Valuation

Introduction

- Up to now, we have taken alphas as given. We must now confront the harder task—forecasting alphas.
- Active management is a competitive game. By its very nature, alpha insights do not last forever. Competition eventually arbitrages them away. We can't provide recipes for this. Only examples that once worked, and a framework for building new alphas.
- This is one reason why indexing is popular.

Why Predicting Returns Might Succeed

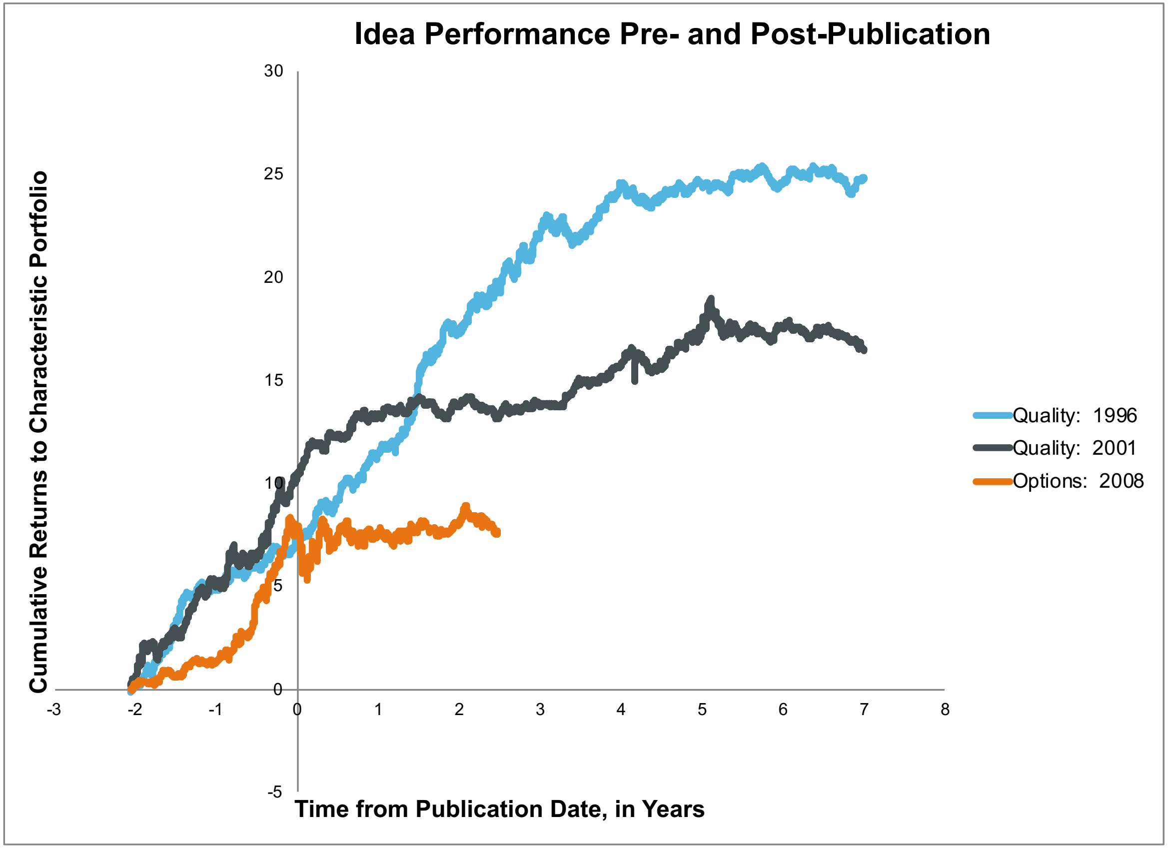
Opportunity:
- Excess volatility (Shiller, 1981)

Specifics:
- Behavioral finance (Kahneman and Tversky, 1979)
- Arbitrage pricing theory (Ross, 1976)
  - Return related to risk factors
  - Broad and persistent sources of return
- Informational Inefficiencies (Grossman and Stiglitz, 1980)
  - Narrow and transient sources of return
- Investor constraints
- Occasional opportunistic trading

On the other hand:
- Arithmetic of Active Management (Sharpe, 1991)

Source: *The Future of Investment Management,* Kahn (2018). For illustrative purposes only.

The Limited Effectiveness of Investment Ideas



Framework for Understanding Return Forecasting

- Start with a tautological decomposition of prices

$$p(t) = \left[\frac{p}{e}(t)\right] \cdot e(t)$$

$$p(t+\Delta t) = \left[\frac{p}{e}(t+\Delta t)\right] \cdot e(t+\Delta t)$$

- Add the definition of return:

$$r(t, t+\Delta t) + i_F = \frac{p(t+\Delta t) + d(t+\Delta t)}{p(t)} - 1$$

Excess

Risk-free

Return Decomposition

- With some algebra, we can show that*:

$$r\left(t,t+\Delta t\right)+i_F \Rightarrow \frac{d\left(t+\Delta t\right)}{p\left(t\right)}+\frac{\Delta e}{e}+\frac{\Delta\left(p/e\right)}{\left(p/e\right)}$$

Dividend Yield　　“Cashflow News”　　“Discount Rate News”

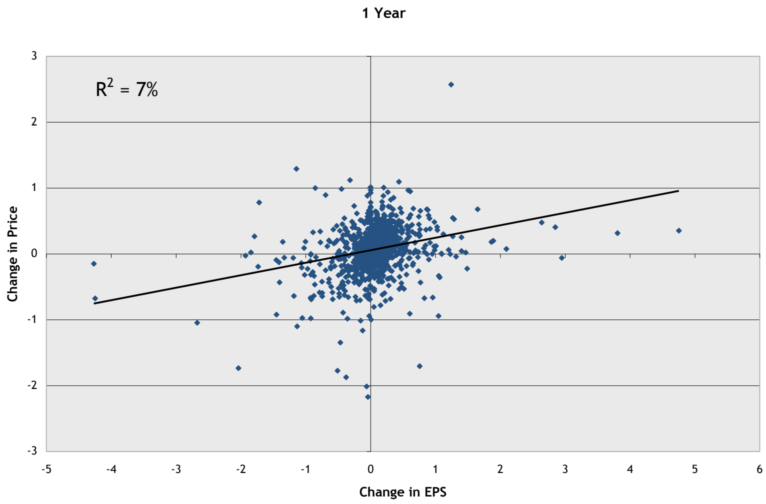
- Unexpected return arises mainly from cashflow news or discount rate news.
- Over the short term, the change in multiple explains much of observed returns. Over the long term, the change in earnings explains much of observed returns.

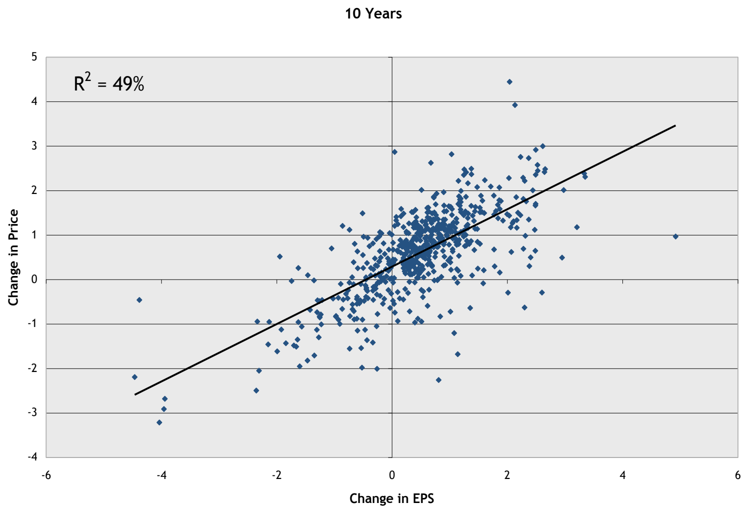
*To derive this result, we ignore the cross-product term (relative change in earnings times relative change in multiple).

The horizon effect

At a one-year horizon, changes in earnings matter slightly for returns

At a ten-year horizon, earnings matter a lot for returns





Source: Paul Scorer

Plan of Attack

- We will present two approaches:
  - Modeling mispricings, which lead to alphas.
  - Modeling alphas directly.
- We will start with the theoretically pure, and move to the ad hoc.

Modeling Mispricing: Theoretically Pure

Dividend Discount Model

- A stock's price should be the present value of its future dividends.

$$p(0) = \sum_{t=1}^{\infty} \frac{d(t)}{(1+y)^t}$$

- Financial theory is very clear on this.* Less clear are the values of those future dividends, and the appropriate discount rate.
- If dividends and discount rate remain constant, the passage of time leads to:

$$y = \frac{p(1) + d(1) - p(0)}{p(0)} = \textit{total return}$$

*John Burr Williams. *Theory of Investment Value*, 1938

Constant Growth DDM

- The simplest possible model:

$$d(t) = d(1) \cdot \left[1 + gr\right]^{t-1}$$

$$p(0) = \frac{d(1)}{y - gr}$$

- This model is very sensitive to growth assumptions—not surprising given that we assume this growth rate to apply forever.
- In the case of zero growth, the expected return is just the dividend yield.

Modeling Growth

- Simple model to provide insight.

$$e(t) = d(t) + I(t)$$
$$d(t) = \kappa \cdot e(t)$$
$$I(t) = [1 - \kappa] \cdot e(t)$$

reinvested earnings

$\kappa \equiv$ payout ratio. In practice, this varies significantly across stocks, from zero for Google to ~50% for Procter & Gamble to 100% for REITs

- What if earnings grow because we can achieve the same *ROE* on the retained earnings:

$$e(t+1) = e(t) + ROE \cdot I(t)$$
$$= [1 + ROE \cdot (1 - \kappa)] \cdot e(t)$$

- Hence:

$$gr = ROE \cdot (1 - \kappa)$$

More on growth

- According to the DDM:

$$p(0)=\frac{d(1)}{y-gr}$$

$$y = gr + \frac{d(1)}{p(0)}$$

- We also know that:

risk-free return

$$y=i_F+\beta f_B+\alpha$$

- Hence:

$$gr=\alpha+\beta f_B+i_F-\frac{d}{P}$$

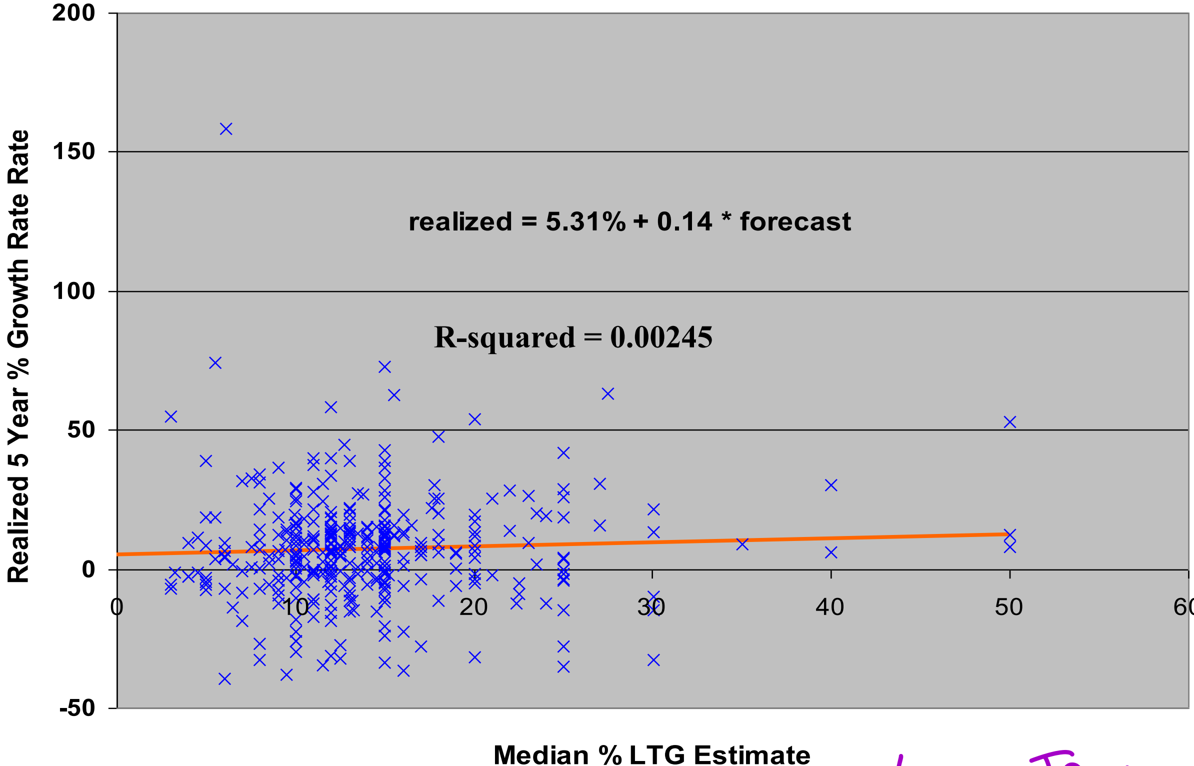
dividend yield

- And if $\alpha=0$:

$$gr_{imp}=\beta f_B+i_F-\frac{d}{P}$$

implied growth

S&P 500: 12/31/99

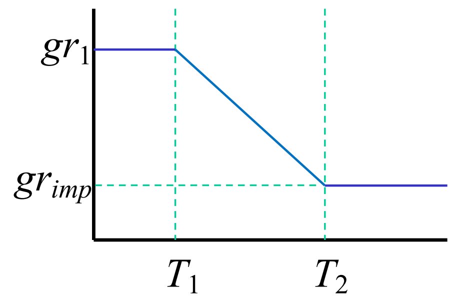


Long Term Growth

Dealing with Unrealistic Growth

- Improve inputs.
  - Compare average growth rates to implied rates.
  - One possibility: match mean and standard deviation of growth rates by sector.

- Three-stage DDM
  - More realistic growth pattern:
  - Short-term growth gr_1 for time T_1.
  - Implied growth rate for $T > T_2$.
  - Interpolate growth between T_1 and T_2.
  - This lowers the sensitivity of prices and alphas to input growth rates, but doesn't eliminate the problem.



Using DDM's for Active Management

- Approach 1: Internal Rate of Return
  - Given market prices, solve for internal rates of return, y.
  - Relate y to α:

$$P(0) = \frac{d(1)}{y-g}$$

$$y = i_F + \beta f_B + \alpha$$

  - Fundamental assumption: mispricing will remain forever. The alpha exists because the mispricing of each dividend disappears as the dividend is paid out.

Approach 2: Net Present Value

- Use consensus expected return to estimate DDM price.

$$p(0) = \frac{d(1)}{y - g}$$

- Compare this to market price to estimate alpha:

$$y = r_F + \beta \cdot f_B$$

$$\alpha = \frac{1}{T} \cdot \left(\frac{p_{DDM} - p_{mkt}}{p_{mkt}} \right)$$

- Problem: what is T?
  - Does it vary by sector or by stock?

Returns to Value Investing

- We observe a market price, $p_{mkt}(t)$, and estimate model value as:

$$p_{model}(t) = \frac{\kappa \cdot e(t+1)}{y - gr}, \quad y = i_F + \beta f_B$$

- We can also think in terms of multiples:

$$m_{mkt} = \frac{p_{mkt}}{e}, \quad m_{model} = \frac{\kappa}{y - gr}$$

- The relative mispricing is:

$$rmp = \frac{p_{model}}{p_{mkt}} - 1 = \frac{m_{model}}{m_{mkt}} - 1$$

Example

- For a given stock, we have:

  $e(1)=\$1$

  $y=8\%$

  $gr=5\%$

  $\kappa=0.45$

  $p_{mkt}(0)=\$10$

  $p_{model}(0)=\$15$

  $m_{mkt}=10$

  $m_{model}=15$

  $rmp=50\%$

- *Hint for solving problems concerning returns or multiples: in the absence of explicit information on earnings, you can often just assume* $e(1)=\$1$.

Returns after One Year

$$return = \frac{d(1) + p_{mkt}(1)}{p_{mkt}(0)} - 1$$

- Case 1: Repricing
  - The market fairly prices the stock at t=1.
  - This corresponds to "discount rate news"
- Case 2: Continuing Mispricing
  - The same mispricing remains at t=1.
  - This corresponds to "cash flow news"
- We expect to experience a combination of these.

*Note on the time convention: At t=0, our estimate of $d(1)$ determines the initial price, $p(0)$.

Case 1: Repricing

$$p_{mkt}(1) = p_{model}(1) = \frac{\kappa \cdot e(2)}{y - gr} = \frac{\kappa \cdot e(1) \cdot (1 + gr)}{y - gr}$$

$$return = \frac{\kappa \cdot e(1) + \left[\dfrac{\kappa \cdot e(1) \cdot (1 + gr)}{y - gr}\right]}{m_{mkt} \cdot e(1)} - 1 \Rightarrow y + rmp + y \cdot rmp$$

- Example:

  $e(2)$=\$1.05

  $d(1)$=\$0.45

  m_{mkt}=15

  $p_{mkt}(1)$=\$15.75

  $return$=62%

Case 2: Continuing mispricing

$$p_{mkt}(1) = m_{mkt} \cdot e(2)$$

$$return = \frac{\kappa \cdot e(1) + m_{mkt} \cdot e(1) \cdot (1 + gr)}{m_{mkt} \cdot e(1)} - 1 \Rightarrow y + y \cdot rmp - gr \cdot rmp$$

$$= y + rmp \cdot \left(\frac{d(1)}{P_{model}(0)} \right)$$

- Example:

  $e(2)$=\$1.05

  $d(1)$=\$0.45

  m_{mkt}=10

  $p_{mkt}(1)$=\$10.50

  $return$=9.5%

- Return still exceeds 8%.

Modeling Mispricing: Ad Hoc

Comparative Valuation

- A more general approach than DDM. Also more ad hoc.

$$p_{DDM} = \frac{d(1)}{y - gr} = c \cdot d(1)$$

$$p_{CV} = c_1 \cdot d + c_2 \cdot e + c_3 \cdot b + c_4 \cdot s + \ldots$$

- Relates to many market conventions:
  - Prevalence of P/E ratios.
  - Investment banking rules of thumb

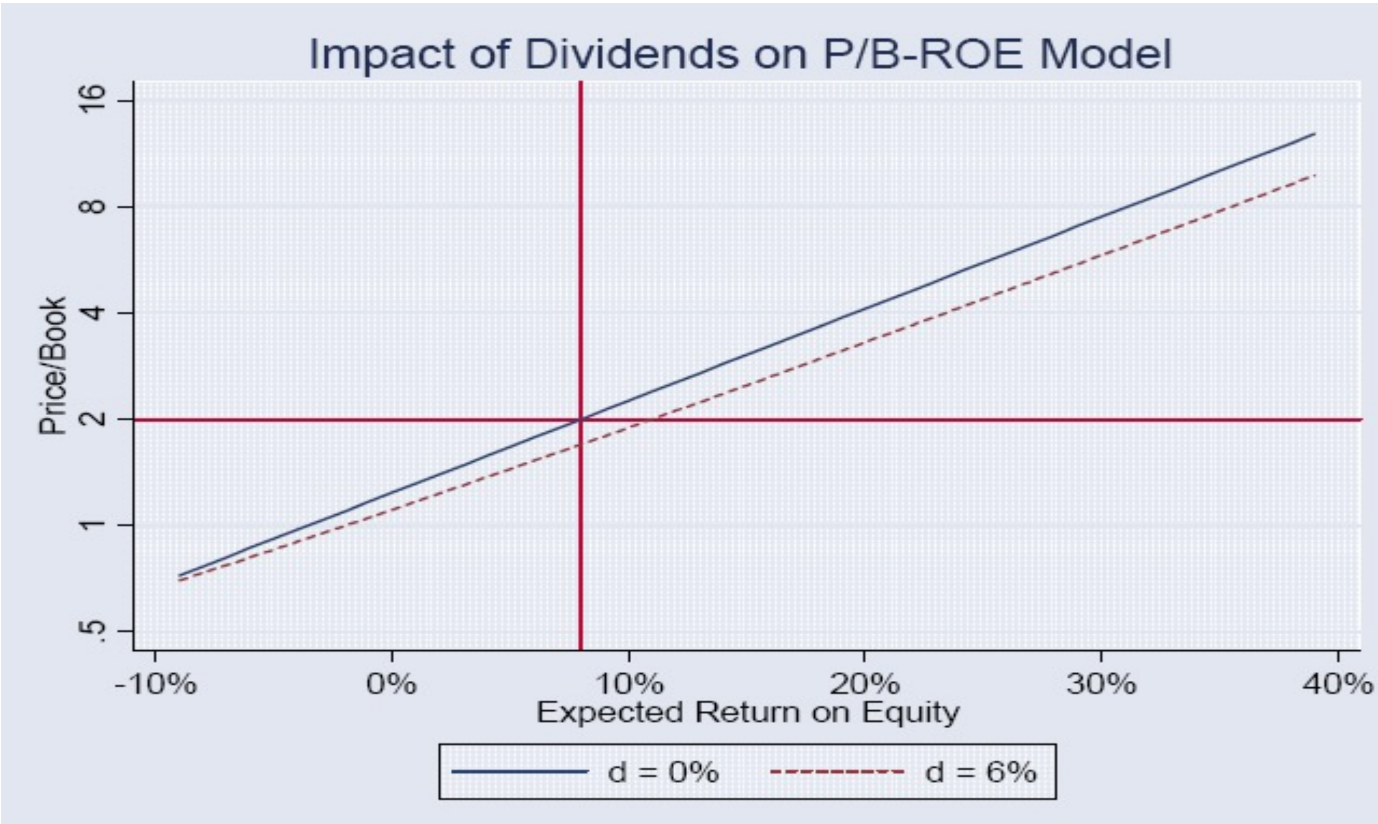
Examples

- Apple versus Alphabet:
  - The comparisons get kinder for Apple when we start applying common valuation metrics. Alphabet trades at a rich 31 times this year's projected profit and 26 times next year's target. The fight on this front is not even close, with Apple fetching 17 times this year's earnings and just 14 times next year's analyst estimate.
  - In terms of revenue multiples, Apple runs away with this race. Apple's enterprise value is 3.9 times its trailing revenue. Alphabet has a loftier multiple of 6.2.
  - Rick Munarriz, The Motley Fool, July 30, 2018
- Shopify:
  - Our target price of $155 implies 2019 EV/Sales of 10.5x.
  - Brad Zelnick, Credit Suisse, July 31, 2018
- Angang Steel:
  - Cut target price to HK$10.5, by lowering target EV/EBITDA by 10% to 6.1x.
  - Yang Luo, Credit Suisse, July 17, 2018
- Australian Equity Market:
  - The market P/E ratio lowered for both June 2018 to 17.0x and for December 2018 to 15.7x.
  - Joel Weiss, Macquarie Research, July 18, 2018

Implementing Comparative Valuation

- Choose appropriate fundamentals.
- Regress observed prices against model to estimate parameters.
  - By sector or industry.
  - Think carefully about appropriate weighting.
  - What about missing factors, persistent mispricings?
- Mispricing, plus horizon, lead to alpha estimates.

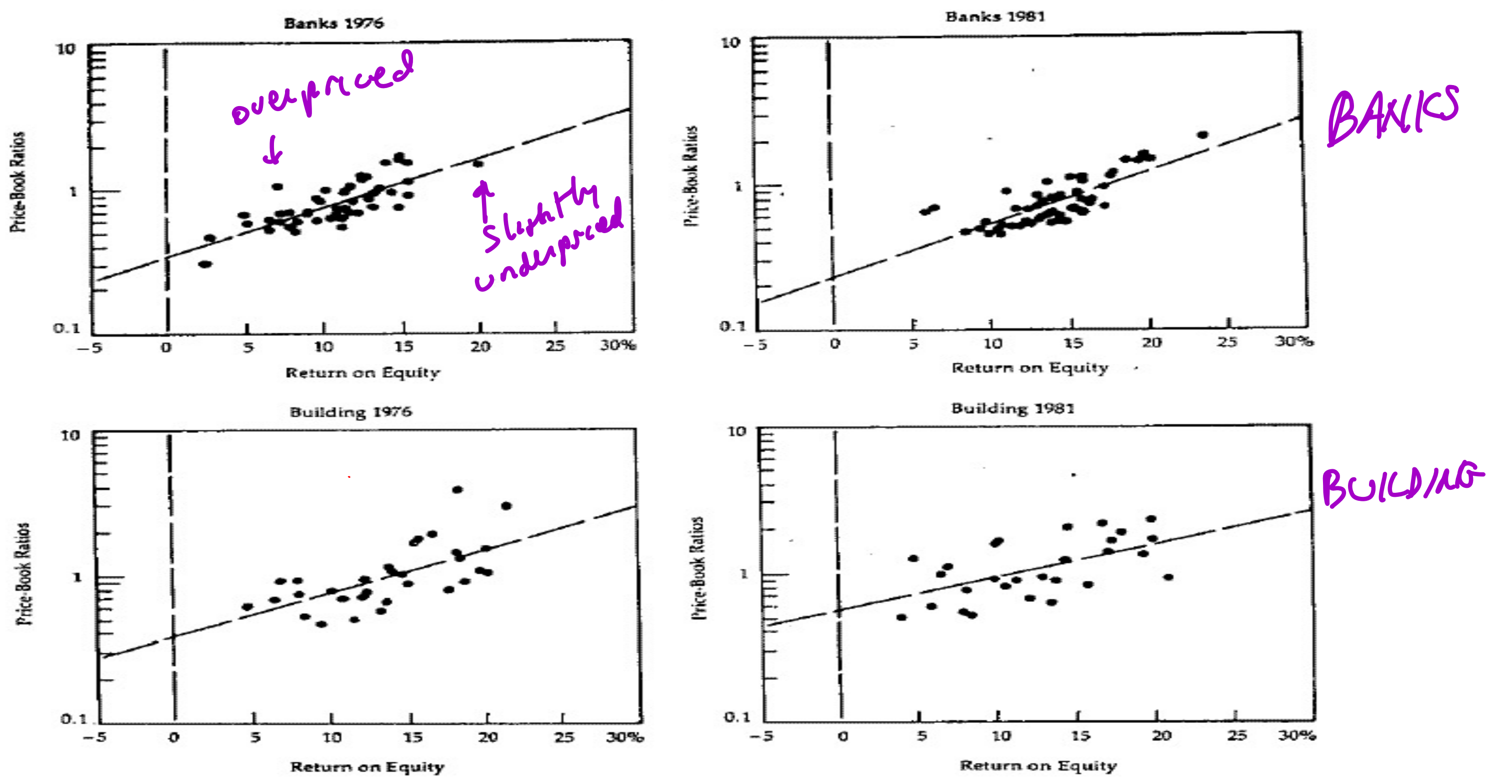
Jarrod Wilcox P/B-ROE Model*



*Jarrod Wilcox, "The P/B-ROE Valuation Model," *Financial Analysts Journal*, Jan-Feb 1984.

Wilcox Model by Industry

Figure C P/B and ROE Across Industries and Over Time



Forecasting Returns Directly: Theoretically Pure

Forecasting Alpha Directly

- Version 1: Arbitrage Pricing Theory (APT)
- This approach backed up by academic theory.
- Start with a factor model

$$\mathbf{r} = \mathbf{X} \cdot \mathbf{b} + \mathbf{u}$$

For a "good" risk model, the specific returns are uncorrelated

$\mathrm{Cov}\{u_n, u_m\} = 0$ unless $n = m$

$E\{u\} = 0$

- APT says that:

$$\mathbf{f} = E\{\mathbf{r}\} = \mathbf{X} \cdot \mathbf{m}$$

- Convert expected excess returns to alpha forecasts:

$$\boldsymbol{\alpha} = \mathbf{X} \cdot \mathbf{m} - \boldsymbol{\beta} \cdot f_B$$

APT Theory

- This looks somewhat like CAPM
  - $E\{\theta\}=0$ versus $E\{u\}=0$.
- But there are significant differences:
  - CAPM based on equilibrium argument versus APT arbitrage argument.
    - Since $\{u\}$ are uncorrelated, unless $E\{u\}=0$, you could build an almost risk free portfolio with expected return.
    - Remember that the CAPM does not require uncorrelated $\{\theta\}$.
      - Of more practical importance, the CAPM identifies the market as the optimal portfolio. The APT supplies neither the identity of the model factors nor the expected factor returns.

Implementing APT

- Requirement 1: The factor model
  - There is an easily satisfied technical requirement
    - The model must be "qualified," i.e. it must explain the risk of diversified portfolios. The CAPM wouldn't qualify, but most of our factor risk models would.
- Requirement 2: Factor forecasts
  - There are many approaches here, though they depend somewhat on the factor model.

Factor Forecasts

- Statistical factor models
  - Without factors explicitly tied to fundamentals, forecasting techniques here are mainly statistical: moving averages or mean reversion based on historical factor returns.
- Fundamental factor models
  - Beyond the same statistical approaches, there may be additional approaches based on fundamental and/or economic intuition.

Forecasting Returns Directly: Ad Hoc

Returns-based Analysis

- This is the most general (and ad hoc) approach. Within the context of linear models, we can use signals (fundamental ratios, past returns, various market indicators, sentiment measures…) to forecast returns:

$$\mathbf{r} = \mathbf{X} \cdot \mathbf{b} + \mathbf{A} \cdot \mathbf{c} + \boldsymbol{\varepsilon}$$

- So what is going on here. We have set this up as a standard factor model, plus additional explanatory factors. Here **A** contains the J return signals for N stocks, and we estimate the coefficients $\{c\}$.
  - While this is written in a very general way, we would typically test one signal at a time. We will discuss how we test such ideas next week.
  - This does not preclude using some of the risk factors to forecast returns. But it allows us to identify return factors that may not be useful in forecasting risk.
- This differs from (and is more general than) APT because these signals may be forecasting specific returns. That is, in this framework, we <u>do not</u> require $E\{u\}=0$. Stated another way, we don't require our alphas to arise from risk factors.

Typical Equity Return-forecasting Signals

- Smart Beta Signals
  - Value: P/E, P/B, P/CF, P/S, DDM, D/P, Low Price
  - Momentum: Price, Earnings
  - Size
  - Low Volatility
  - Quality: Profitability, Earnings Quality
- Growth/ROE Signals
  - Projected Growth, ROE
- Revision/Surprise
  - Estimate revision, Rating revision, EPS Surprise, EPS Torpedo
- Other Risk Premia
  - Beta, EPS Variability, Debt/Equity, Neglect, Duration, Estimate Dispersion, Foreign Exposure

A few newer ideas*

THE JOURNAL OF FINANCE • VOL. LXIII, NO. 4 • AUGUST 2008

Economic Links and Predictable Returns

LAUREN COHEN and ANDREA FRAZZINI*

ABSTRACT

This paper finds evidence of return predictability across economically linked firms. We test the hypothesis that in the presence of investors subject to attention constraints, stock prices do not promptly incorporate news about economically related firms, generating return predictability across assets. Using a data set of firms' principal customers to identify a set of economically related firms, we show that stock prices do not incorporate news involving related firms, generating predictable subsequent price moves. A long–short equity strategy based on this effect yields monthly alphas of over 150 basis points.

Customer – Supplier Linkages

*Many new ideas appear on SSRN, e.g. at
https://papers.ssrn.com/sol3/JELJOUR_Results.cfm?npage=1&form_name=journalBrowse&journal_id=1175282&Network=no&lim=false

Mutual Fund Herding and the Impact on Stock Prices

49 Pages • Posted: 21 Oct 1998

Russ Wermers
University of Maryland - Robert H. Smith School of Business

Date Written: August 1998

Abstract

We analyze the trading activity of the mutual fund industry between 1975 and 1994 to determine whether funds "herd" when they trade stocks and to investigate the impact of herding on stock prices. Although we find little herding by mutual funds in the average stock, we find much higher levels in trades of small stocks and in trading by growth-oriented funds. Stocks that herds buy outperform stocks that they sell by four percent during the following six months; this return difference is much more pronounced among small stocks. Our results are consistent with mutual fund herding speeding the price-adjustment process.

The Wisdom of Twitter Crowds: Predicting Stock Market Reactions to FOMC Meetings via Twitter Feeds

https://doi.org/10.3905/jpm.2016.42.5.123

Posted: 20 May 2019

Pablo Azar
Massachusetts Institute of Technology, Sloan School of Management, Students

Andrew W. Lo
Massachusetts Institute of Technology (MIT) - Sloan School of Management; National Bureau of Economic Research (NBER); Massachusetts Institute of Technology (MIT) - Computer Science and Artificial Intelligence Laboratory (CSAIL)

Date Written: March 11, 2016

Abstract

With the rise of social media, investors have a new tool to measure sentiment in real time. However, the nature of these sources of data raises serious questions about its quality. Since anyone on social media can participate in a conversation about markets -- whether they are informed or not -- it is possible that this data may have very little information about future asset prices. In this paper, we show that this is not the case by analyzing a recurring event that has a high impact on asset prices: Federal Open Market Committee (FOMC) meetings. We exploit a new dataset of tweets referencing the Federal Reserve and shows that the content of tweets can be used to predict future returns, even after controlling for common asset pricing factors. To gauge the economic magnitude of these predictions, the authors construct a simple hypothetical trading strategy based on this data. They find that a tweet-based asset-allocation strategy outperforms several benchmarks, including a strategy that buys and holds a market index as well as a comparable dynamic asset allocation strategy that does not use Twitter information.

Rise and Fall of Calendar Anomalies over a Century

University of Pretoria Department of Economics Working Paper Series (2019)

45 Pages • Posted: 25 Apr 2019 • Last revised: 8 May 2019

Oleksiy Plastun
Sumy State University

Xolani Sibande
University of Pretoria - Department of Economics

Rangan Gupta
University of Pretoria - Department of Economics

Mark E. Wohar
University of Nebraska at Omaha

Date Written: January 7, 2019

Abstract

In this paper, we conduct a comprehensive investigation of calendar anomaly evolution in the US stock market (given by the Dow Jones Industrial Average) for the 1900 to 2018 period. We employ various statistical techniques (average analysis, Student's t-test, ANOVA, the Kruskal-Wallis and Mann-Whitney tests) and the trading simulation approach to analyse the evolution of the following calendar anomalies: day of the week effect, turn of the month effect, turn of the year effect, and the holiday effect. The results revealed that 'golden age' of calendar anomalies was in the middle of the 20th century. However, since the 1980s all calendar anomalies disappeared. This is consistent with the Efficient Market Hypothesis.

On the Capital Market Consequences of Alternative Data: Evidence from Outer Space

9th Miami Behavioral Finance Conference 2018

67 Pages • Posted: 15 Mar 2019 • Last revised: 29 May 2019

Zsolt Katona
University of California, Berkeley - Haas School of Business

Marcus Painter
University of Kentucky, Gatton College of Business and Economics, Department of Finance & Quantitative Methods

Panos N. Patatoukas
University of California, Berkeley - Haas School of Business

Jean Zeng
University of California, Berkeley - Haas School of Business

Date Written: July 30, 2018

Abstract

We study the emergence of satellite imagery of parking lot traffic across major U.S. retailers as a source of alternative data in capital markets. We find that while measures of parking lot traffic from outer space embed timely value-relevant information, such information is not incorporated into stock prices prior to the public disclosure of retailer performance for the quarter. This creates opportunities for sophisticated investors, who can afford to incur the costs of acquiring and processing satellite imagery data, to formulate profitable trading strategies at the expense of individual investors, who tend to be on the other side of the trade. Our evidence suggests that unequal access to alternative data increases information asymmetry among market participants without necessarily facilitating stock price discovery.

When Do Investors Freak Out?: Machine Learning Predictions of Panic Selling

40 Pages • Posted: 9 Aug 2021

Daniel Elkind
affiliation not provided to SSRN

Kathryn Kaminski
Massachusetts Institute of Technology (MIT)

Andrew W. Lo
Massachusetts Institute of Technology (MIT) - Laboratory for Financial Engineering; Santa Fe Institute

Kien Wei Siah
Massachusetts Institute of Technology (MIT) - Laboratory for Financial Engineering

Chi Heem Wong
Massachusetts Institute of Technology (MIT) - Computer Science and Artificial Intelligence Laboratory (CSAIL); Massachusetts Institute of Technology (MIT); Massachusetts Institute of Technology (MIT) - Sloan School of Management

Date Written: August 4, 2021

Abstract

Despite standard investment advice to the contrary, individuals often engage in panic selling, liquidating significant portions of their risky assets in response to large losses.Using a novel dataset of 653,455 individual brokerage accounts belonging to 298,556 households, we document the frequency, timing, and duration of panic sales, which wedefine as a decline of 90% of a household account's equity assets over the course of onemonth, of which 50% or more is due to trades. We find that a disproportionate numberof households make panic sales when there are sharp market downturns, a phenomenonwe call 'freaking out'. We show that panic selling and freakouts are predictable andfundamentally different from other well-known behavioral patterns such as overtradingor the disposition effect. Investors who are male, or above the age of 45, or married, orhave more dependents, or who self-identify as having excellent investment experience orknowledge tend to freak out with greater frequency. We use a five-layer neural networkmodel to predict freakout events one month in advance, given recent market conditionsand an investor's demographic attributes and financial history, which exhibited truenegative and positive accuracy rates of 81.5% and 69.5%, respectively, in an out-of-sample test set. We measure the opportunity of cost of panic sales and find that, whilefreaking out does protect investors during a crisis, such investors often wait too longto reinvest, causing them to miss out on significant profits when markets rebound.

Benefits of Having a Female CFO

54 Pages • Posted: 16 Jul 2021

Julia Klevak
Prudential Financial - Quantitative Management Associates

Joshua Livnat
New York University; Prudential Financial - Quantitative Management Associates

Kate Suslava
Bucknell University Freeman College of Management

Date Written: July 14, 2021

Abstract

We examine gender differences in the language of CFOs that participate in quarterly earnings calls. Female executives are more concise, less optimistic, are clearer, use fewer idioms or clichés, and provide more numbers in their speech. These differences are particularly strong in the more spontaneous Questions and Answers (QA) section of the calls. The tone of female CFOs is positively associated with future earnings surprises, while for male CFOs it is more related to future firm expansion. Finally, firms with female CFOs earn higher abnormal returns around the call date than those with male CFOs after controlling for variables that are related to the contents of the call.

Ancillary Tests

1. Does the signal $\{g\}$ predict returns??

2. Does it predict something* related to returns?

   * Earnings surprise
   Estimate revisions
   Revenue surprise / growth