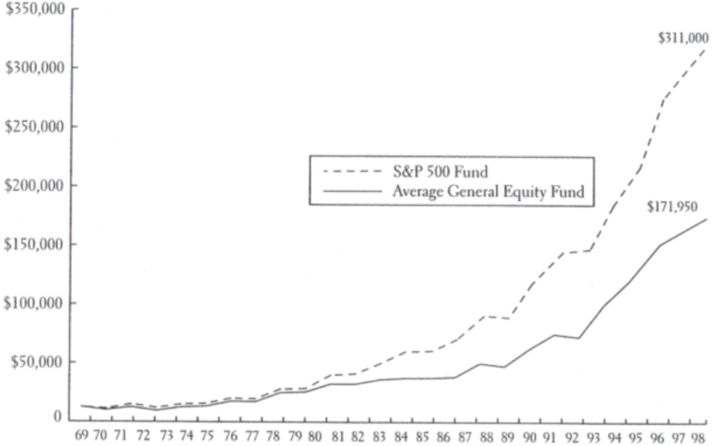
Test	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
(1, 50, 0)	722	415	0.0050	0.0000	0.5803	0.5422	0.0049
			(2.1931)	(−0.9020)			(2.2801)
(1, 50, 0.01)	248	252	0.0082	−0.0008	0.6290	0.5397	0.0090
			(2.7853)	(−1.0937)			(2.8812)
(1, 150, 0)	512	214	0.0046	−0.0030	0.5762	0.4953	0.0076
			(1.7221)	(−1.8814)			(2.6723)
(1, 150, 0.01)	159	142	0.0086	−0.0035	0.6478	0.4789	0.0120
			(2.4023)	(−1.7015)			(2.9728)
(1, 200, 0)	466	182	0.0043	−0.0023	0.5794	0.5000	0.0067
			(1.4959)	(−1.4912)			(2.1732)
(1, 200, 0.01)	146	124	0.0072	−0.0047	0.6164	0.4677	0.0119
			(1.8551)	(−1.9795)			(2.7846)
Average			0.0063	−0.0024			0.0087

Summary of the Results

- Technical trading rules have predictive power.
- Technical trading rules outperform standard time series models (e.g. an AR(1) model).
belong to the castle in the air model (the reduced form model)
- However: Transaction costs should be considered carefully!

The Performance of Mutual Funds

- How good are mutual fund managers?
- Is it worthwhile to invest in mutual funds?



Empirical Evidence on Mutual Fund Performance

- Empirical evidence on mutual fund performance shows mixed results:
  - Jensen (1968): Performance of mutual funds (after expenses) was inferior to the performance of randomly selected portfolios with equivalent risk over the period 1945 through 1964.
  - Henriksson (1984) and Chang/Lewellen (1984) show that during the 1970s, the net returns to fund investors lie along the Sharpe-Lintner market line.

    on the efficient frontier
  - Hendricks/Patel/Zeckhauser (1993) and Goetzmann/Ibbotson (1994) find evidence for "hot hand phenomenon": Past mutual fund returns predict future returns.

The Study by Malkiel (1995)

- Problems in previous literature: Studies focus only on those funds which still exist at the end of the period which generates survivorship bias.
- Reasons for the existence of a survivorship bias:
  - A mutual fund that accepts very high risk will have a high probability of failure.
  - The mutual fund industry systematically tries to avoid bad performances.
  - Tendency to overstate the success of mutual fund management.
- Malkiel (1995): Data on mutual fund returns during 1971-1991. Includes all existing funds in that periods.
- Allows to estimate the impact and extent of survivorship bias.

Estimation of Survivorship Bias

incl. expenses (so incl. the fees they charge their customers)

	All Mutual Funds in Existence Each Year (%)	Funds in Existence in 1982 the Survived Through 1994 (%)	S&P 500 Index (%)	All Mutual Funds in Existence Each Year Gross of Expenses
Capital appreciation funds	16.32	18.08	17.52	17.49
Growth funds	15.81	17.89	17.52	16.81
Small company growth funds	13.46	14.03	17.52	14.53
Growth and income funds	15.97	16.41	17.52	16.89
Equity income funds	15.66	16.90	17.52	16.53
All general equity mutual funds	15.69	17.09	17.52	16.70

still can't win over S&P

removed losers

Differences in Returns of Surviving and Non-Surviving Funds

Year	Total Funds in Existence		Total Number of Funds Surviving Until 1992		Funds that Did Not Survive Until 1992			T-test for Difference Between Means of Surviving and Nonsurviving Funds
	Mean Return	Number	Mean Return	Number	Mean Return	Number	Mortality Rate	
1982	25.03	331	26.03	272	20.42	59	17.8	3.09
1983	20.23	353	21.66	296	12.80	57	16.1	7.15
1984	−2.08	395	−1.25	331	−6.39	64	16.2	3.67
1985	27.17	431	28.10	371	21.42	60	13.9	5.77
1986	13.39	511	14.39	425	8.45	86	16.8	6.29
1987	0.47	581	0.92	489	−1.91	92	15.8	3.04
1988	14.44	686	15.48	586	8.35	100	14.6	7.54
1989	23.99	720	24.91	639	16.73	81	11.3	7.57
1990	−6.27	724	−6.00	685	−11.07	39	5.4	4.07

survivorship bias

Does there exist a "hot hand phenomenon"? related to market efficiency

yes, in the 70s there is one

Initial Year		Next Year Winner	Next Year Loser	Percentage Repeat Winners	Z-Test Repeat Winners
1971	Winner	68	37	64.8	3.0
	Loser	39	66		
1972	Winner	55	55	50.0	0.0
	Loser	56	54		
1973	Winner	72	43	62.6	2.7
	Loser	41	74		
1974	Winner	61	56	52.1	0.5
	Loser	55	62		
1975	Winner	87	30	74.4	5.3
	Loser	30	87		
1976	Winner	80	37	68.4	4.0
	Loser	38	79		
1977	Winner	85	35	70.8	4.6
	Loser	37	83		
1978	Winner	85	37	69.7	4.3
	Loser	39	83		
1979	Winner	89	35	71.8	4.8
	Loser	36	88		
1971–1979	Winner	682	365	65.1	
	Loser	371	675		

no, there's the opposite of hothand phenomenon (cause lower than 50)

Performance of winners/losers over one-year periods during the 80's

Initial Year		Next Year Winner	Next Year Loser	Percent Repeat Winners	Z-Test Repeat Winners
1980	Winner	46	80	36.5	−3.0
	Loser	80	46		
1981	Winner	81	49	62.3	2.8
	Loser	46	84		
1982	Winner	77	59	56.6	1.5
	Loser	53	83		
1983	Winner	83	65	56.1	1.5
	Loser	64	85		
1984	Winner	89	76	53.9	1.0
	Loser	76	89		
1985	Winner	110	75	59.5	2.6
	Loser	70	115		
1986	Winner	128	84	60.4	3.0
	Loser	93	119		
1987	Winner	96	148	39.3	−3.3
	Loser	145	99		
1988	Winner	120	173	41.0	−3.1
	Loser	176	117		
1989	Winner	190	129	59.6	3.4
	Loser	121	189		
1990	Winner	169	173	49.4	−0.2
	Loser	173	169		
1980–1990	Winner	1189	1111	51.7	
	Loser	1087	1203		

Investing in top performing funds – can we beat the market?

Simulated Annual Returns—Strategy of Buying Mutual Funds with Best One-Year Performance

This table simulates the returns that would have been earned by investors over various periods from buying funds with the best performance over the past year.

	1973–1977		1978–1981		1982–1986		1987–1991	
	Simulated Return	S&P Return	Simulated Return	S&P Return	Simulated Return	S&P Return	Simulated Return	S&P Return
Buy top 10 funds previous year	4.36	−0.18	26.73	12.29	19.96	19.80	14.59	15.29
Buy top 20 funds previous year	4.39	−0.18	25.23	12.29	19.70	19.80	13.95	15.29
Buy top 30 funds previous year	4.54	−0.18	24.54	12.29	19.71	19.80	14.28	15.29
Buy top 40 funds previous year	4.17	−0.18	23.90	12.29	20.11	19.80	14.31	15.29

How stable is the performance of mutual funds through time?

	1970–1980		1980–1990	
	Rank	Average Annual Return (%)	Rank	Average Annual Return (%)
1. Twentieth Century Growth	1	27.12	151	11.24
2. Templeton Growth	2	22.34	101	12.68
3. Quasar Associates	3	20.56	161	10.99
4. 44 Wall Street	4	20.13	260	−16.83
5. Pioneer II	5	20.12	112	12.49
6. Twentieth Century Select	6	19.95	17	15.78
7. Security Ultra	7	19.74	249	2.22
8. Mutual Shares Corp.	8	19.52	29	15.23
9. Charter Fund	9	19.50	97	12.78
10. Magellan Fund	10	18.87	1	21.27
11. Over-the-counter	11	18.13	210	9.24
12. Amer. Cap. Growth	12	18.11	243	4.90
13. Amer. Cap. Venture	13	17.97	136	11.75
14. Putnam Voyager	14	17.41	65	13.88
15. Janus Fund	15	17.29	18	15.74
16. Weingarten Equity	16	17.28	30	15.21
17. Hartwell Leverage Fund	17	16.92	222	8.44
18. Pace Fund	18	16.82	50	14.53
19. Acorn Fund	19	16.50	147	11.36
20. Stein Roe Special Fund	20	15.75	48	14.54
Average of 20 funds		19.01		10.87
Overall fund average		9.74		11.56
S&P 500		8.45		13.87
No. of funds with 10-year record		211		260

Market Anomalies

- Weekend effect: Systematic fall in returns between Friday closing and Monday opening.
- January effect: Highly positive daily returns during early days of January.

kinda survivorship bias

- Small firm effect: Small capitalized companies earn on average a higher rate of return than large-capitalized firms.
- Post-earnings announcement effect: Market processes new information on the market not immediately.
- Winner-loser effect: Past "loser stocks" tend to outperform past "winner stocks" in the future.

The Winner-Loser Effect (DeBondt/Thaler, 1985)

- Overreaction hypothesis:
  - Bayes' rule is not an appropriate characterization of how individuals actually respond to new information (Kahneman/Tversky, 1982).
  - Individuals tend to overweight recent information and underweight prior data.
- Question: How does the anomaly survive the process of arbitrage?
- If stock prices systematically overshoot, then their reversal should be predictable from past return data alone
  $\Longrightarrow$ violation of market efficiency.
- Testing whether the overreaction hypothesis is predictive: Analyzing the performance of winner and loser portfolios.

The Winner-Loser Effect (DeBondt/Thaler, 1985)

- Data: Monthly data from common NYSE stocks from 1926 through 1983. Market index: Equally weighted average rate of the return on all securities.
- The period is divided into 16 three-year periods $n = 1, ..., N$; $N = 16$. At the beginning of each three-year period winner and loser portfolios are constructed.
- At the portfolio formation date $t = 0$ in each three-year period n: Computation of cumulative excess returns of asset i for the prior 36 month period:

$$CU_{in} = \sum_{t=-35}^{0} Z_{i,nt}$$

  where $Z_{i,nt} = R_{i,nt} - R^m_{nt}$ denotes the abnormal (excess) return of stock i at month t in period n with respect to the return of the market index, R^m_{nt}.

- According to the ranked CU's, winner and loser portfolios consisting of the top 35 and bottom 35 stocks are constructed.
- For both the winner and loser portfolio in each of the 16 non-overlapping three-year periods, the cumulative average excess returns of all securities in the portfolio for the next 36 months are computed:

company

$$CAR^W_{nt} = \frac{1}{35}\sum_{i=1}^{35}\sum_{j=1}^{t} Z^W_{i,nj}; \quad CAR^L_{nt} = \frac{1}{35}\sum_{i=1}^{35}\sum_{j=1}^{t} Z^L_{i,nj}$$

which 3-year-perios

which month (1-35)

where CAR^W_{nt} and CAR^L_{nt} denote the resulting cumulative average excess return for the winner and loser portfolio, respectively, and $Z^W_{i,nj}$ ($Z^L_{i,nj}$) the excess return of stock i in the winner (loser) portfolio at month j in period n.

The Winner-Loser Effect (DeBondt/Thaler, 1985)

but all are winners cause they survived

- Using CAR_{nt}^{W} and CAR_{nt}^{L}, the average CAR's are calculated for both portfolios and each month t:

$$\overline{CAR}_t^W = \frac{1}{N}\sum_{n=1}^{N} CAR_{nt}^{W}; \quad \overline{CAR}_t^L = \frac{1}{N}\sum_{n=1}^{N} CAR_{nt}^{L}$$

the loser will have better performance

- The overreaction hypothesis predicts: $\overline{CAR}_t^L - \overline{CAR}_t^W > 0$.
- A pooled estimate of the sample variance of the CAR's is given by:

$$\hat{S}_t^2 = \frac{1}{2(N-1)}\sum_{n=1}^{N}\left[\left(CAR_{nt}^{W} - \overline{CAR}_t^W\right)^2 + \left(CAR_{nt}^{L} - \overline{CAR}_t^L\right)^2\right]$$

- Then, a t-statistic for each month t is computed as

$$T_t = \left(\overline{CAR}_t^L - \overline{CAR}_t^W\right) / \sqrt{2\hat{S}_t^2/N}$$

The Winner-Loser Effect (DeBondt/Thaler, 1985)

- In order to judge whether, for any month t, the average excess return for the winner or loser portfolio is significantly different from zero, we can compute the corresponding sample standard deviations as

$$s_t^{W/L} = \sqrt{\sum_{n=1}^{N} \left(AR_{nt}^{W/L} - AR_t^{W/L} \right)^2 / (N-1)}$$

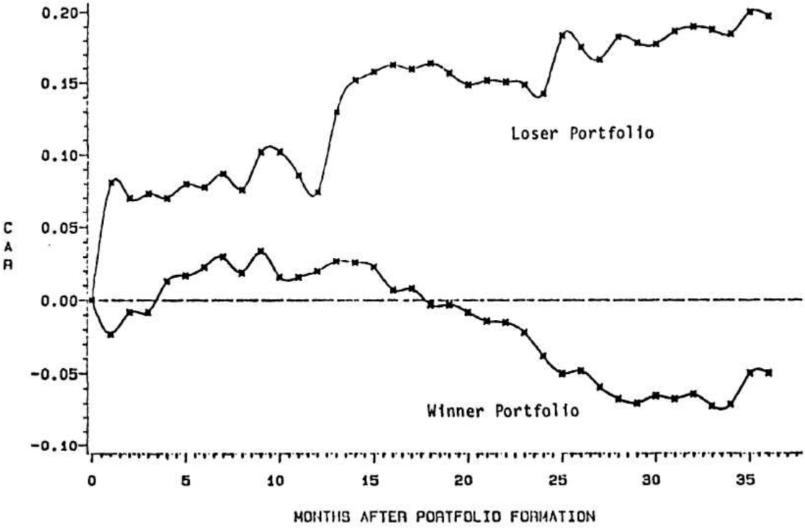
where

$$AR_{nt}^{W/L} = \frac{1}{35} \sum_{i=1}^{35} Z_{i,nt}^{W/L}; \quad AR_t^{W/L} = \frac{1}{N} \sum_{n=1}^{N} AR_{nt}^{W/L}$$

- Then, the corresponding t-statistic equals

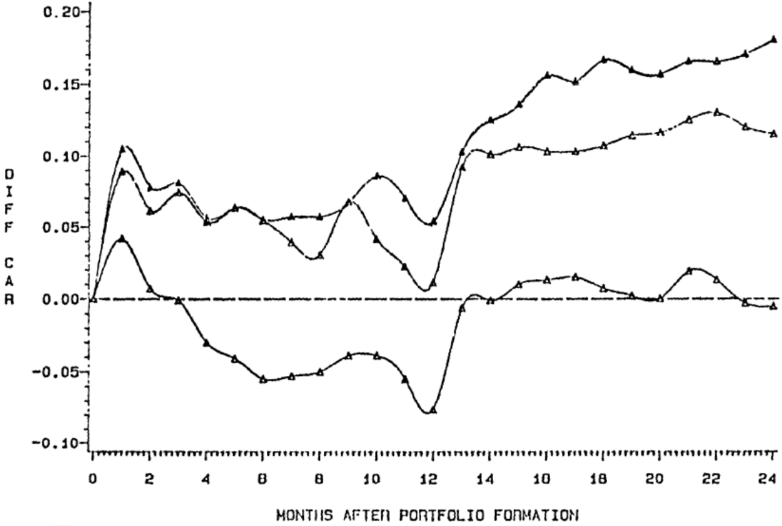
$$T_t^{W/L} = AR_t^{W/L} / (s_t^{W/L} / \sqrt{N})$$

Average CAR's for winner and loser portfolios of 35 stocks

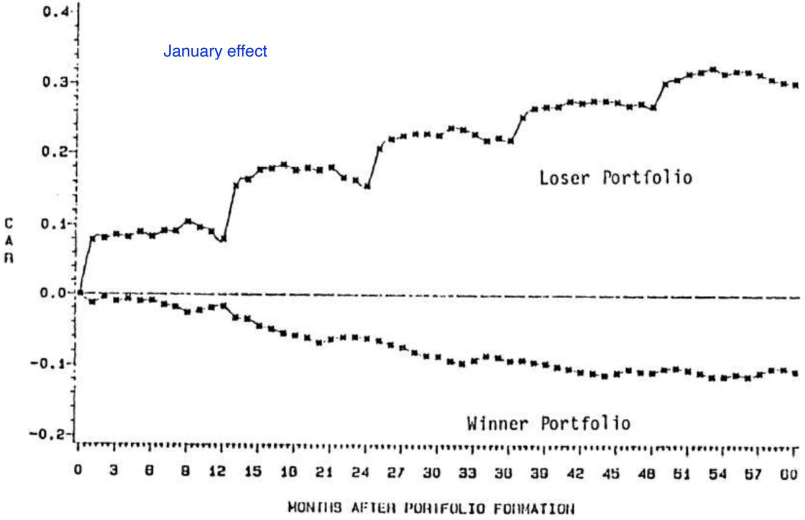


losers = previous period's ranking's last 16 places e.g.

Differences in CAR's between winner and loser portfolios (formed over the previous one, two, or three years)



Cumulative average excess returns
for winner and loser portfolios of 35 stocks over 5 years



Results

- Significant empirical evidence for overreaction: Loser portfolios outperform winner portfolios.
- Asymmetric overreaction: On average 19.6% (5%) outperformance (underperformance) of losers (winners).
- Most of the excess returns are realised in January and during the second and third year after the portfolio formation.
- Conclusions:
  - Clear evidence against market efficiency.
  - Profitability of contrarian investment strategies.
- Possible explanations for these effects?

Table of Contents

Event Studies

- Event studies play an important role to study the impact of an economic event on the value of an asset.
- Examples for event studies:
  - The impact of macroeconomic announcements.
  - The impact of (firm individual) earnings announcements.
  - The impact of stock splits.
  - The impact of the issue of new debt/equity.
  - The impact of mergers and acquisitions.
  - The impact of a change in the political environment.
  - The impact of a change in the institutional and regulatory environment.
  - ...

Outline of an Event Study

1. Event definition:
   - Define the event of interest.
   - Define the event-window.
2. Fixing the selection criteria for the inclusion of an asset in the study. Example: Certain industries/branches, asset classes, market capitalization etc.
3. Measuring normal and and abnormal (log) returns:

$$Z_{it} = R_{it} - \mathrm{E}[R_{it}|X_t]$$

where Z_{it}, R_{it} and $\mathrm{E}[R_{it}|X_t]$ are the abnormal (excess), actual, and normal returns, respectively, for time period t. Moreover, X_t denotes the conditioning information for the normal performance model.

Outline of an Event Study

4. Estimation of the normal performance model using a subset of the data (estimation window). Generally, the event period itself is not included in the estimation period.
5. Computation of abnormal returns and design of a testing framework for the abnormal returns.
6. Presentation of empirical results and testing diagnostics.
7. Interpretation of empirical results and conclusions.

Models for Measuring Normal Performance

- Constant-Mean-Return Model

$$R_{it} = \mu_i + \varepsilon_{it} \quad \varepsilon_{it} \sim IID(0, \sigma^2_{\varepsilon_i}) \tag{19}$$

- Market Model

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad \varepsilon_{it} \sim IID(0, \sigma^2_{\varepsilon_i}) \tag{20}$$

where R_{mt} denotes the market portfolio.

- Multi-Factor Model

$$R_{it} = \alpha_i + \beta_{i,1} f_{1,t} + \beta_{i,2} f_{2,t} + \dots + \beta_{i,N} f_{1,N} + \varepsilon_{it} \tag{21}$$

where $\varepsilon_{it} \sim IID(0, \sigma^2_{\varepsilon_i})$ and $f_{j,t}$ denotes the return of a factor portfolio.

Measuring and Analyzing Abnormal Returns

- Define $\tau = 0$ as the event date.
- Moreover $[T_0, T_1]$ represents the estimation window, $[T_1, T_2]$ the event window and $[T_2, T_3]$ the post-event window with $T_0 < T_1 < T_2 < T_3$.
- Let $L_1 = T_1 - T_0$, $L_2 = T_2 - T_1$ and $L_3 = T_3 - T_2$ are the length of the estimation window, event window and post-event window, respectively.
- If the event being considered is an announcement on a given date, then $T_2 = T_1 + 1$ and $L_2 = 1$.
- Assume that the event is exogenous with respect to the change in market value of the security.

Estimation of the Market Model

- The market model for security i and observation τ in event time is $R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \varepsilon_{i\tau}$.
- Denote $R_i = (R_{i,T_0+1}, ..., R_{i,T_1})'$ and $R_m = (R_{m,T_0+1}, ..., R_{m,T_1})'$ as the $L_1 \times 1$ vectors of estimation window returns and market returns, respectively. Then, we have the regression

$$R_{it} = X_i\theta_i + \varepsilon_i$$

where $X_i = [\iota, R_m]$, ι is a vector or ones and $\theta_i = (\alpha_i, \beta_i)'$
- By OLS, we obtain the estimates:

$$\begin{aligned} \hat{\theta}_i &= (X_i'X_i)^{-1}X_i'R_i \\ \mathrm{V}[\hat{\theta}_i] &= (X_i'X_i)^{-1}\sigma^2_{\varepsilon_i} \\ \hat{\sigma}^2_{\varepsilon_i} &= \frac{e_i'e_i}{L_1 - 2} \end{aligned}$$

where $e_i = R_i - \hat{R}_i = R_i - X_i'\hat{\theta}_i$

- Using the estimates for the market model, we can compute the abnormal return vector

$$\hat{Z}_i = R_i^* - \hat{\alpha}_i \iota - \hat{\beta}_i R_m^* = R_i^* - X_i^* \hat{\theta}_i$$

where $R_i^* = (R_{i,T_1+1}, \ldots, R_{i,T_2})'$ and $R_m^* = (R_{m,T_1+1}, \ldots, R_{m,T_2})'$ are $L_2 \times 1$ vectors and $X_i^* = (\iota, R_m^*)$.

- Then, the conditional mean and variance given the market returns over the event window are given by

$$\begin{aligned} \mathrm{E}[\hat{Z}_i | X_i^*] &= 0 \\ V_i = \mathrm{V}[\hat{Z}_i | X_i^*] &= \sigma_{\varepsilon_i}^2 I + X_i^* (X_i' X_i)^{-1} X_i^* \sigma_{\varepsilon_i}^2 \end{aligned}$$

where I denotes an $L_2 \times L_2$ identity matrix.

use same parameters for pre-event window and event window and test if the real observations deviate; the null = no impact on the economy

- Therefore, under the null hypothesis H_0 that the given event has no impact on the mean or variance of returns, and the assumption that the asset returns are normally distributed, we have

$$\hat{Z}_i \sim N(0, V_i).$$

Aggregation of Abnormal Returns

- Typically, we want to conduct statistical inference for all securities over the complete event-period. This requires to aggregate in both the time dimension as well as the cross-sectional dimension.
- Define $CAR_i(\tau_1, \tau_2)$ as the cumulative abnormal return for asset i from τ_1 to τ_2 with $T_1 < \tau_1 \leq \tau_2 < T_2$. Moreover, let γ be an $L_2 \times 1$ vector with ones in positions $\tau_1 - T_1$ to $\tau_2 - T_1$ and zero elsewhere.
- Then we have

$$\widehat{CAR}_i(\tau_1, \tau_2) = \gamma' \hat{Z}_i$$
$$\mathrm{V}[\widehat{CAR}_i(\tau_1, \tau_2)] = \sigma_i^2(\tau_1, \tau_2)$$

where $\sigma_i^2(\tau_1, \tau_2) = \gamma' V_i \gamma$.

Aggregation of Abnormal Returns

- Under the i.i.d. assumptions it follows that

$$\widehat{CAR}_i(\tau_1, \tau_2) \;\sim\; N(0, \sigma_i^2(\tau_1, \tau_2))$$

- Therefore, we can construct a test of H_0 for security i constructing the standardized cumulative abnormal return

$$\widehat{SCAR}_i(\tau_1, \tau_2) = \frac{\widehat{CAR}_i(\tau_1, \tau_2)}{\hat{\sigma}_i(\tau_1, \tau_2)}$$

  where $\hat{\sigma}_i(\tau_1, \tau_2)$ is calculated by substituting $\sigma^2_{\varepsilon_i}$ by $\hat{\sigma}^2_{\varepsilon_i}$.
- Under the H_0, we have

$$\widehat{SCAR}_i(\tau_1, \tau_2) \;\sim\; t_{L_1-2}$$

- However, for a large estimation window, the distribution of $\widehat{SCAR}_i(\tau_1, \tau_2)$ can be well approximated by the standard normal distribution.

Aggregation of Abnormal Returns

- Define $\bar{Z} = N^{-1} \sum_{i=1}^{N} \hat{Z}_i$ as the sample average of the N abnormal return vectors. Then, we define the cumulative average abnormal return by

$$\overline{CAR}(\tau_1, \tau_2) = \gamma' \bar{Z}$$

with $\mathrm{V}[\overline{CAR}(\tau_1, \tau_2)] = \bar{\sigma}^2(\tau_1, \tau_2) = \gamma' V \gamma$, and

$$V = \mathrm{V}[\bar{Z}] = \frac{1}{N^2} \sum_{i=1}^{N} V_i$$

- Equivalently, we can compute $\overline{CAR}(\tau_1, \tau_2)$ by

$$\overline{CAR}(\tau_1, \tau_2) = \frac{1}{N} \sum_{i=1}^{N} \widehat{CAR}_i(\tau_1, \tau_2)$$

with $\mathrm{V}[\overline{CAR}(\tau_1, \tau_2)] = N^{-2} \sum_{i=1}^{N} \sigma_i^2(\tau_1, \tau_2)$.

Aggregation of Abnormal Returns

- Under the null hypothesis and the assumed normality, we have

$$\overline{CAR}(\tau_1, \tau_2) \ \sim \ N(0, \bar{\sigma}^2(\tau_1, \tau_2))$$

- By using $\hat{\bar{\sigma}}^2(\tau_1, \tau_2) = N^{-2} \sum_{i=1}^{N} \hat{\sigma}_i^2(\tau_1, \tau_2)$ as a consistent estimator of $\bar{\sigma}^2(\tau_1, \tau_2)$, we can construct the test statistic

$$J_1 = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{\hat{\bar{\sigma}}^2(\tau_1, \tau_2)}} \ \overset{a}{\sim} \ N(0, 1)$$

- An alternative test statistic can be constructed by averaging over the individual $SCAR_i$'s. By defining

$$\overline{SCAR}(\tau_1, \tau_2) = \frac{1}{N} \sum_{i=1}^{N} \widehat{SCAR}_i(\tau_1, \tau_2)$$

we obtain

$$J_2 = \sqrt{\frac{N(L_1 - 4)}{L_1 - 2}} \overline{SCAR}(\tau_1, \tau_2) \ \overset{a}{\sim} \ N(0, 1)$$

The Case of Heteroscedasticity

- So far we focused on the null hypothesis that the given event has no impact on the behaviour of returns. Therefore, both a mean effect and a variance effect represent a violation.
- However, whenever we are interested exclusively in a mean effect, we need a heteroscedasticity-consistent estimation of the variances contained in the individual test statistics.
- Under the assumption that there are no cross-sectional correlations between the individual returns, we can replace the estimated variances by the corresponding cross-sectional sample variances:

$$
\begin{aligned}
\hat{\mathrm{V}}[\overline{CAR}(\tau_1,\tau_2)] &= \frac{1}{N^2}\sum_{i=1}^{N}(CAR_i(\tau_1,\tau_2) - \overline{CAR}(\tau_1,\tau_2))^2 \\
\hat{\mathrm{V}}[\overline{SCAR}(\tau_1,\tau_2)] &= \frac{1}{N^2}\sum_{i=1}^{N}(SCAR_i(\tau_1,\tau_2) - \overline{SCAR}(\tau_1,\tau_2))^2
\end{aligned}
$$

Modelling Expected Abnormal Returns

- In the previous sections, we specified a return model which holds only in non-event ("normal") market periods.
- Alternatively, we can specify a model which holds in both non-event periods as well as event periods. However, this requires to specify in which way the event influences the return process.
- Assume a market model which is valid in non-event as well as event periods:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta g_{it}(R_{mt}, Y_{it}) + \varepsilon_{it}$$

  where Y_{it} denotes a vector of event-specific characteristics and $g_{it}(R_{mt}, Y_{it})$ is a function capturing the reaction of the return process in the event period.
- Then, we can test for the impact of an event on the return process $H_0 : \delta = 0$.

Empirical Illustration

- Study by Campbell/Lo/MacKinlay (1997): The informational content of earnings announcements.
- Data: 30 firms of the Dow-Jones index, 1989-1993.
  - Quarterly earnings announcements for all firms (600 announcements).
  - Daily return data for the corresponding stocks.
- When markets are efficient, only non-anticipated information should matter.
  The market's prior expectation is quantified based on quarterly earnings forecast.

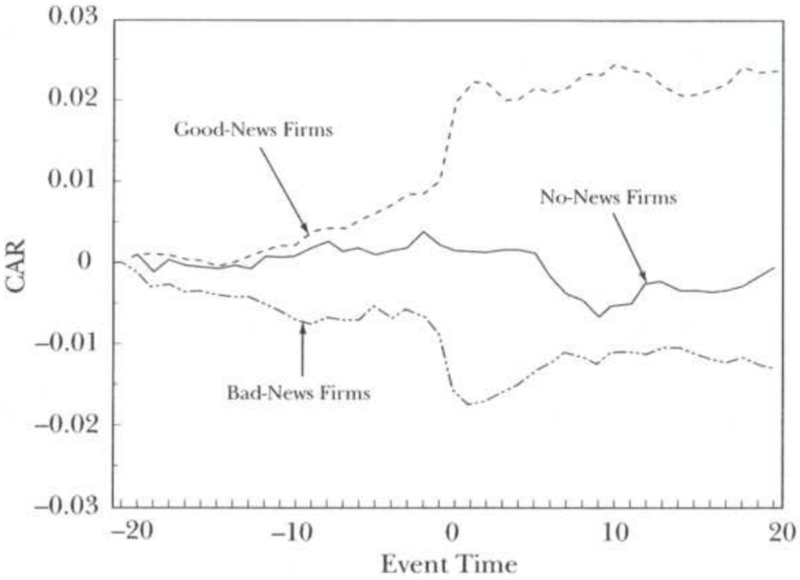
$\Longrightarrow$ Surprise = Announced earning - Forecast.

Empirical Illustration

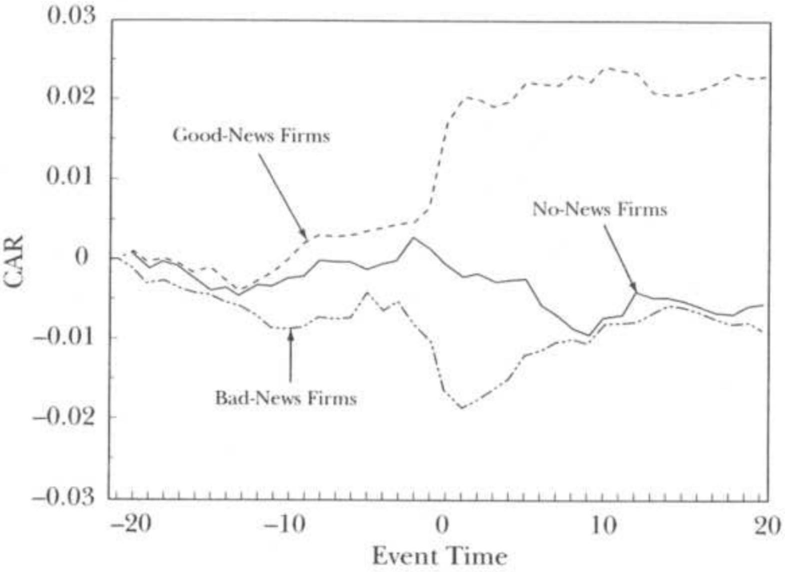
- Categorization of the surprises in "good" news, no news, "bad" news.
- 41-day event window: 20 pre-event and post-event days.
- 250 trading day period prior to the event window as estimation window.

$$ \tag{22} $$

Cumulative Market-Model Abnormal Returns



Cumulative Constant-Mean-Return-Model Abnormal



Thank you!