Big Data Asset Pricing

Lecture 2: A Primer on Empirical Asset Pricing

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Overview of the Course

Lectures

- Quickly getting the research frontier
  1. A primer on asset pricing
  2. **A primer on empirical asset pricing**
  3. Working with big asset pricing data (videos)
- Twenty-first-century topics
  4. The factor zoo and replication
  5. Machine learning in asset pricing
  6. Asset pricing with frictions

Exercises

1. Beta-dollar neutral portfolios
2. Construct value factors
3. Factor replication analysis
4. High-dimensional return prediction
5. Research proposal

Overview of this Lecture

- Basic questions in empirical asset pricing
- How to make factors
- Factor models: how to use factors
- Regressions:
  - Time series
  - Cross-sectional
  - Fama-MacBeth
- Predictability: Regressions and event studies
- Empirical methods
  - Frequentist vs. Bayesian vs. ML

Basic Questions in Empirical Asset Pricing

Basic Questions in Empirical Asset Pricing

- **State prices empirically:**
  - Does arbitrage exist?
  - (If not) can we find m empirically?
  - Can we find mimicking portfolio for m? Beta relation?
  - Does a theory-implied m work for prices or returns?
- **Risk and expected return:**
  - How to measure risk and expected return?
  - What is the relation between risk and expected return?
  - Do expected returns vary in the
    - cross section? If so, which assets outperform? Why?
    - time series? If so, when is the expected return high?
  - Variation in cond. expected returns also called "predictability"
- **Investors:**
  - How do investors behave and why?
  - How do their trades affect prices and expected returns?
  - What is the optimal portfolio?

How to Make Factors

How to Make a Tradable Factor

- Collect data on excess returns, r_t^i
- Collect data on some characteristic (or signal), s_t^i
  - Make sure that the set of securities is free of selection bias
  - Make sure that s_t^i was known before the beginning of period t (no look-ahead bias)
  - Clean the data (without introducing biases)
- Go long stocks with high signals, short stocks with low signals

$$f_{t+1} = \sum_i x_t^{i,L} r_{t+1}^i - \sum_i x_t^{i,S} r_{t+1}^i$$

with weights of the longs, $x_t^{i,L}$, and shorts, $x_t^{i,S}$

How to Make a Factor: Choosing the Weights

- Dollar-neutral, $1 long and $1 short
  - Decile (or quintile/tercile) sorts: Long top, short bottom
    - Value-weighted
    - Capped-value-weighted (See Jensen et al. (2022))
    - Equal-weighted
    - Risk-weighted
  - Fama-French factors
  - Rank-weighted
  - Signal-weighted
- Beta-neutral
  - Leverage long- and short-side to $\beta = 1$ (Frazzini and Pedersen (2014))
  - Hedge with market
  - Beta-dollar neutral: ensure both, if possible (not BAB)
- Risk-adjusted factor
  - First construct factor in one of the above ways
  - Then re-scale it to keep it at constant ex-ante volatility

Typical Table for Factor Construction

Tercile sorts

	P1	P2	P3	P3–P1
Mean	9.5%	10.6%	13.2%	3.7%
(t-stat)	(3.31)	(4.33)	(5.19)	(1.83)
Stdev	17.9%	15.4%	15.9%	12.8%
Sharpe	0.53	0.69	0.83	0.29
Alpha	−1.7%	0.8%	3.6%	5.3%
(t-stat)	(−1.59)	(1.02)	(3.17)	(2.66)

Well-Known Factors

- **Fama-French factors**: see next slides
- **"Everywhere factors"**: factors that work across asset several classes (e.g., stocks, bonds, FX, commodities, real estate, ...)
  - Value and momentum (Stattman (1980), Jegadeesh and Titman (1993), Asness et al. (2013))
  - Betting against beta, BAB, (Frazzini and Pedersen (2014))
  - Time series momentum (Moskowitz et al. (2012))
  - Carry (Koijen et al. (2018))
- **Other well-known factors**
  - Accruals (Sloan (1996))
  - Short-term reversal (Jegadeesh (1990))
  - Long-term reversal (De Bondt and Thaler (1985))
  - Quality-minus-junk, QMJ, (Asness et al. (2018))
  - Environmental, social, governance, ESG, (Pedersen et al. (2021))
  - Liquidity risk (Pastor and Stambaugh (2003), Acharya and Pedersen (2005))

Fama-French Factors

Fama-French Three-Factor Model

- Fama and French (1993) three-factor model
  1. MKT-RF: market
  2. SMB (small-minus-big): size
  3. HML (high-minus-low): value
- Construction (lots of details – see paper and problem set):

$$\begin{aligned} \text{MKT-RF} &= \text{All stocks, value weighted} \\ \text{SMB} &= \frac{1}{3}(\text{Small Value}+\text{Small Neutral}+\text{Small Growth}) \\ &\quad -\frac{1}{3}(\text{Big Value}+\text{Big Neutral}+\text{Big Growth}) \\ \text{HML} &= \frac{1}{2}(\text{Small Value}+\text{Big Value}) - \frac{1}{2}(\text{Small Growth}+\text{Big Growth}) \end{aligned}$$

Median ME

70^{th} percentile of B/M–	Small Value	Big Value
30^{th} percentile of B/M–	Small Neutral	Big Neutral
	Small Growth	Big Growth

- What is the idea of this construction?

Fama-French Five-Factor Model

- Fama and French (2015) five-factor model
  1. MKT-RF: market – as in FF3
  2. SMB: size – similar to FF3, but different construction
  3. HML: value – as in FF3
  4. RMW (robust-minus-weak): profitability
  5. CMA (conservative-minus-aggressive): low investment
     - Note that "investment" is really the percentage change in total assets over the past year, which also captures equity issuance and redistributions, debt changes, etc., not just "real investment" such as capex
- Construction:
  - SMB: here they try to make it neutral to HML, RMW, CMA
  - RMW=$\frac{1}{2}$(Small Robust+Big Robust)-$\frac{1}{2}$(Small Weak+Big Weak)
  - CMA=$\frac{1}{2}$(Small Conservative+Big Conservative)-$\frac{1}{2}$(Small Aggressive + Big Aggressive)
- No attempt to make HML, RMW, CMA uncorrelated
  - Correlation of especially HML and CMA

Fama-French Motivation: Present Value Relation

- Define k as the "internal rate of return" given by DDM

$$p_t = \sum_{\tau=1}^{\infty} \frac{\mathrm{E}_t\left[d^i_{t+\tau}\right]}{(1+k)^{\tau}}$$

- Accounting variables:
  - "Clean surplus accounting relation," $B_t = B_{t-1} + e_t - d_t$
  - So p can be written in terms of earnings and asset growth

$$p_t = \sum_{\tau=1}^{\infty} \frac{\mathrm{E}_t\left[e_{t+\tau} - \Delta B^i_{t+\tau}\right]}{(1+k)^{\tau}}$$

  - or residual income model, w/residual income, $RI^i_t = e_t - kB_{t-1}$

$$p_t = B_t + \sum_{\tau=1}^{\infty} \frac{\mathrm{E}_t\left[RI^i_{t+\tau}\right]}{(1+k)^{\tau}}$$

Fama-French Motivation: Present Value Relation, cont.

- Fama-French motivate their 3- or 5-factor models as follows:
- Look at DDM+accounting versions:

$$p_t = \sum_{\tau=1}^{\infty} \frac{\mathrm{E}_t\left[d^i_{t+\tau}\right]}{(1+k)^\tau} = \sum_{\tau=1}^{\infty} \frac{\mathrm{E}_t\left[e_{t+\tau} - \Delta B^i_{t+\tau}\right]}{(1+k)^\tau} = B_t + \sum_{\tau=1}^{\infty} \frac{\mathrm{E}_t\left[RI^i_{t+\tau}\right]}{(1+k)^\tau}$$

  - Low p means high future returns, k, *holding everything else fixed* (e.g., *for given* expected dividend growth in the left eqn.)
  - High B/p (or low p/B) means high future returns *holding everything else fixed*
  - High profitability (i.e., high earnings e or residual income) means high expected return *holding everything else fixed*
  - High asset growth (ΔB), e.g., high investment, means low returns *holding everything else fixed*
- Does this mean that FF factors are signs of efficiency?

Fama-French Motivation: Present Value Relation, cont.

- Does PV relation mean that FF factors are signs of efficiency?
- No!
  - The PV relation just based on accounting identities
    - Accounting identities always hold, no need for empirics
    - I.e., DDM holds for efficient or inefficient market when k is free (not linked to rational risk)
  - In fact, whole logic is what a believer in inefficiency might use
    - Arguments above are always "...*holding everything else fixed*," which is then ignored – as if it does not matter that prices adjust to earnings etc.
    - Hope that prices have "random" variation
    - If we can ignore that prices are endogenous, where can we hope to find high returns? FF factors
  - In rational market, expected returns are driven by risk
    - Really. Just risk
    - Saying: "in an efficient market, profitable firms must have high expected returns" sounds like the wrong answer in an MBA exam...
    - We must identify the rational risk of profitable firms in order to say that they should have high or low expected returns

Fama-French: Alternative Motivations

- A potential description of the tangency portfolio
  - Does the Fama-French factor model "work"?
    - Do the factors have positive returns?
    - Do other portfolios have zero alpha relative to FF?
  - If so, we learn the "building blocks" of the tangency portfolio
    - Whether rational or not
- A short-hand way to capture existing knowledge about returns
  - E.g., suppose someone comes with a new factor with positive average excess return
    - Is this factor truly new or just a way to repackage old stuff?
    - We can check by regressing on FF

Factor Models: Time Series Regressions

See Cochrane (2009) ch. 12 for more details and test statistics

Testing $\alpha = 0$ Using Time Series Regressions

- We have N "test assets," e.g. 25 Fama-French portfolios
  - Portfolios are easy to work with: balanced panel
  - Portfolios reduce noise, although reduce information too
- Want to test whether these assets are priced by tradable factors
- Run time series regression for each asset i

$$r_t^i = \alpha^i + \sum_k \beta^{i,k} f_t^k + \varepsilon_t^i$$

- So we can test for "pricing," for each asset i

$$\alpha^i = 0$$

- or that that all alphas are jointly zero ("GRS test," Gibbons et al. (1989)):

$$\alpha = 0$$

- Betas also interesting – show factor exposures

Typical Table for Time Series Regression

- Test asset: QMJ (and its parts, profitability, safety, growth)
- We test whether it is priced by MKT, SMB, HML, UMD

$$QMJ_t = \alpha + \beta^{MKT} MKT_t + \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{UMD} UMD_t + \varepsilon_t$$

	QMJ	Profitability	Safety	Growth
Excess Returns	**0.29**	**0.25**	**0.23**	**0.17**
	(3.62)	(3.69)	(2.44)	(2.46)
CAPM-alpha	**0.39**	**0.32**	**0.40**	**0.16**
	(5.43)	(4.75)	(5.52)	(2.28)
3-factor alpha	**0.51**	**0.40**	**0.52**	**0.28**
	(8.90)	(6.97)	(9.06)	(5.17)
4-factor alpha	**0.60**	**0.50**	**0.51**	**0.46**
	(9.95)	(8.32)	(8.39)	(8.29)
MKT	**−0.20**	**−0.12**	**−0.32**	**−0.04**
	(−14.35)	(−8.47)	(−22.30)	(−2.81)
SMB	**−0.26**	**−0.22**	**−0.30**	−0.04
	(−11.92)	(−10.01)	(−13.55)	(−1.76)
HML	**−0.37**	**−0.29**	**−0.28**	**−0.49**
	(−15.85)	(−12.57)	(−11.91)	(−23.09)
UMD	**−0.09**	**−0.10**	0.01	**−0.16**
	(−4.34)	(−4.87)	(0.32)	(−9.17)
Sharpe Ratio	0.47	0.48	0.32	0.32
Information Ratio	1.40	1.17	1.18	1.16
Adjusted R2	0.50	0.34	0.62	0.46

Interpreting Alphas for Tradable Factors

$$r_t^i = \alpha^i + \beta^i f_t + \varepsilon_t^i$$

- An excess return, r_t^i, can be seen as "self-financing strategy"
  - long \$1 of the risky asset
  - financed by borrowing \$1
- Therefore, any linear combination of excess returns is a self-financing strategy, e.g.

  $$r_t^i - \beta^i f_t = \alpha^i + \varepsilon_t^i$$

  which has expected return

  $$E(r_t^i - \beta^i f_t) = \alpha^i$$

- A self-financing strategy with no factor exposure must have $\alpha^i = 0$ if f prices the assets (as discussed before)
- Note that this argument does <u>not</u> hold for
  - total returns (here r^f gets messed up)
  - non-tradable factors

Interpreting Alphas for Non-Tradable Factors

- Suppose that f is a non-traded factor such as GDP growth or liquidity risk
- In this case, $r_t^i - \beta^i f_t$ is not a trading strategy
- As shown before, we cannot expect $\alpha = 0$ in a time series regression because the risk price λ is not $E(f)$
  - The problem is even worse if f is related to the pricing kernel, but its scale is unclear, e.g., there exists unknown constants a and b s.t. $m_t = a + bf_t$
  - For example, if f_t is a measure of liquidity computed via bid-ask spreads, then the scale is somewhat arbitrary (e.g., should commissions be added?)
  - E.g., what happens to α when a is higher?
- However, we are still interested in testing $\mathrm{E}_t[r_{t+1}^i] = \beta_t^i \lambda_t$
  - I.e., do riskier assets have higher expected return?
- How to test?
  - Find tradable mimicking factor(s), and then use these in time series regression
  - Use instead a cross-sectional regression - see next slides

Factor Models: Cross-Sectional Regressions

See Cochrane (2009) ch. 12 for more details and test statistics

Two-Pass Cross-Sectional Regression

- Want to use a cross-sectional regression to test $E[r_t^i] = \beta^i \lambda$
  - Cannot use time series when factor is non-traded
  - Can use either time series or cross-section for traded factor

Two-pass method:

1. First estimate betas, $\hat{\beta}^i$, using time series regressions:

$$r_t^i = \alpha^i + \beta^i f_t + \varepsilon_t^i$$

   and expected returns, $E(r_t^i)$, as sample counterpart, $E_T(r_t^i) := \frac{1}{T}\sum_t r_t^i$

2. Estimate factor premia, λ, via regression across assets

$$E_T(r_t^i) = c + \hat{\beta}^i \lambda + u^i$$

   where c is an intercept (which can be excluded) and u^i is noise

- Tests of interest:
  - is the risk price significantly positive, $\lambda > 0$?
  - is the intercept zero as it should be, $c = 0$?
  - are all the pricing errors zero, $E_T(r_t^i) - \hat{\beta}^i \lambda = 0$ for all i ?

Fama-MacBeth Regression: In General

We want to estimate $b \in \mathbb{R}^K$ for the panel

$$r_{t+1}^i = b\, s_t^i + \varepsilon_{t+1}^i$$

1. Each time t, get estimates $\hat{b}_t$, by running a cross-sectional regression of r_{t+1}^i on s_t^i:

$$r_{t+1}^i = b_t s_t^i + \varepsilon_{t+1}^i$$

   where b_t is the regression coefficient and u_t^i is noise
2. Compute the time series average of $\hat{b}_t$ over the T time periods:

$$\hat{b} = \frac{1}{T} \sum_t \hat{b}_t$$

3. Estimate of the standard error of $\hat{b}$ based on the idea that returns have low correlations over time (or using more advanced ways - see Cochrane):

$$\sigma(\hat{b}) = \frac{1}{\sqrt{T}} \sqrt{\frac{1}{T} \sum_t (\hat{b}_t - \hat{b})^2}$$

Fama-MacBeth Regression: To Estimate Beta Pricing

Want to test $\mathrm{E}[r_t^i] = \beta^i \lambda$

1. Each time t, get an estimate of the risk premium, $\hat{\lambda}_t$:
   - estimate betas, $\hat{\beta}_t^i$, using time series regressions
     - use past data, e.g., the 5 past years
     - note that $\hat{\beta}_t^i$ plays the role of s_t^i in the previous slide
     - or alternatively use full-sample betas
   - Then run a cross-sectional regression of realized returns, r_{t+1}^i, on betas:

   $$r_{t+1}^i = c_t + \hat{\beta}_t^i \lambda_t + u_{t+1}^i$$

   where λ_t is the slope coefficient, c_t is the intercept (can be excluded), and u_t^i is noise
2. Estimate the risk premium as the time series average of the slopes:

$$\hat{\lambda} = \frac{1}{T} \sum_t \hat{\lambda}_t$$

3. Estimate of the standard error of $\hat{\lambda}$, e.g., as:

$$\sigma(\hat{\lambda}) = \frac{1}{\sqrt{T}} \sqrt{\frac{1}{T} \sum_t (\hat{\lambda}_t - \hat{\lambda})^2}$$

Factor Models as Risk Models

Factor Models to Capture Risk

- A specification of the variance-covariance matrix, $\mathrm{Var}(r_t)$, is also called a "risk model"
- A factor model, $r_t = \alpha + \beta f_t + \varepsilon_t$, implies a risk model
$$\mathrm{Var}(r_t) = \beta \mathrm{Var}(f_t)\beta' + \mathrm{Var}(\varepsilon_t^i)$$
- This can be implemented in different ways:
  1. (Observed factors) Start with observed factors f_t
     - these should be important for $\mathrm{Var}(r_t)$
     - estimate factor model and its risks using time series regression
  2. (PCA) Do as in 1, but using principal components
  3. (BARRA) Start with observed characteristics (e.g., industry, B/M, etc.) interpreted as factor loadings, β_t, and consider factor returns, f_{t+1}, to be unobserved in
$$r_{t+1}^i = c_t + \beta_t^i f_{t+1} + u_{t+1}^i$$
     - Each t, run a cross-sectional regression of r_{t+1}^i on β_t, where the slope coefficients are interpreted as the realized factor returns, f_{t+1}
     - Estimate the factor risk, $\mathrm{Var}(f_t)$, and idiosyncratic risk, $\mathrm{Var}(\varepsilon_t^i)$, using time series

Return Predictability

See Cochrane (2011), Presidential Address: Discount Rates

Return Predictability

- An interesting issue is how expected returns change over time and across assets
- In other words, can returns be predicted?
- If so, how can returns be predicted?
- This issue can be addressed using predictive regressions

$$r_{t+1}^{i} = a + b\, s_t^{i} + \varepsilon_{t+1}$$

where the signal s_t^i is known ex ante

Return Predictability: Time Series I

- Take a single asset, typically an overall market like the equity market, and consider predictive regression:

$$r_{t+1} = a + b\, s_t + \varepsilon_{t+1}$$

- Suppose r_{t+1} is annualized, $s_t = \frac{D_t}{P_t}$ is annual dividend yield
- What do you think b is? What is the interpretation of
  - $b = 0$?
  - $b = 1$?
  - $b \in (0, 1)$?
  - $b > 1$?

Return Predictability: Time Series II

- Example from Cochrane (2011):

Table I
Return-Forecasting Regressions

The regression equation is $R^e_{t\to t+k} = a + b \times D_t/P_t + \varepsilon_{t+k}$. The dependent variable $R^e_{t\to t+k}$ is the CRSP value-weighted return less the 3-month Treasury bill return. Data are annual, 1947–2009. The 5-year regression t-statistic uses the Hansen–Hodrick (1980) correction. $\sigma[E_t(R^e)]$ represents the standard deviation of the fitted value, $\sigma(\hat{b} \times D_t/P_t)$.

Horizon k	b	$t(b)$	R^2	$\sigma[E_t(R^e)]$	$\frac{\sigma[E_t(R^e)]}{E(R^e)}$
1 year	3.8	(2.6)	0.09	5.46	0.76
5 years	20.6	(3.4)	0.28	29.3	0.62

- Discuss the magnitude of
  - predictive coefficient b
  - its statistical significance, $t(b)$
  - the time-varying in expected returns, $\sigma[E_t(r_{t+1})]$
  - explanatory power, R^2

Return Predictability: Time Series III

- Comments on time series predictability
  - Out-of-sample predictability is much weaker, and small for most predictors of the market
    - Welch and Goyal (2008), update Goyal et al. (2021)
  - b may suffer from Stambaugh (1999) bias and other biases
    - See Campbell (2017) ch. 5.4 for responses
  - Predictive regression on the dividend yield can be understood via present value relation
    - See Campbell (2017) ch. 5.1-3 and Cochrane (2011)
  - A pervasive phenomenon (cf. "everywhere factors"), from Cochrane (2011):

    - *Stocks*. Dividend yields forecast returns, not dividend growth.[6]
    - *Treasuries*. A rising yield curve signals better 1-year returns for long-term bonds, not higher future interest rates. Fed fund futures signal returns, not changes in the funds rate.[7]
    - *Bonds*. Much variation in credit spreads over time and across firms or categories signals returns, not default probabilities.[8]
    - *Foreign exchange*. International interest rate spreads signal returns, not exchange rate depreciation.[9]
    - *Sovereign debt*. High levels of sovereign or foreign debt signal low returns, not higher government or trade surpluses.[10]
    - *Houses*. High price/rent ratios signal low returns, not rising rents or prices that rise forever.

Return Predictability: Cross Section

- Suppose that we have many assets, $r^1_{t+1}, \ldots, r^N_{t+1}$
- Each asset has its own signal, s^i_t, at each time
- The predictive regression is now a panel:

$$r^i_{t+1} = a + b\, s^i_t + \varepsilon_{t+1}$$

- We can run using
  - a pooled regression (be careful with standard errors, see Petersen (2009)), or
  - Fama and MacBeth (1973) as described previously, where
    - $\hat{b}_t$ can be interpreted as the profit of a trading strategy
    - $\hat{b}$ as the average profit
    - Sharpe ratio times $\sqrt{T}$ provides simple t-statistic
    - see Pedersen (2015) ch. 3.4

Predictability: Link to Factors and Trading Strategies

- Note the economic equivalence of
  1. a multivariate predictive regression
  2. a long short factor
- More broadly, Pedersen (2015) ch. 3.4 states

Metatheorem. Any predictive regression can be expressed as a portfolio sort, and any portfolio sort can be expressed as a predictive regression. Specifically:

(a) A time series regression corresponds to a market timing strategy.
(b) A cross-sectional regression corresponds to a security selection strategy.
(c) A univariate regression corresponds to sorting securities by one signal; a bivariate regression corresponds to double-sorting securities by two signals, allowing you to determine whether one signal adds value beyond the other; and a multivariate regression corresponds to sorting by multiple signals.

Event Studies: Event Time vs. Calendar Time

- Another way to study predictability is using an event study
- An event study is used to analyze
  - stock returns before and after an event, e.g.,
    - a stock split, merger, earnings announcement, issuance
    - note: returns before the event obviously have selection bias (but still interesting), while returns after are predictive
  - and also the firm fundamentals around the event
- How to make an event study:
  - firms are aligned in "event time" rather than calendar time
  - compute average (abnormal) return at each event time, e.g., 1 month after the event, 2 months after, and so on
- A factor rebalance can be used as an "event"
  - That means that we have an event each time period
- Notes on event studies
  - If many firms have events at the same time, then biases can arise and standard errors in an event study might be wrong
  - Good idea to also check the result in calendar time, e.g.:
    - Event time: look at performance for firms the months after they issue shares (each firm is counted equally)
    - Calendar time: go long/short firms based on their issuance; look time series of returns (each time period counted equally)

Event Studies: Post-Earnings Announcement Drift

- PEAD: a classic example of using an event study to document predictability, Ball and Brown (1968)
- Here from Bernard and Thomas (1989):

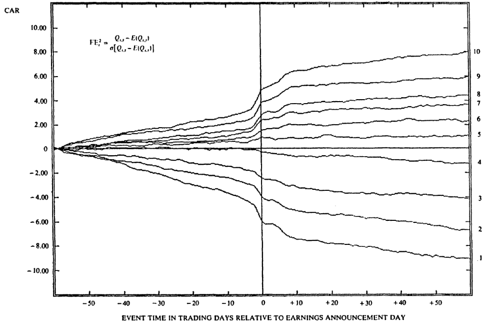
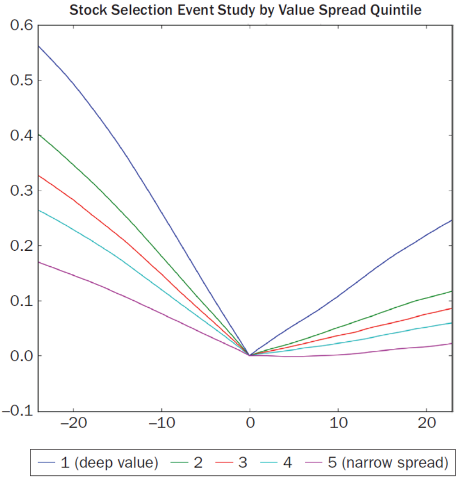


FIG. 1.—Cumulative abnormal returns for FOS earnings-based model (*EBM*) tests. Earnings announcements are assigned to deciles based on standing of standardized unexpected earnings (*SUE*) relative to prior-quarter *SUE* distribution. Portfolio 10 includes firms with the highest *SUE* ranking. Based on data from 1974–81. Cumulative abnormal returns are the sums over 120 trading days surrounding the earnings announcement, of the difference between daily returns and returns for NYSE firms in the same size decile. *SUE* represents forecast error from a first-order autoregressive earnings expectations model (in seasonal differences) scaled by its estimation-period standard deviation. (Reprinted, by permission of the publisher, from G. Foster, C. Olsen, and T. Shevlin, "Earnings Releases, Anomolies, and the Behavior of Security Returns," *The Accounting Review* [October 1984]: 589.)

Event Studies: Example of Factor Return in Event Time

- Example from Asness et al. (2021)



Notes: an event study tracking historical and future returns to value portfolios having different levels of valuation spreads.

Other Signs of Predictability: Excess Volatility and Bubbles

- Excess volatility: Cochrane (2009) page 396 says it so well:

> The volatility test literature starting with Shiller (1981) and LeRoy and Porter (1981) (see Cochrane [1991c] for a review) started out trying to make a completely different point. *Predictability* seems like a sideshow. The stunning fact about the stock market is its extraordinary *volatility*. On a typical day, the value of the U.S. capital stock changes by a full percentage point, and days of 2 or 3 percentage point changes are not uncommon. In a typical year it changes by 16 percentage points, and 30 percentage point changes are not uncommon. Worse, most of that volatility seems not to be accompanied by any important news about future returns and discount rates. Thirty percent of the capital stock of the United States vanished in a year and nobody noticed? Surely, this observation shows directly that markets are "not efficient"—that prices do not correspond to the value of capital—without worrying about predictability?
>
> It turns out, however, that "excess volatility" is *exactly* the same thing as return predictability. Any story you tell about prices that are "too high" or "too low" necessarily implies that subsequent returns will be too low or too high as prices rebound to their correct levels.

- Bubbles: several recent papers, e.g., Giglio et al. (2016)

Views on Predictability

Old school view (1960s and 1970s)

- Stock returns are relatively unpredictable
- i.e., expected returns do not move around
- so price changes must be due to news about cash flows
- and market efficient in simplest sense: random walk hypothesis
- CAPM works pretty well, although low-beta effect discovered in the 1970s

Modern view of the facts (1980s-)

- Stock returns are predictable
  - in the cross section by stock characteristics (value, mom, etc.)
  - in the time series
- I.e., expected returns move around
- CAPM works poorly: SML is relatively flat and, more broadly, market betas explain little of the cross-section of exp. returns

Views on Predictability, continued

Interpretations of modern facts

- Rational
  - Markets can be efficient even though expected returns vary
  - Expected returns driven by risk, but risk is not CAPM beta
  - Joint hypothesis problem
  - New models of utility (habit, long-run risk), macro-finance, etc.
- Behavioral
  - Markets are inefficient
  - Mispricings (bubbles and crashes) drive expected returns
- Frictions (more in Lecture 6)
  - Leverage constraints cause the low-beta effect
  - Market/funding liquidity risk affect expected returns
    - in the time series (high ER during crises, esp. illiquid assets)
    - in the cross section
- Replication crisis (more in Lecture 4)
  - Modern facts are driven by data mining
  - Predictability weaker out of sample, especially time-series predictability of the market
  - Maybe the old school was not all wrong?

Further Empirical Methods

Standard Errors and Test Statistics

- Getting the "right" standard errors an important issue
- Not enough time to cover this topic in this course
- Some well-known methods
  - OLS
  - Bootstrap
  - Newey and West (1987)
  - Fama and MacBeth (1973)
  - Clustering (by time and/or firm)
  - Overview of several approaches in Petersen (2009)

Three Tricks for Causality

1. Instrumental variables
2. Difference in differences
3. Regression discontinuity

- Not the topic of this class – see
  - Book by Angrist and Pischke (2008)
  - Short Ph.D. class at Copenhagen Business School by Kasper Meisner Nielsen

Frequentist Stats, Bayesian Stats, and Machine Learning

- Three tool sets
  1. **Frequentist statistics** (e.g., book by Cochrane (2009))
     - Maximum likelihood estimation (MLE), generalized method of moments (GMM), etc.
  2. **Bayesian statistics** (e.g., free book by Gelman et al. (2020))
     - Full Bayes, empirical Bayes, hierarchical models, etc.
  3. **Machine learning** (e.g., free book by Hastie et al. (2009))
     - Penalized regressions, trees, neural networks, etc.
- All are useful in different situations
- Different views on data-generating process (DGP), see Breiman (2001)

	Model view	Goal
1. **Frequentist**	There is a true DGP	Estimate true parameters
2. **Bayesian**	DGP is random	Compute posterior
3. **ML**	What DGP?	Get an algo to work

- Learn about the details of these in other classes
  - We later consider some applications (frequentist in this lecture, Bayesian in Lecture 4, ML in Lecture 5)

Links to Books/Notes on Empirical Asset Pricing

- General empirical asset pricing
  - "Financial Decisions and Markets: A Course in Asset Pricing," Campbell (2017)
  - "Asset Pricing," Cochrane (2009)
  - "Empirical Dynamic Asset Pricing: Model Specification and Econometric Assessment," Singleton (2006)
- More applied
  - "Efficiently Inefficient," Pedersen (2015)
  - "Empirical asset pricing: The cross section of stock returns" Bali et al. (2016)
- Lecture notes
  - John Cochrane
    `https://www.johnhcochrane.com/empirical-asset-pricing`
  - Ralph Koijen and Stijn Van Nieuwerburgh:
    `https://www.koijen.net/phd-notes-empirical-asset-pricing.html`

References Cited in Slides I

Acharya, V. and L. H. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*, 375–410.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics*. Princeton university press.

Asness, C., A. Frazzini, and L. H. Pedersen (2018). Quality minus junk. *Review of Accounting Studies, forthcoming*.

Asness, C., J. Liew, L. H. Pedersen, and A. Thapar (2021). Deep value. *The Journal of Portfolio Management 47*(4), 11–40.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013). Value and momentum everywhere. *The Journal of Finance 68*(3), 929–985.

Bali, T. G., R. F. Engle, and S. Murray (2016). *Empirical asset pricing: The cross section of stock returns*. John Wiley & Sons.

Ball, R. and P. Brown (1968). An empirical evaluation of accounting income numbers. *Journal of accounting research*, 159–178.

Bernard, V. L. and J. K. Thomas (1989). Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research 27*, 1–36.

Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). *Statistical science 16*(3), 199–231.

Campbell, J. Y. (2017). *Financial decisions and markets: a course in asset pricing*. Princeton University Press.

Cochrane, J. H. (2009). *Asset pricing: Revised edition*. Princeton university press.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance 66*, 1047–1108.

De Bondt, W. F. and R. Thaler (1985). Does the stock market overreact? *The Journal of finance 40*(3), 793–805.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of financial economics 116*(1), 1–22.

References Cited in Slides II

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy 81*(3), 607–636.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1 – 25.

Gelman, A., J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin (2020). *Bayesian data analysis*. Chapman and Hall, Free electronic version.

Gibbons, M. R., S. A. Ross, and J. Shanken (1989). A test of the efficiency of a given portfolio. *Econometrica*, 1121–1152.

Giglio, S., M. Maggiori, and J. Stroebel (2016). No-bubble condition: Model-free tests in housing markets. *Econometrica 84*(3), 1047–1091.

Goyal, A., I. Welch, and A. Zafirov (2021). A comprehensive look at the empirical performance of equity premium prediction ii. *Available at SSRN 3929119*.

Hastie, T., R. Tibshirani, and J. Friedman (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer series in statistics. Springer.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance 48*(1), 65–91.

Jensen, T. I., B. T. Kelly, and L. H. Pedersen (2022). Is there a replication crisis in finance? *Journal of Finance, forthcoming*.

Koijen, R. S., T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt (2018). Carry. *Journal of Financial Economics 127*(2), 197–225.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012). Time series momentum. *Journal of financial economics 104*(2), 228–250.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica 55*(3), 703–708.

Pastor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*, 642–685.

Pedersen, L. H. (2015). *Efficiently inefficient*. Princeton University Press.

References Cited in Slides III

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski (2021). Responsible investing: The esg-efficient frontier. *Journal of Financial Economics 142*(2), 572–597.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of financial studies 22*(1), 435–480.

Singleton, K. J. (2006). *Empirical dynamic asset pricing: model specification and econometric assessment*. Princeton University Press.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting review*, 289–315.

Stambaugh, R. F. (1999). Predictive regressions. *Journal of financial economics 54*(3), 375–421.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A journal of selected papers 4*(1), 25–45.

Welch, I. and A. Goyal (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies 21*(4), 1455–1508.