*Discussion of:*

# Testing Behavioral Finance Theories Using Trends and Sequences in Financial Performance

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# Behavioral Finance – Motivations

1. The “anomalies” literature has caused many to question the standard efficient markets paradigm.

2. There is now a large catalog of return patterns inconsistent with standard asset pricing models:
   - Size, Reversal, Book-to-market, price- and earnings-momentum effects.
   - Accruals effects (Sloan (1996))
   - NOA effects (Hirshleifer, Hou, Teoh, and Zhang (2003))
   - Issuance effects (**?**)
   - “Liquidity risk” effects (Pastor and Stambaugh (2003))

# Behavioral Finance – Motivations

1. Given the Fama critique, why are we so concerned about these anomalies?
    - High Sharpe Ratios relative to the market
        - Hansen and Jagannathan (1991), MacKinlay (1995)
    - Lack of correlation of returns with economic variables.
    - Out of sample evidence.

# Sharpe Ratios – The data

- From Pastor and Stambaugh (2003) - Table 10:

Panel A. Weights in the ex-post tangency portfolio, Jan 1966- Dec 1999

| MKT | SMB | HML | MOM | $LIQ^V$ | $LIQ^E$ | Sharpe ratio |
|---|---|---|---|---|---|---|
| 100.00 | – | – | – | – | – | 0.12 |
| 35.08 | 5.83 | 59.10 | – | – | – | 0.22 |
| 20.05 | 16.07 | 43.03 | 20.85 | – | – | 0.33 |
| 22.34 | 18.77 | 36.41 | – | 22.49 | – | 0.31 |
| 17.32 | 22.33 | 29.10 | – | – | 31.25 | 0.40 |
| 17.70 | 20.62 | 34.23 | 11.86 | 15.59 | – | 0.37 |
| 15.88 | 22.51 | 29.56 | 6.47 | – | 25.58 | 0.42 |

Including accrual, issuance effects increases max SR significantly.

# Sharpe Ratios

- Hansen and Jagannathan (1997) show that, based on the FOC from the investor portfolio optimization problem in a Rational-expectations setting:

  $$E[\tilde{m}\,\tilde{r}] = 0$$

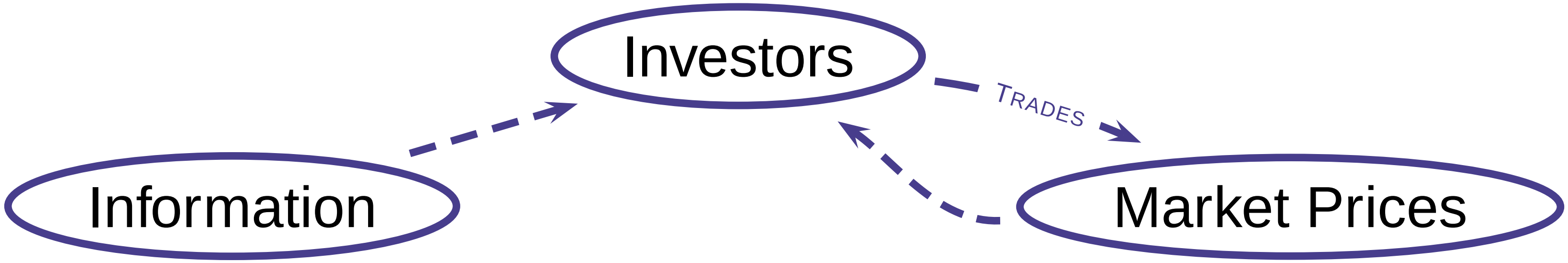
  for the excess return $\tilde{r}$ of *any* asset of portfolio, that:

  $$\begin{aligned} \frac{\sigma_m}{E[m]} &= \frac{-1}{\rho_{m,r}} \frac{E[r]}{\sigma_r} \\ \frac{\sigma_m}{E[m]} &\geq \frac{E[r]}{\sigma_r}. \end{aligned}$$

  - That is, the high Sharpe ratios we see are only consistent with extreme preferences.

# The Standard EMH Model

- The standard RE model assumption is that all investors "see" all available information, and process it perfectly ...



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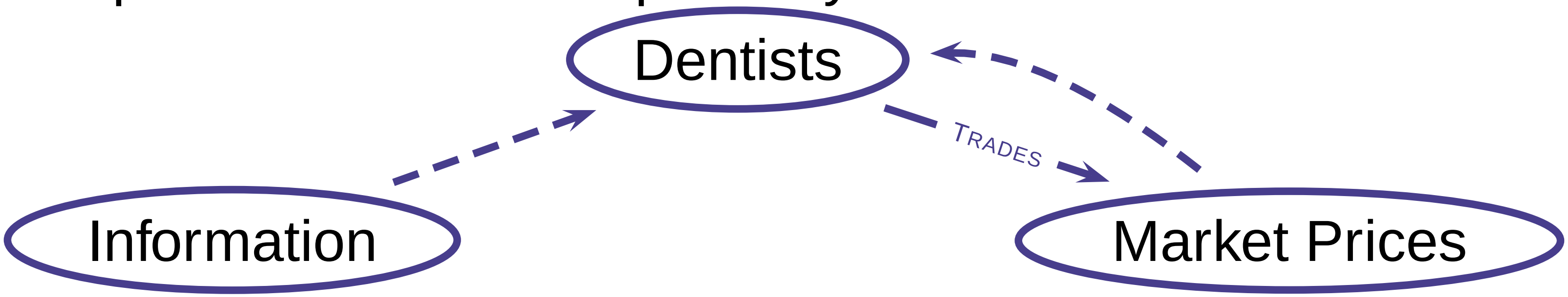

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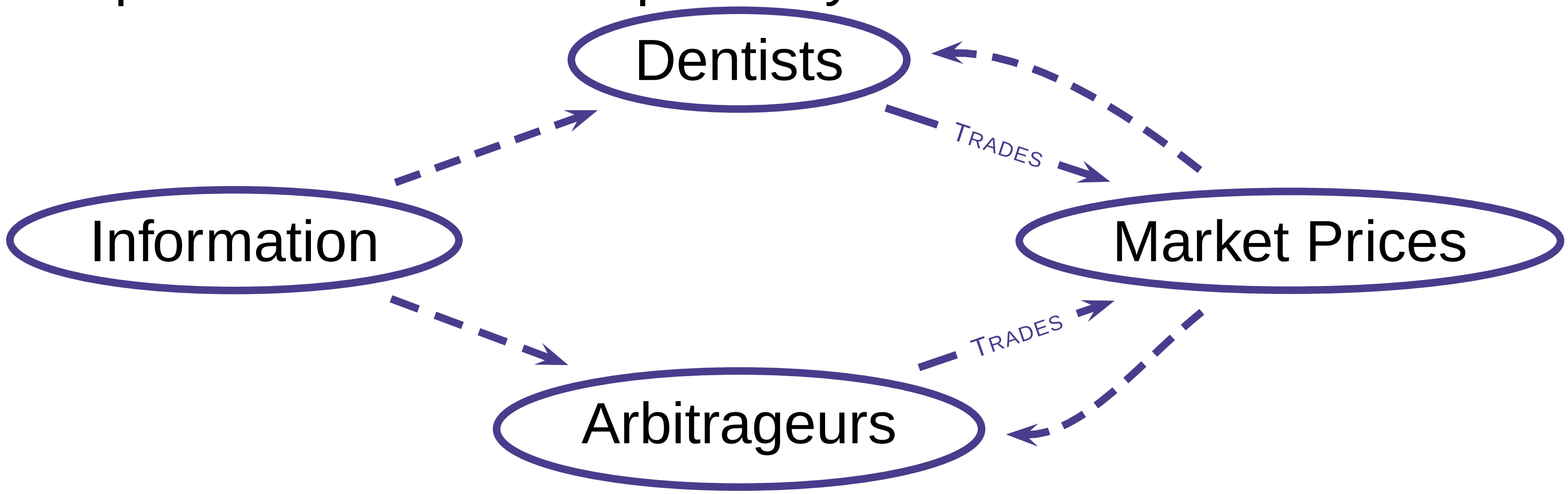
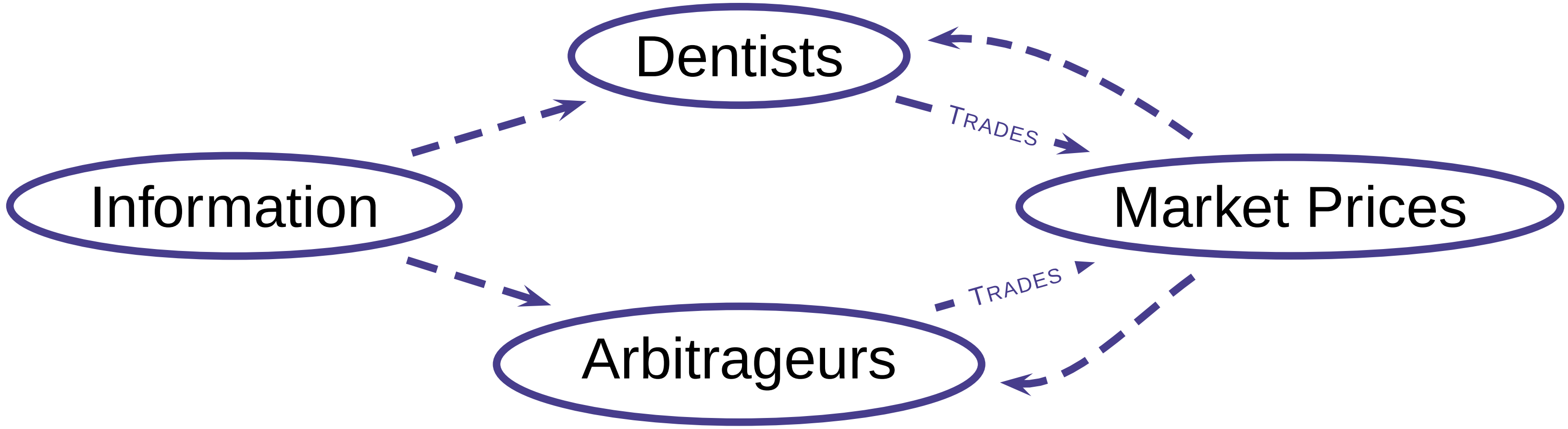



However, the standard response to this argument is that, if market prices went wrong, Arbitrageurs would force them back into line,

# The “Sophisticated” EMH Model

Much evidence (and common sense) shows that many investors *don’t* process information perfectly:

# Behavioral Biases and Prices

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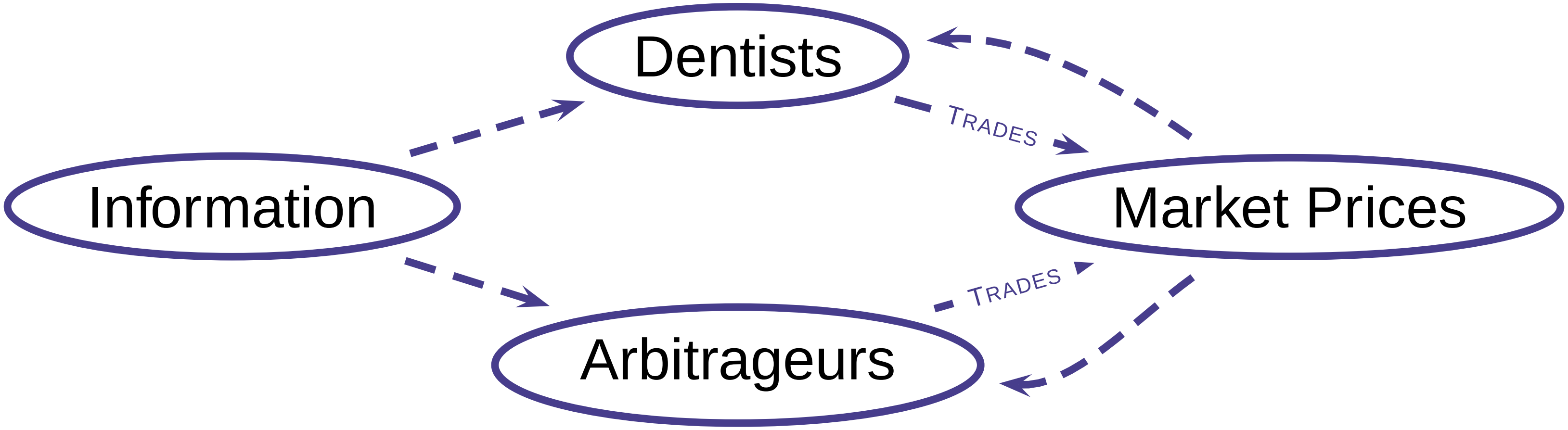
# Behavioral Biases and Prices




- However, there is new theoretical and empirical evidence suggesting that arbitrage is incomplete:
  - Shleifer and Vishny (1997) (“Limits to Arbitrage”)
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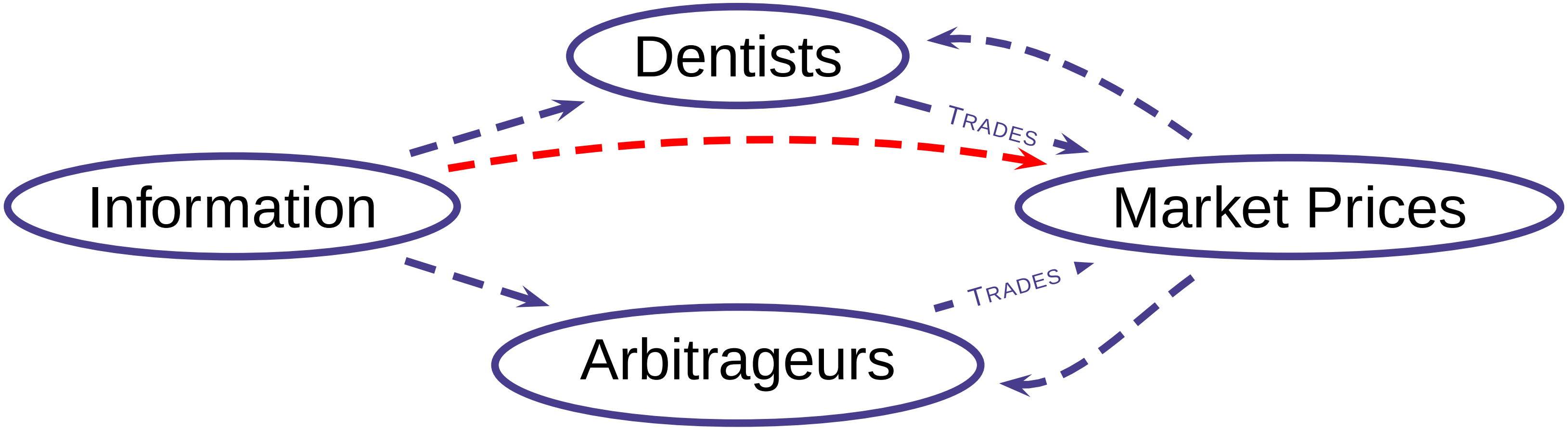


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- Incomplete arbitrage might mean that the behavioral biases of the “dentists” are reflected in security return patterns.

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  - Hong and Stein (1999):
    - Groups of “newswatchers” and “momentum traders.”

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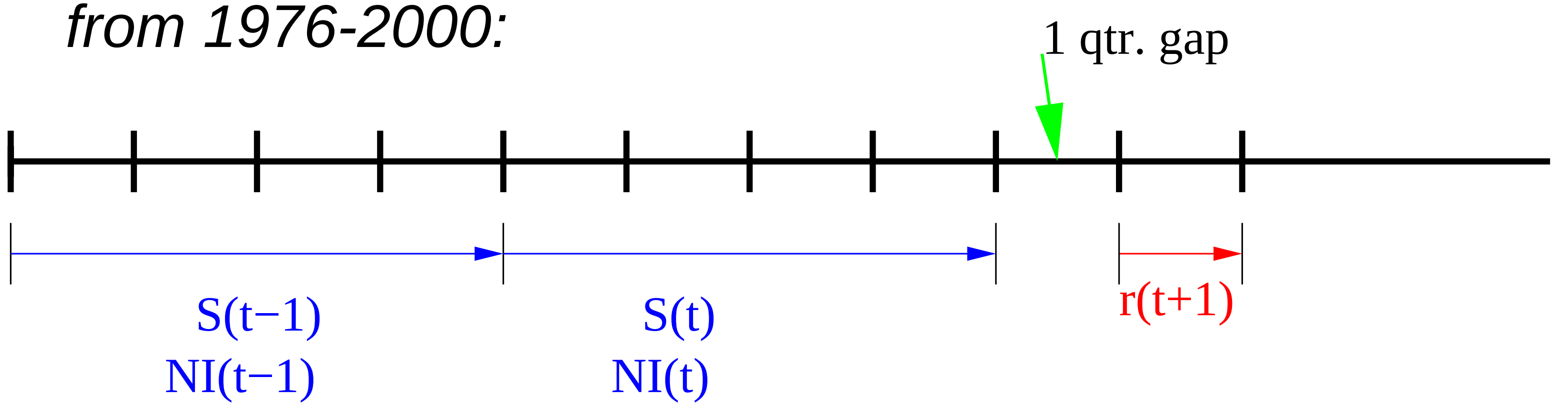
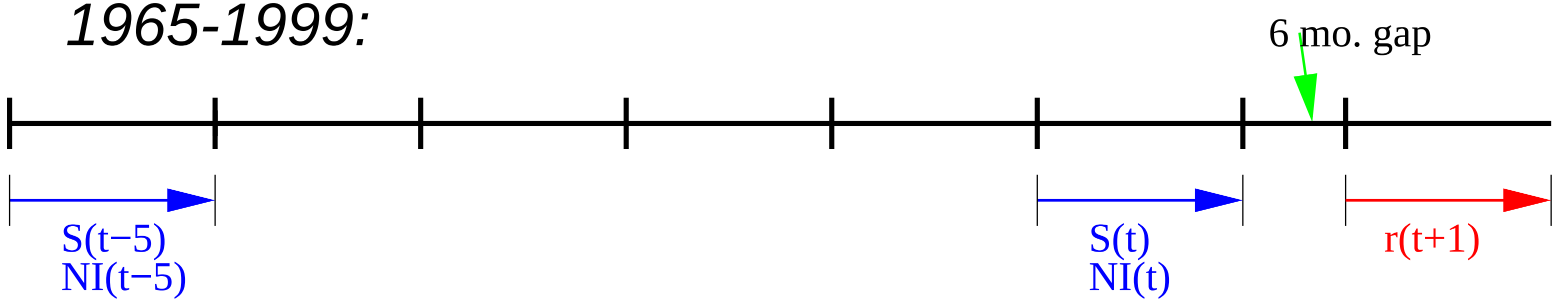
  - *Representativeness:*
    - However, following a *series* of good earnings announcements, representativeness causes people to infer a trend too quickly, pushing up the price too far.
  - *CFK also argue that the implications of the DHS and HS models are virtually identical to those of BSV.*

# Basic Empirical Tests

- *Medium Horizon Tests use Quarterly COMPUSTAT Data from 1976-2000:*

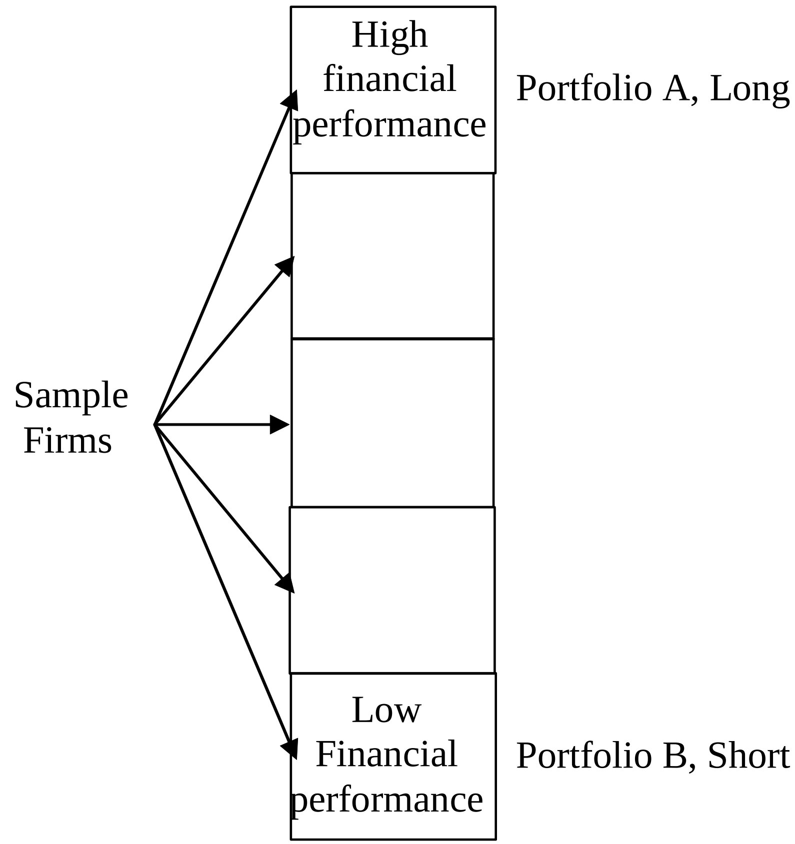



- *Long Horizon Tests use Annual COMPUSTAT Data from 1965-1999:*




- Also look at past OI growth and past returns.

# Long-Short Portfolio Construction




“Difference” = Return (A) – Return (B)

Prediction: “Difference” < 0

# Results - Basic Tests

- *One Year Growth Measures* (Tables 3-4):
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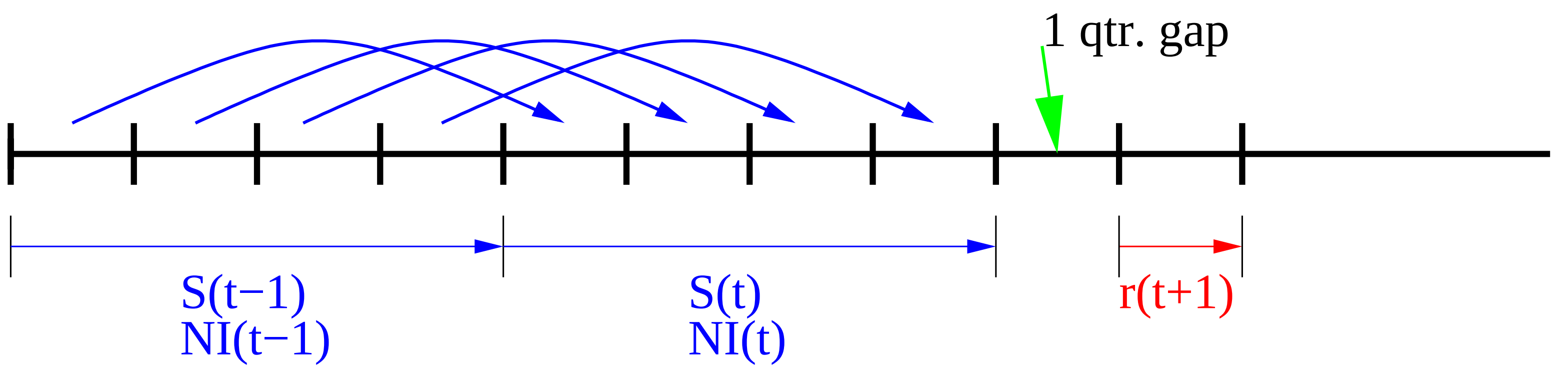
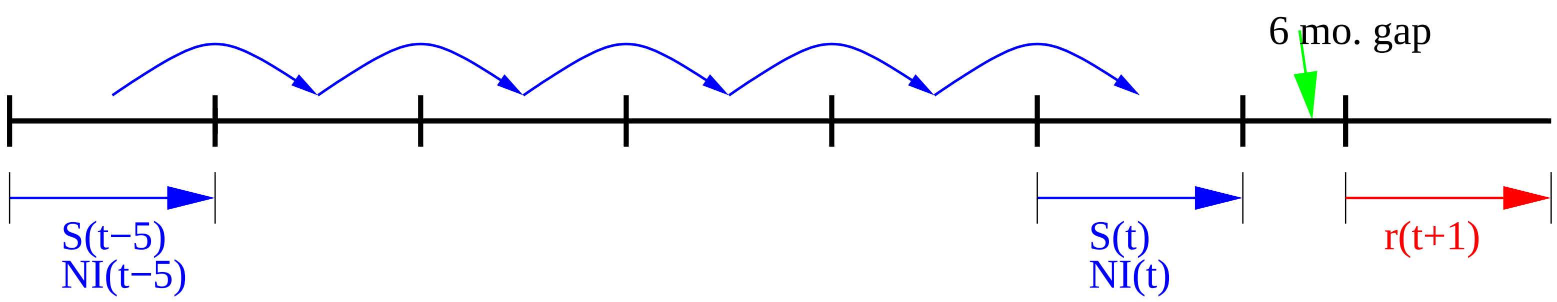
- *Five-Year Growth Measures* (Table 5):
  - No evidence of "reversals" for Sales, NI or OI measures.
    - If anything, there is some evidence of continuation.
  - Return reversals evidence consistent with extant evidence.

# Consistency Tests

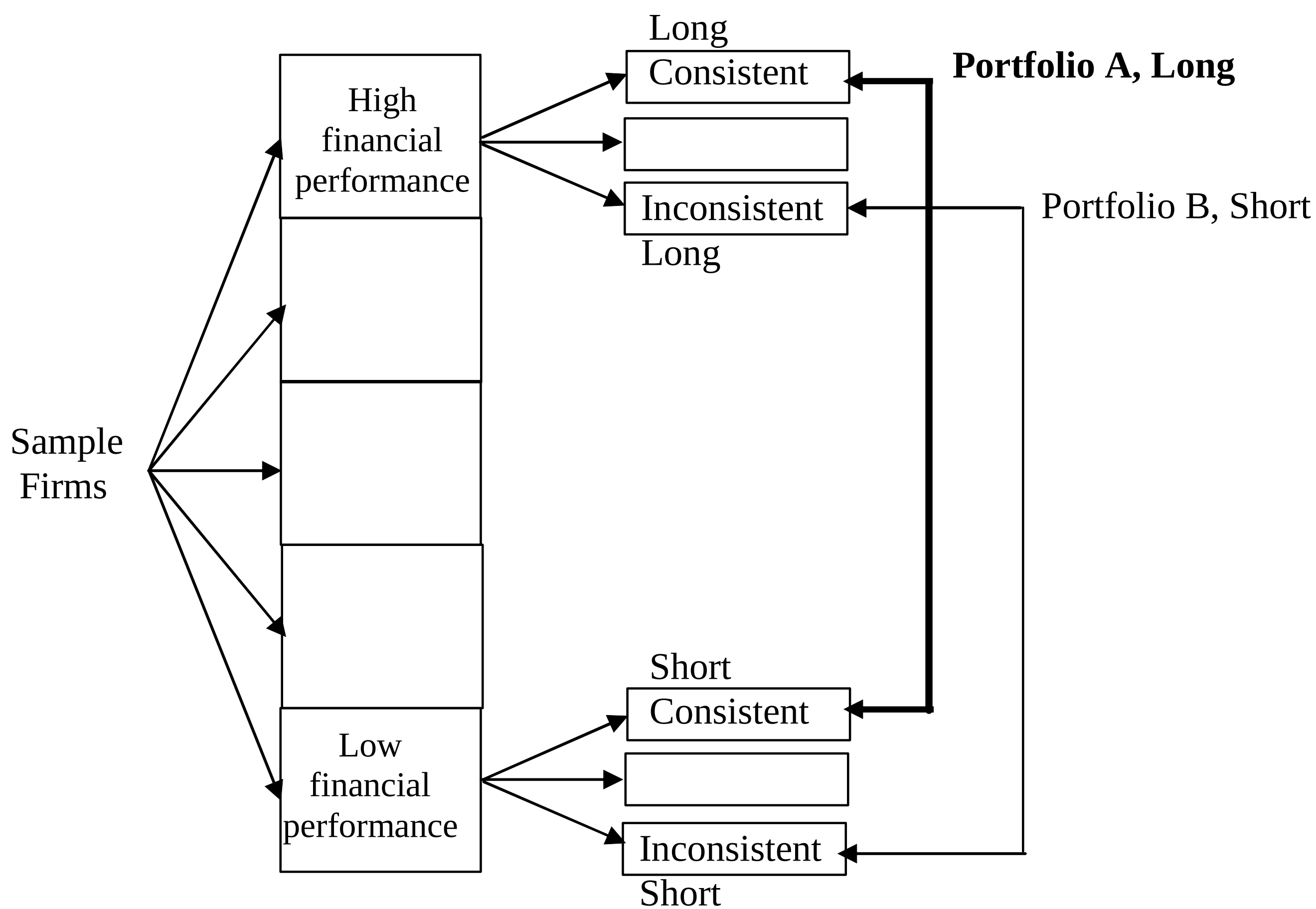
- Medium Horizon Consistency Tests:




- Long Horizon Consistency Tests:



# *Consistency* Test Portfolio

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  - Strong consistency effect for past return measures ($t = 7.6$ at 6 mos.)
- *Five-Year Growth Measures* (Table 7):
  - No consistency effects for Sales, NI or OI growth measures.
  - Return reversals somewhat stronger with consistency.

# Econometric Issues:

- *One Year Growth Measures* (Table 6):
  - Further sorting high and low past growth firms into "consistent" and "inconsistent" performers probably results in further stratification of the growth measures.
  - Also, momentum effect is known to be much stronger for extreme firms
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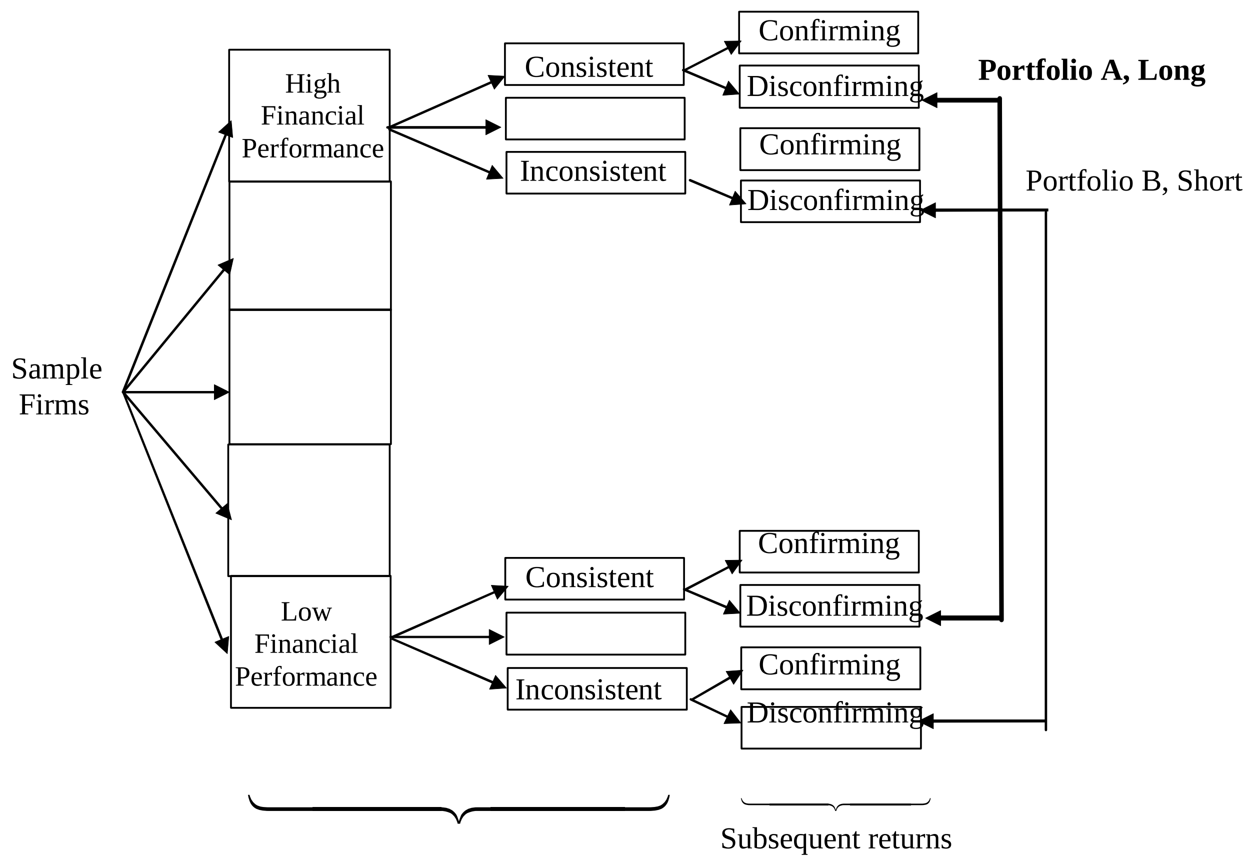
  - Thus, it might be important to impose a tighter control on past performance.
- *Five-Year Growth Measures* (Table 7):
  - The same stratification is probably occurring for the 5-yr. past ret. measures, and could be driving the results.

# *Disconfirming* L-S Portfolio




"Difference" = Return (A) – Return (B)

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# What Hypothesis are CFK Rejecting?

- CFK fail to reject the null that past financial-growth measures are unrelated to future returns at long horizons.
  - CFK do this for more complicated measures of past performance than examined by Dechow and Sloan (1997) or by **?**.
- However, CFK don't address biases in interpreting other sources of information
- Is it possible that representativeness and conservatism are influence the marginal investor's interpretation of non-financial information.

# Interpreting the Results

- These results provide no evidence that long-horizon earnings trends results in low future returns:
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- Of course, these results raise several questions:
  1. What are investors doing to cause the predictability that is observed?
  2. Lakonishok, Shleifer, and Vishny (1994) find that past-sales growth strongly forecasts future returns. What is this paper doing differently?

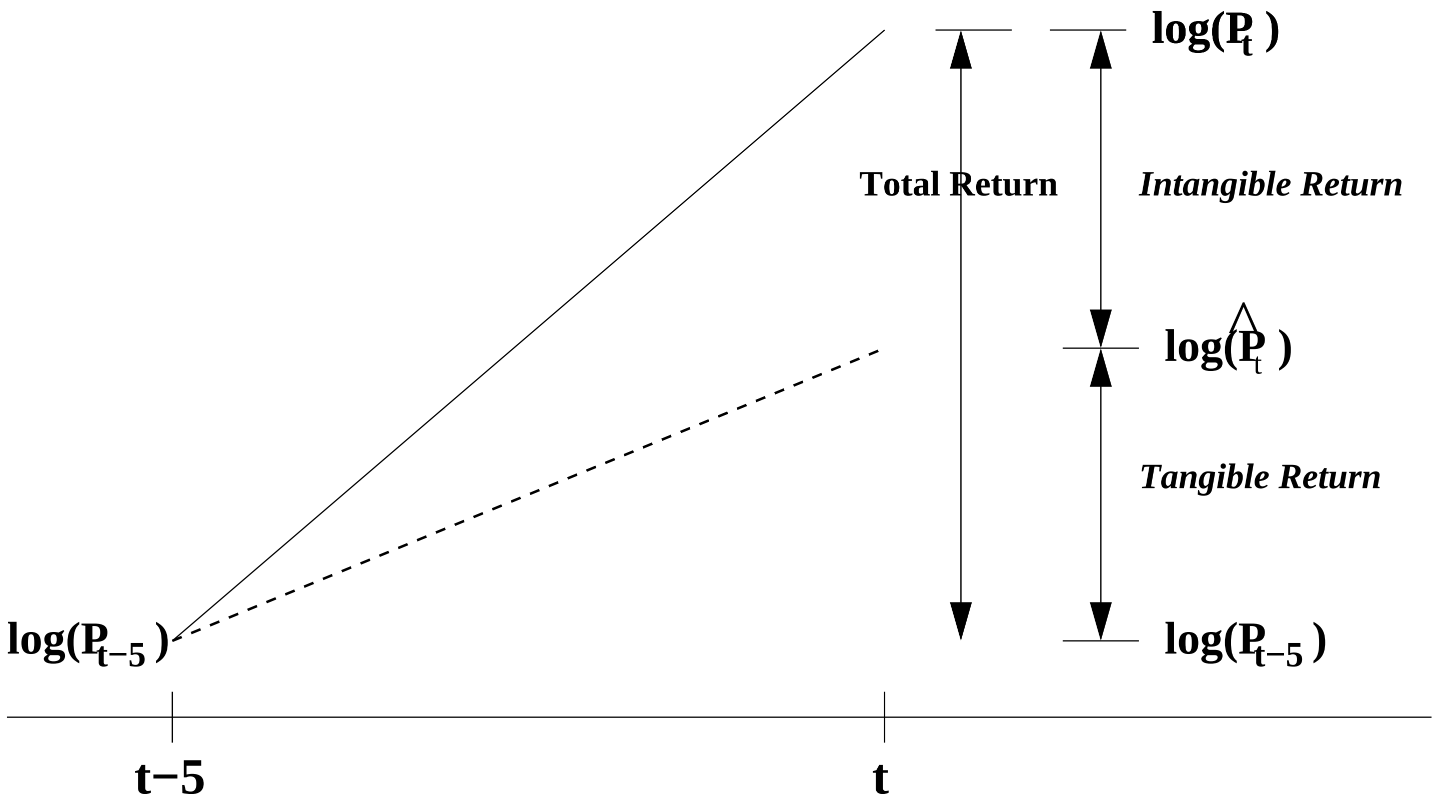
# Predictability ⇒ Misinterpretation

- The FOC from the investor's optimization problem is:

$$\frac{E[Y_{i,T}|\mathcal{F}_t]}{P_{i,t}} = e^{r_i(T-t)}$$

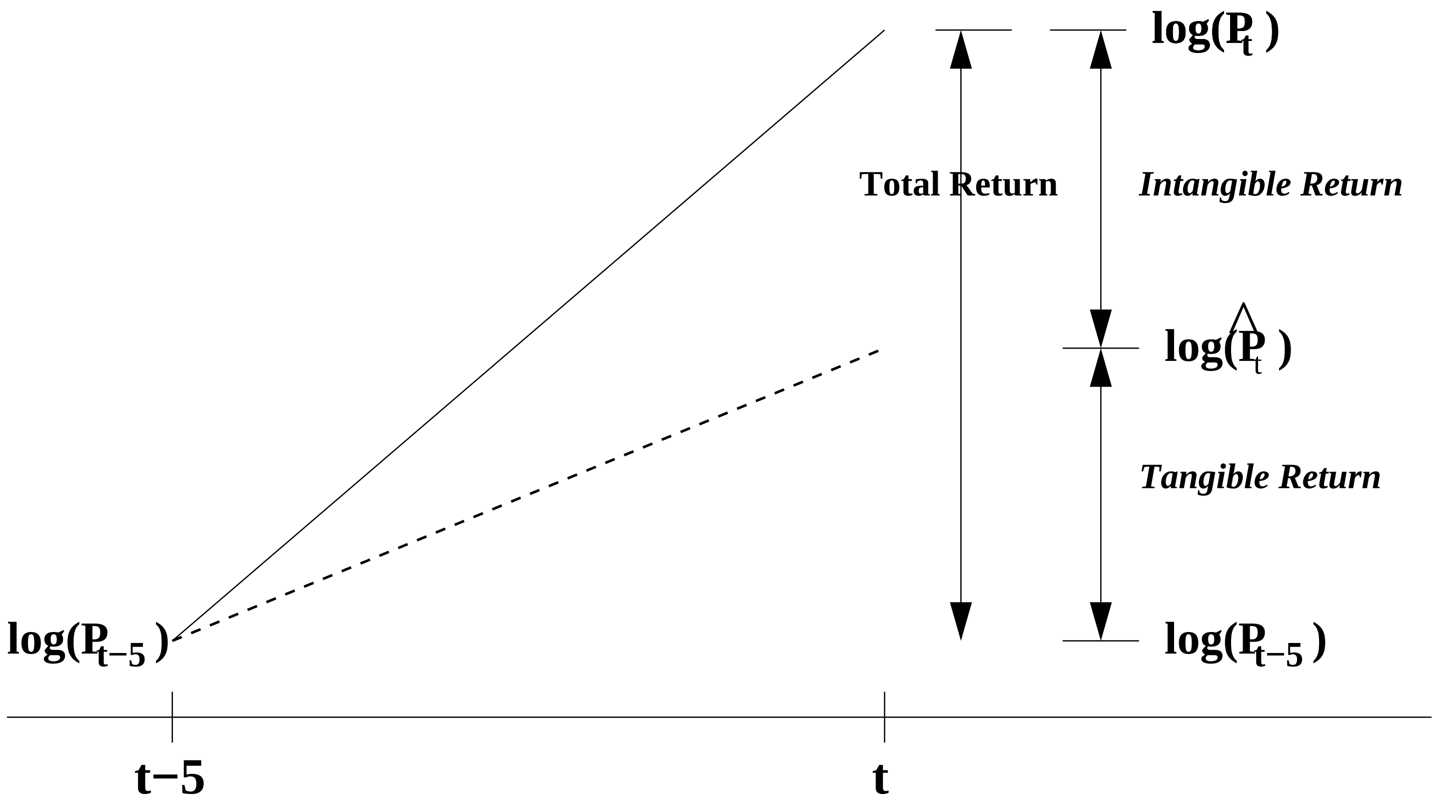
- If this is violated (as it appears to be in the data), then either:
  1. Investors don't optimize;
  2. Frictions prevent investors from optimizing;
  3. We're not measuring risk right;
  4. Investors aren't correctly using $\mathcal{F}_t$ in forming expectations of future payoffs.
- If it is 4., then there must be some identifiable way in which the representative investor is incorrectly processing the information in $\mathcal{F}_t$.

# *Intangible* Returns




- In Daniel and Titman (2002), we attempt to identify what information is mis-processed

# *Intangible* Returns




- We define the tangible return is the fitted component of the cross-sectional regression of the 5-year log-return on fundamental information:

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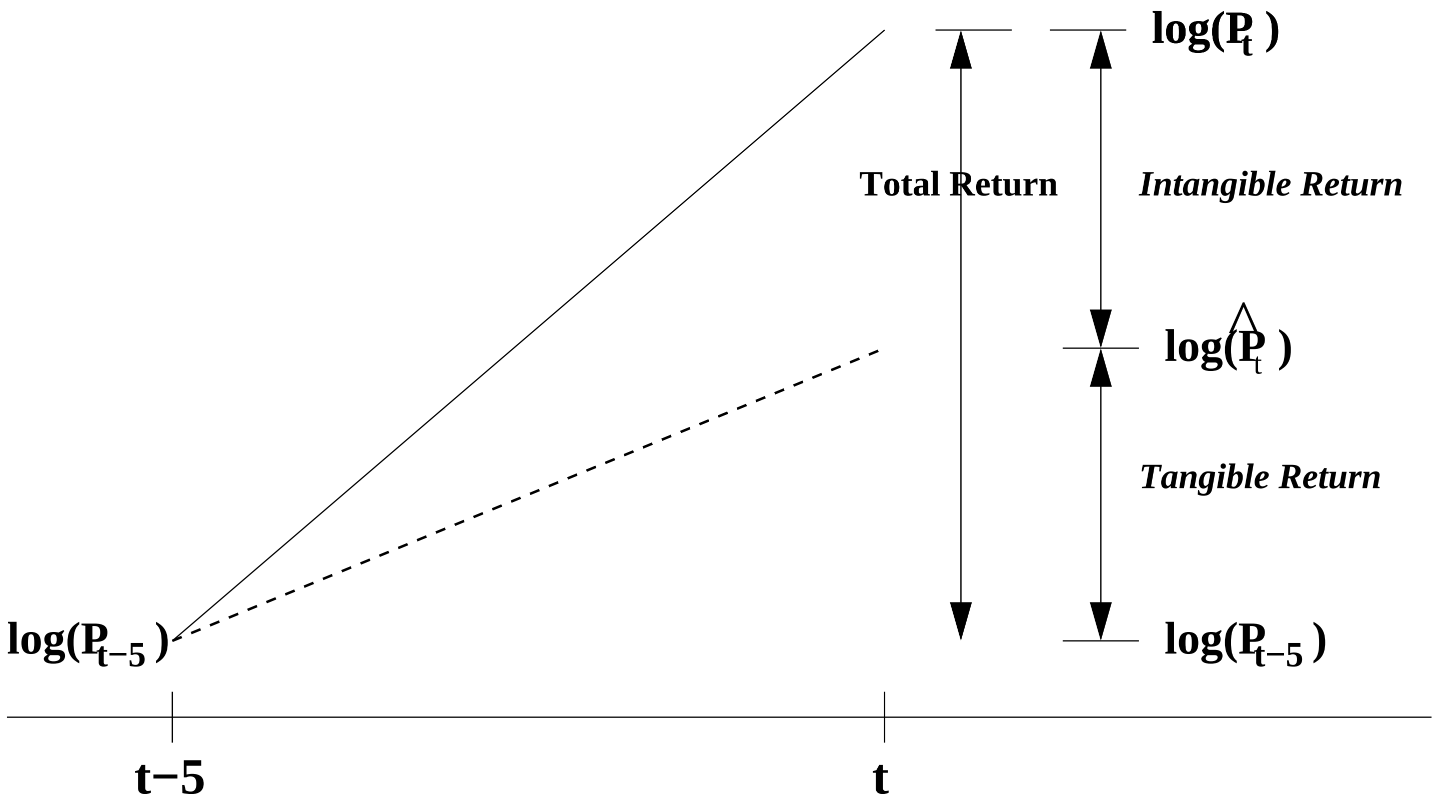
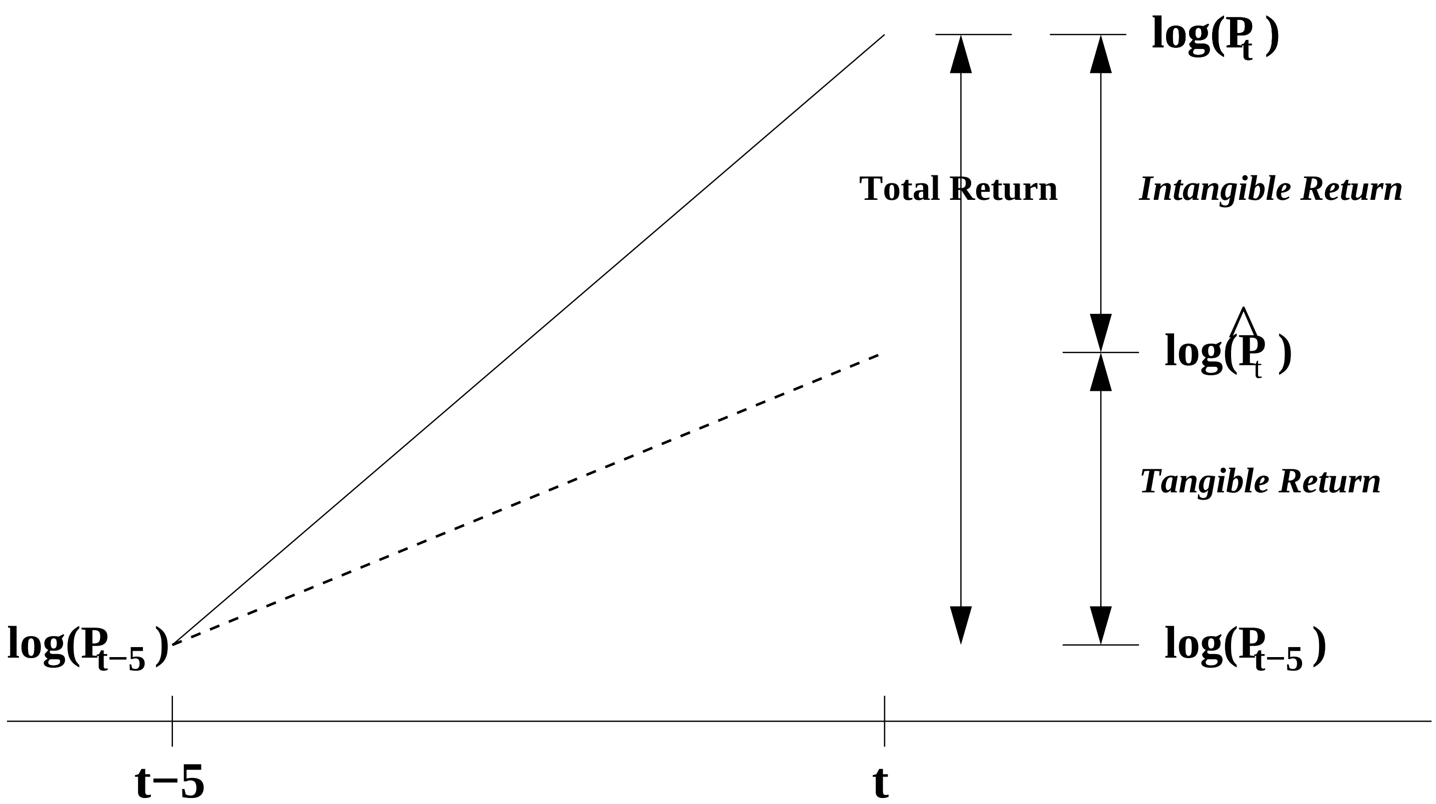



- Empirically, we use unanticipated book, sales, cash-flow, or earnings-*return* as tangible information proxies
  - or on all of these.

# *Intangible* Returns




- The $R^2$s for the full cross-sectional regression is about 60%.

# Intangible Return Reversals

| | Const | $bm_{t-5}$ | $r^B(t-5,t)$ | $r^{I(B)}$ | $R^2_{avg}$ |
|---|---|---|---|---|---|
| 1 | 1.206 | 0.097 | -0.062 | -0.344 | 36.63% |
| | (4.64) | (1.37) | (-0.92) | (-3.45) | |
| | Const | $sp_{t-5}$ | $r^{SLS}(t-5,t)$ | $r^{I(S)}$ | $R^2_{avg}$ |
| 2 | 1.041 | 0.084 | 0.105 | -0.333 | 21.32% |
| | (3.93) | (1.67) | (1.92) | (-3.85) | |
| | Const | $cp_{t-5}$ | $r^{CF}(t-5,t)$ | $r^{I(C)}$ | $R^2_{avg}$ |
| 9 | 1.348 | 0.073 | -0.049 | -0.479 | 47.03% |
| | (5.42) | (1.05) | (-1.11) | (-4.36) | |
| | Const | $ep_{t-5}$ | $r^{ERN}(t-5,t)$ | $r^{I(E)}$ | $R^2_{avg}$ |
| 12 | 1.323 | 0.064 | -0.003 | -0.454 | 45.58% |
| | (5.37) | (0.97) | (-0.09) | (-4.10) | |
| | Const | $r^{T(Tot)}(t-5,t)$ | | $r^{I(Tot)}$ | $R^2_{avg}$ |
| 13 | 1.278 | -0.125 | | -0.450 | 59.67% |
| | (5.21) | (-1.76) | | (-3.87) | |

*Note:* Coefficients are $\times 100$;
$R^2_{avg}$ is the avg. $R^2$ from the cross-sectional regressions.

# Analyst Forecasts

- Our results are consistent with Dechow and Sloan (1997), who also argue against the simple earnings-growth extrapolation story that LSV propose.
- However, Dechow and Sloan (1997) present evidence that stock prices reflect biases in analysts' forecasts.

# Reinterpreting LSV's Results

- In DT(2003), we show that LSV obtain their results because their *total sales growth* measure is also a proxy for share issuance:
  - We find that composite share issuance is a strong predictor of future returns.
  - We find no evidence of overreaction to LSV growth measure after controlling for share-issuance.
  - Also, if the 10% of the firms that had the greatest issuance activity are removed from the sample, future returns are no longer associated with past cash-flow growth.

# DHS model implications

- CFT argue that the BSV, DHS and HS models have similar implications:

  We note that neither Hong and Stein (1999) nor Daniel et. al. (1998) rely on representativeness or conservatism *per se* to motivate the behavior of traders in their models. *However, in each case, their assumptions can be viewed as operationally similar to investors' inferences subject to representativeness and/or conservatism heuristic applied to a sequence of prior firm performance.* (p. 11)

# DHS and BSV model implications

... if consistent sequences of public signals imply a correspondence between private signals and public signals, Daniel et. al. predict investors will over-infer from a sequence of good news announcements in forming trending expectations, which ultimately leads to overpriced stocks and subsequent price reversals (see figure 1 and section III.B in Daniel et. al. 1998) (pp. 10-11)

# DHS (1998) – Figure 1



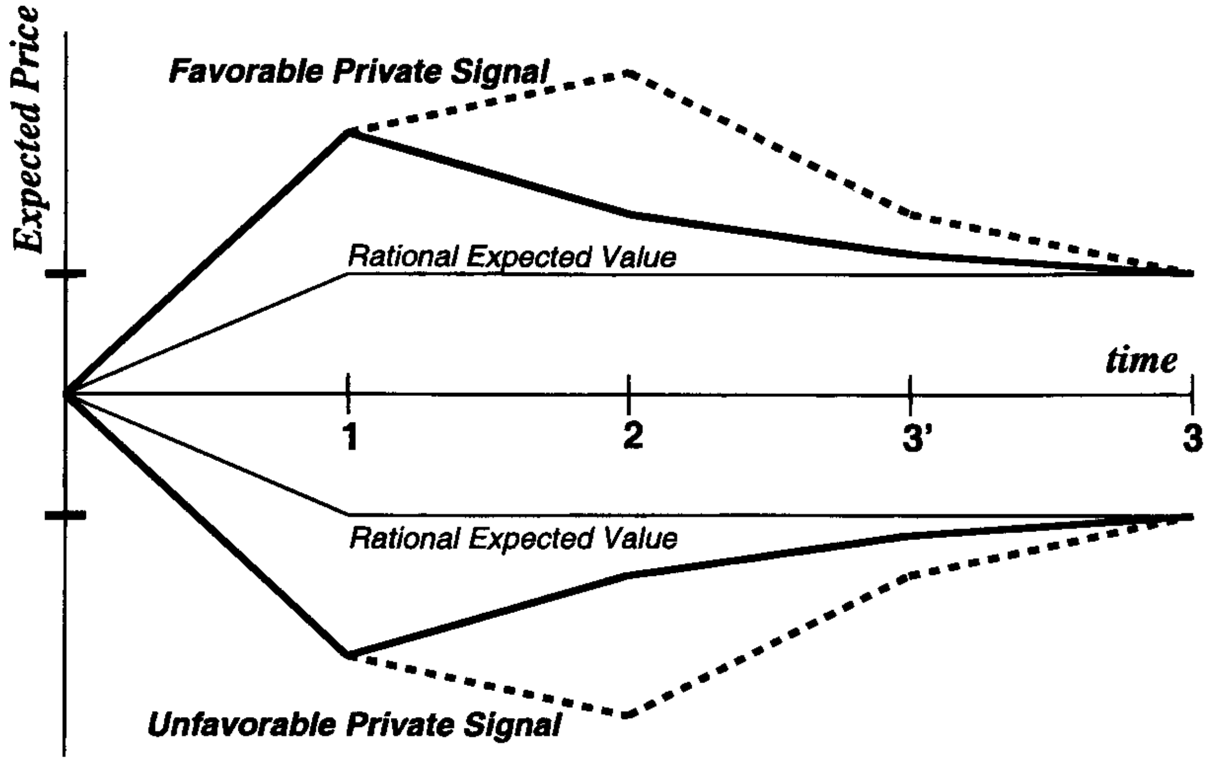



**Figure 1. Average price as a function of time with overconfident investors.** This figure shows price as a function of time for the dynamic model of Section III with (dashed line) and without (solid line) self-attribution bias.

# DHS (1998) – Figure 4



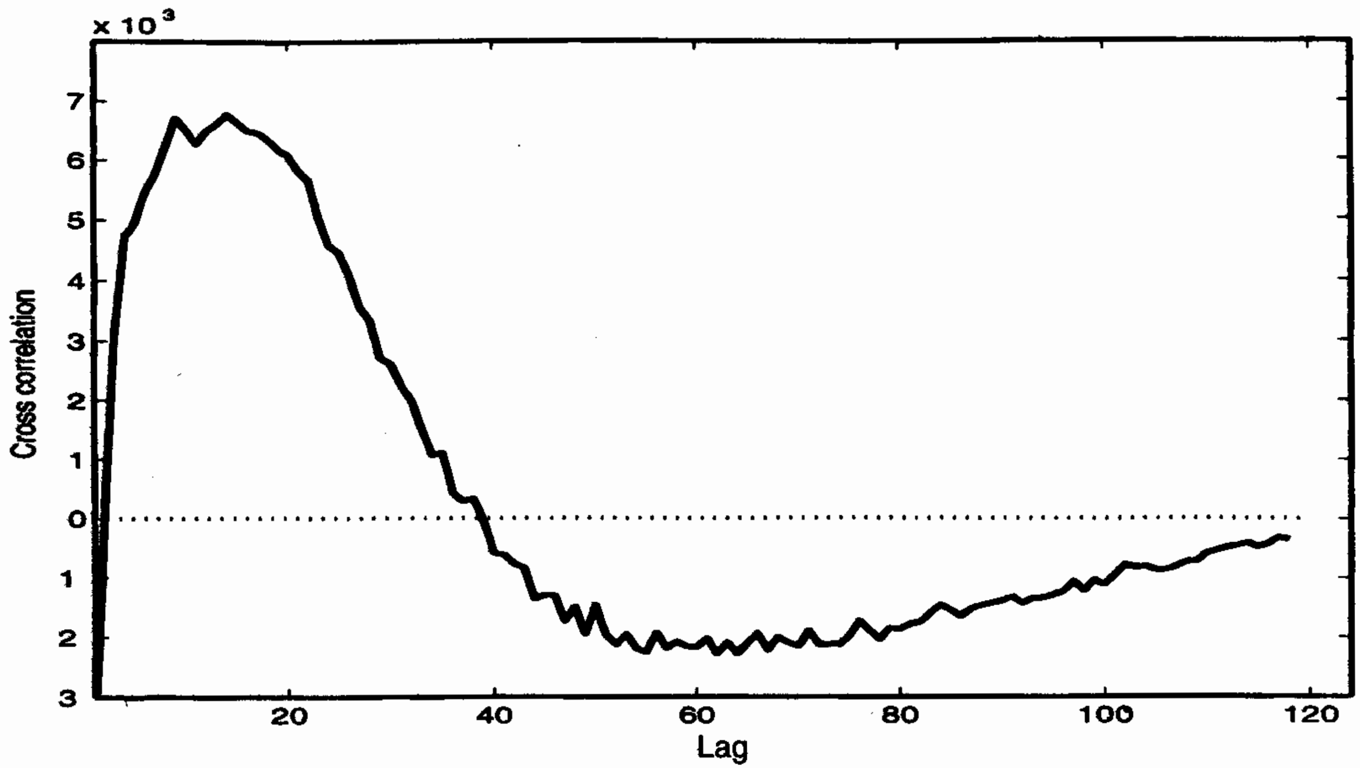
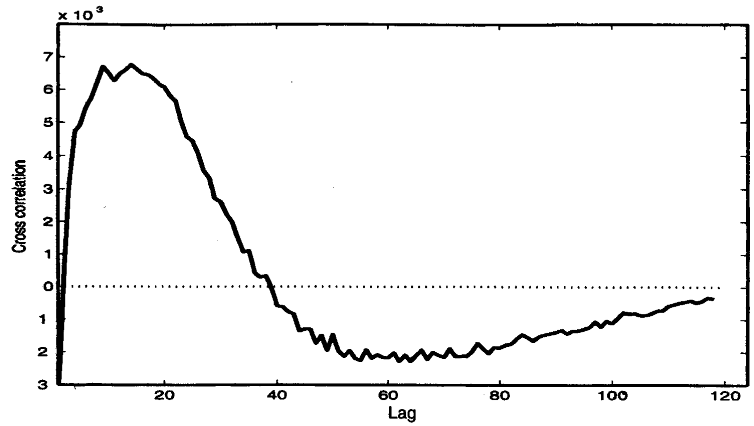



**Figure 4. Correlation between information changes and future price changes.** This figure shows the set of average sample correlations between the $\Delta e_t$ and price changes $\tau$ periods in the future $\Delta P_{t+\tau} = P_{t+\tau} - P_{t+\tau-1}$. These are calculated using the simulated dynamic model of Section III.B.3.

# DHS (1998) – Figure 4



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To evaluate the above conjecture, we again calculate average correlations using our simulation as follows. For each $\tilde{\phi}_t$ (for $t = 2{,}120$) we calculate the "earnings" surprise, defined as

$$\Delta e_t = \tilde{\phi}_t - \Phi_t = \tilde{\phi}_t - E[\tilde{\phi}_t | \phi_2, \phi_3, \ldots, \phi_{t-1}], \tag{21}$$

the deviation of $\phi_t$ from its expected value based on all past public signals. Then, we calculate the set of sample correlations between the $\Delta e_t$ and price changes $\tau$ periods in the future $\Delta P_{t+\tau} = P_{t+\tau} - P_{t+\tau-1}$. These correlations are then averaged over the Monte Carlo draws. The average correlations are plotted in Figure 4. This simulation yields the following result.

*Result 4:* In the biased self-attribution setting of Section III.B, short-lag correlations between single-period stock price changes and past earnings are positive, and long-lag correlations can be positive or negative.

# DHS (1998) – Result 4

*Result 4:* In the biased self-attribution setting of Section III.B, short-lag correlations between single-period stock price changes and past earnings are positive, and long-lag correlations can be positive or negative.

# Picky Econometric Issues

1. Better control for past performance in consistency tests.
2. FF(93) benchmark portfolios are VW, yet test portfolios here are EW.
   - This will bias up the calculated returns of illiquid portfolios.
   - Use VW test portfolios (or at least buy and hold)
3. How are splits, dividends, issues, *etc.*, dealt with in calculating per-share growth rates?

# Directions for Behavioral Finance

- There are now a host of behavioral models that can capture general features of the data,
- But, a model is only valuable to the extent that it predicts as yet untested features of the data
- Thus, more careful empirical explorations of the implications of these models are necessary
- Something that is generally missing from all of these analyses is magnitudes.
  - Can parameterized behavioral models match what we see in the data?
  - How to treat arbitrageurs is an issue

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