Week 8:
(In)efficient Markets:
Behavioural Explanations for Anomalies

Dr Christian Engels
ce50@st-andrews.ac.uk

FI5614 Behavioural Finance

Department of Finance
University of St Andrews Business School

Readings and Topics

Required readings:

- Ackert & Deaves, Chapters 13 and 14
- Frydman and Wang (2020), “The Impact of Salience on Investor Behavior” (tutorial)

Topics covered:

1. The anomaly landscape: value, momentum, and reversals
2. Limits to arbitrage: why smart money cannot fix mispricing
3. Three behavioural models of mispricing (BSV, DHS, Hong-Stein)
4. Prospect theory and asset prices
5. Sentiment, survival, and the verdict on anomalies

Review Quiz

Interactive quiz on Vevox

Quick review of Week 7 materials
Home bias, representativeness, anchoring, and attention

Please open Vevox and enter the session code

Outline

If Markets Are Efficient, Why Do Dozens of Anomalies Persist for Decades?

The evidence

- Anomalies like momentum, value, and low volatility deliver 5–12% annually in long-short portfolios
- They survive out-of-sample, across asset classes, and across countries
- Standard risk models cannot fully explain them

Three competing explanations

1. **Rational risk:** anomaly stocks are riskier in ways standard models miss
2. **Mispricing:** behavioural biases create predictable patterns, sustained by limits to arbitrage
3. **Data mining:** researchers find patterns in noise

→ This week: we map the territory—from documenting anomalies, to explaining why arbitrage fails, to building models that generate the patterns we observe.

The Anomaly Landscape

At Least Twenty-Three Anomalies Challenge the Efficient Market Hypothesis

Risk & volatility

- Idiosyncratic volatility
- Market capitalisation
- Maximum daily return
- Expected idio. skewness
- Failure probability
- Z-score
- Difference of opinion

Return patterns

- Value
- Momentum
- Short-term reversal
- Long-term reversal
- Post-earnings drift
- Capital gain overhang

Fundamentals & issuance

- Gross profitability
- Return on assets
- Asset growth
- Investment
- Net operating assets
- Accrual
- Net stock issuance
- Composite equity issuance
- External finance
- Organisational capital

→ Each generates predictable return patterns that standard models cannot fully explain. Why do they exist, and why do they persist?

Source: Cao et al. (2021).

Recall: The Key Magnitudes

Return-pattern anomalies

- **Long-term reversal:** past losers beat winners by 25% over 3 years (De Bondt and Thaler, 1985)
- **Momentum:** buying winners/selling losers earns ∼12%/yr; all 32 strategies profitable (Jegadeesh and Titman, 1993)
- **Value premium:** value beats glamour by 10–11%/yr—even in recessions (Lakonishok et al., 1994)
- **Post-earnings drift:** prices continue drifting for months after earnings surprises

Risk- and issuance-based anomalies

- **Idiosyncratic volatility:** high-vol stocks earn *lower* returns—opposite of risk models
- **Net issuance & accruals:** firms issuing equity or inflating accruals subsequently underperform
- **Profitability & investment:** profitable, conservative firms outperform aggressive ones

These are ubiquitous: value and momentum exist across 8 asset classes (Asness et al., 2013).

→ The 23 anomalies span return patterns, risk characteristics, and corporate actions. No single model explains all of them—but together, the models we explore today cover much of this landscape.

Factor Models Describe the Cross-Section—but Cannot Explain *Why*

What risk models capture

The Fama and French (2015) five-factor model (market, size, value, profitability, investment) outperforms FF3—and HML becomes redundant once profitability and investment are included.

These factors *describe* much of the cross-section of returns.

What they miss

- Momentum is the main anomaly not captured by five factors
- Labelling a pattern as a "factor" does not explain the underlying economic mechanism
- The model does not distinguish between risk compensation and mispricing

→ If these are risk premia, what is the economic risk? If mispricing, why does arbitrage not eliminate them? That is what the rest of this lecture addresses.

Limits to Arbitrage

Arbitrage Requires Capital, and Capital Is Performance-Sensitive

Performance-Based Arbitrage (PBA)

Arbitrageurs use *other people's money*. Capital allocation depends on past performance: poor returns trigger withdrawals, forcing liquidation precisely when mispricing is greatest.

The Shleifer and Vishny (1997) model

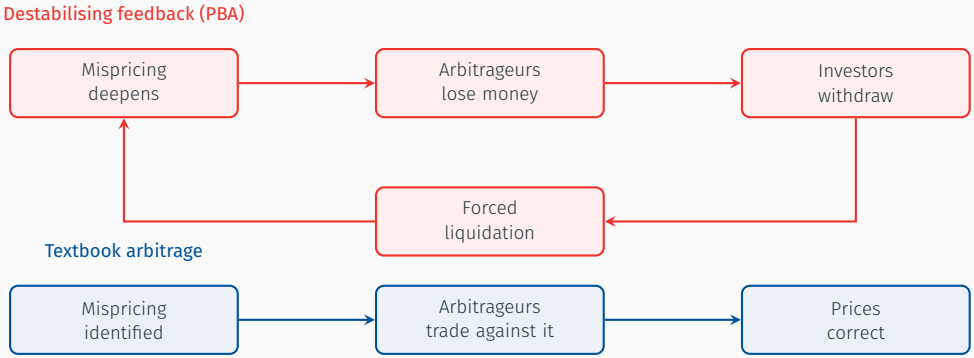
Three-period setup: arbitrageurs identify mispricing at $t = 1$ and invest. If mispricing deepens before correcting, they face margin calls and investor withdrawals.

Even idiosyncratic risk—not just systematic risk—deters specialised arbitrageurs.

Why this matters

- Week 6 introduced limits to arbitrage as a concept
- Shleifer-Vishny formalise *why* rational arbitrageurs cannot always correct mispricing
- The key insight: arbitrage is least effective when most needed

When Mispricing Deepens, Arbitrageurs Are Forced to Liquidate



→ Under PBA, the very mechanism that should correct mispricing can amplify it—smart money retreats when prices are furthest from value.

3Com Was Worth Less Than Its Palm Stake—for 47 Trading Days

The law of one price violated

Lamont and Thaler (2003) document 18 tech-bubble carve-outs (1996–2000) where parent price $<$ ownership stake in subsidiary—implying negative value for the rest of the parent.

The 3Com/Palm case: stub value $= -\$63$/share, implying $-\$22$ bn for 3Com's non-Palm business.

Why arbitrage failed

- Overpriced subsidiaries were impossible to sell short—negative rebate rates, put-call parity violations
- The mispricing was widely publicised yet persisted for 47 trading days

Two conditions needed for persistent mispricing:

1. Short-sale constraints blocking arbitrage
2. Irrational demand from uninformed buyers

$\rightarrow$ Markets can fail to add and subtract—even when the mispricing is obvious and public.

Relaxing Short-Sale Constraints Causally Weakens Anomalies by 72 bps/month

A natural experiment

Chu et al. (2020) exploit SEC Reg SHO (2005–2007): quasi-random removal of the uptick rule for every third Russell 3000 stock.

This creates a clean treatment/control comparison for the causal effect of short-sale constraints on anomaly strength.

Key findings

- Pilot stocks' anomaly L/S returns fell 72 bps/month ($t = -4.37$) vs. non-pilot stocks
- Effect comes entirely from the short leg: overpricing corrected faster
- After the pilot ended, the gap disappeared

Consistent with mispricing, *not* risk—a risk premium would not depend on short-sale rules.

→ This is causal evidence: limits to arbitrage sustain anomalies. Remove the limits, and the anomalies weaken.

Two Ingredients Are Required for Behavioural Anomalies to Persist

Ingredient 1: Biased investors

Representativeness, conservatism, overconfidence, loss aversion, and other biases cause investors to set prices that deviate from fundamental value.

Weeks 3–7 documented these biases in detail.

Ingredient 2: Limited arbitrage

Short-sale constraints, noise trader risk, and performance-based capital flows prevent rational arbitrageurs from fully correcting the mispricing.

Shleifer and Vishny (1997), Lamont and Thaler (2003), and Chu et al. (2020) establish this empirically and theoretically.

→ Neither ingredient alone is sufficient. Biases create mispricing; limits to arbitrage allow it to survive. The question now: can we build models that generate the specific patterns we observe?

Three Behavioural Models of Mispricing

Conservatism and Representativeness Together Explain Both Momentum and Reversals

The BSV Model (Barberis et al., 1998)

A single model in which **conservatism** (too little updating after one surprise) and **representativeness** (seeing patterns in streaks) jointly generate short-horizon momentum and long-horizon reversals.

Setup

Earnings actually follow a random walk. But the representative investor believes earnings switch between two regimes:

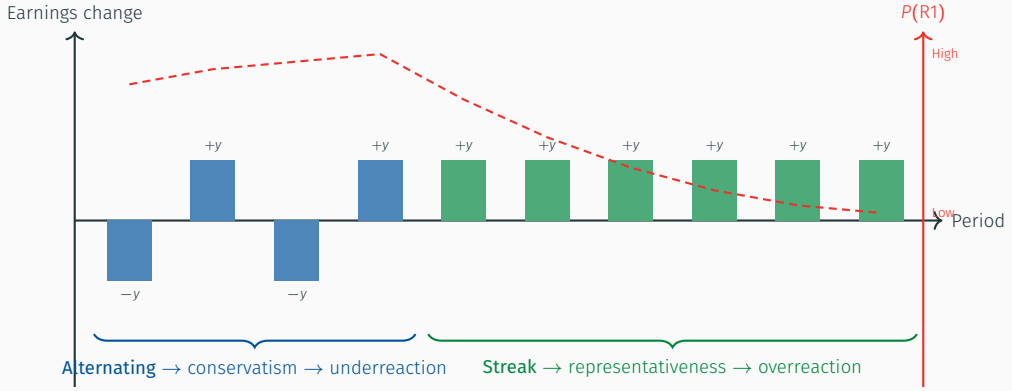
- **Regime 1:** mean-reverting (changes tend to reverse)
- **Regime 2:** trending (changes tend to continue)

How biases do the work

- After *one* surprise: investor assumes mean-reversion → underreacts → momentum
- After a *string* of same-sign surprises: investor sees a trend → overreacts → eventual reversal

→ Two biases from a single agent generate both canonical anomalies—a parsimonious and elegant framework.

After One Surprise Investors Underreact; After a Streak They Overreact



→ Alternating shocks make the investor believe in mean-reversion (underreaction). A streak makes the investor believe in a trend (overreaction). Both beliefs are wrong—earnings are a random walk.

The BSV Model Generates Both Short-Run Momentum and Long-Run Reversal

Simulated long-short returns based on the BSV model (Barberis et al., 1998)

	1 Year	2 Years	3 Years	4 Years
Earnings sort	+3.91%	+1.31%	−0.72%	−3.09%
Returns sort	+2.80%	+1.02%	−0.94%	−1.81%

Short-run momentum

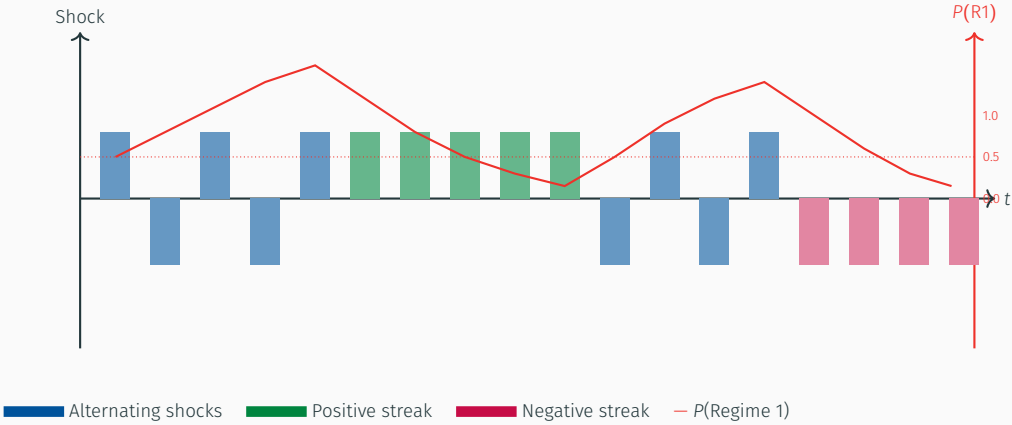
At 1–2 year horizons, both sorts generate positive returns. Conservatism causes underreaction to earnings news, so prices continue to drift.

Long-run reversal

At 3–4 year horizons, returns turn negative. Representativeness causes overreaction to streaks, which eventually corrects.

→ A single model generates both patterns—the sign change from positive to negative as the horizon lengthens is the distinctive BSV prediction.

The BSV Simulation Shows How Regime Beliefs Track Earnings Sequences



→ Beliefs about the earnings regime swing with the sequence of shocks. Alternating patterns raise *P*(Regime 1); streaks lower it. In reality, earnings are always a random walk.

Overconfident Investors Overweight Private Signals and Overreact

The DHS Model (Daniel et al., 1998)

Informed investors are overconfident about the precision of their private signals. They overreact to private information and underreact to public information.

Setup

Private signal: $s_1 = \theta + \varepsilon$, where θ is the true value and ε is noise (σ_ε^2).

Rational price:

$$p_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\varepsilon^2}(\theta + \varepsilon)$$

With overconfidence

Overconfident investors believe noise variance is $\sigma_C^2 < \sigma_\varepsilon^2$:

Overconfident price:

$$p_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_C^2}(\theta + \varepsilon)$$

Because $\sigma_C^2 < \sigma_\varepsilon^2$, investors overweight their signal $\rightarrow$ overreaction.

Self-Attribution Bias Converts Overreaction into Short-Run Momentum

The dynamic mechanism

1. At $t = 1$: overconfident investors receive private signals and overreact
2. At $t = 2$: public information arrives
3. **If public news confirms** the private signal: self-attribution boosts confidence further $\rightarrow$ continuing overreaction $\rightarrow$ momentum
4. **Eventually**: enough contrary public information arrives $\rightarrow$ correction $\rightarrow$ reversal

Self-attribution bias

Investors attribute:

- Confirming outcomes to their own skill
- Disconfirming outcomes to bad luck

This asymmetric attribution means:

- Good news $\rightarrow$ confidence rises
- Bad news $\rightarrow$ confidence unchanged

The result: a systematic drift in the direction of the initial overreaction before eventual correction.

$\rightarrow$ Overconfidence explains overreaction; self-attribution explains why it persists as momentum before reversing.

Overconfidence Creates an Overshoot-then-Reversal Price Path

Numerical example

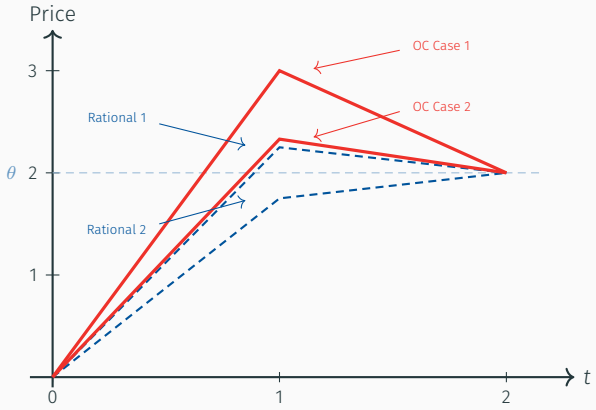
$\theta = 2, \quad \sigma_\theta^2 = \sigma_\varepsilon^2 = 1$

Overconfident: $\sigma_C^2 = 0.5$

Case 1: $\varepsilon = 2.5$
$s_1 = 4.5$
Rational: $p_1 = 2.25$
Overconfident: $p_1 = 3.00$

Case 2: $\varepsilon = 1.5$
$s_1 = 3.5$
Rational: $p_1 = 1.75$
Overconfident: $p_1 = 2.33$

True value: $\theta = 2$



→ In both cases, overconfident investors push prices beyond the rational level. When the true value is revealed, prices correct—generating the reversal pattern.

Selective Events Predict Post-Announcement Drift with the Same Sign

A novel DHS prediction

The DHS model distinguishes between:

- **Nonselective events:** earnings announcements—exogenous timing, not chosen by managers
- **Selective events:** share repurchases, equity issuances—managerial actions that *respond* to perceived mispricing

Testable implications

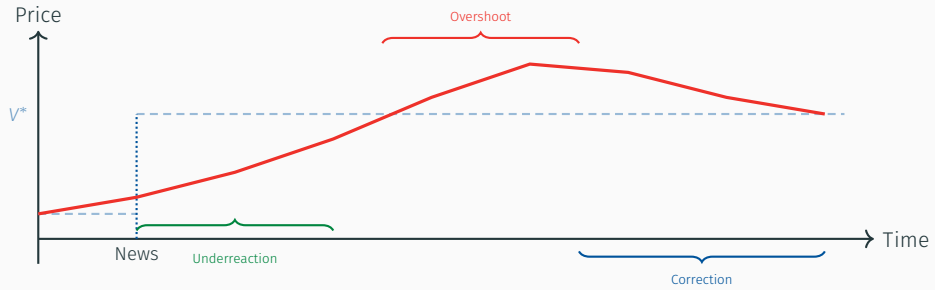
- Nonselective events: post-event drift should reflect continuing overreaction or correction
- Selective events: managers exploit mispricing, so post-event drift should have the same sign as the announcement return

Empirically confirmed: share repurchase announcements predict positive long-run drift; equity issuances predict negative drift.

→ DHS generates a distinctive prediction that BSV does not: managerial actions are *endogenous* to mispricing, creating a unique channel for post-event drift.

The Hong-Stein Model (Hong and Stein, 1999)

Two types of boundedly rational agents: **newswatchers** observe fundamentals but ignore prices; **momentum traders** condition on past prices but use only simple strategies.



→ Slow diffusion among newswatchers creates underreaction; momentum traders exploit it but inevitably push prices past fundamentals.

Overreaction Is Inevitable—Early Momentum Buyers Profit at Late Buyers' Expense

Proposition 1: overshoot is unavoidable

The impulse response to a positive news shock *always* overshoots the fundamental value. This is not a pathological case—it is a general property of the model.

Why? Momentum traders cannot distinguish between:

- Price movements from fundamental news (worth chasing)
- Price movements from other momentum traders (not worth chasing)

Proposition 2: negative externality

Early momentum traders earn profits. But their buying activity creates a negative externality: it generates further price movement that attracts late momentum traders, who buy at inflated prices.

Late entrants bear the cost of the eventual correction—they buy near the peak and sell during the reversal.

→ Unlike BSV and DHS, the Hong-Stein model features heterogeneous agents interacting.

→ The model explains why momentum profits eventually decay: late entrants bid prices too high, and the reversal destroys their gains.

Bad News Travels Slowly—Momentum Is Stronger for Low-Coverage Stocks

Testing Hong-Stein's prediction

If momentum is driven by gradual information diffusion, it should be stronger where information diffuses more slowly.

Hong et al. (2000) sort on residual analyst coverage (orthogonalised to size) and firm size. 6/6 momentum strategy; NYSE/AMEX/Nasdaq, 1980–1996.

Key findings

- Momentum profits are ∼60% greater for low-coverage stocks than high-coverage stocks, holding size fixed
- The effect is asymmetric: coverage matters more for past losers than past winners
- Bad news gets incorporated into prices more slowly: firms with good news disclose; firms with bad news do not

→ "Bad news travels slowly" — analysts' marginal contribution is greatest when the news is negative, exactly as Hong-Stein predicts.

All Three Models Generate Momentum and Reversals from Different Biases

	BSV (1998)	DHS (1998)	Hong-Stein (1999)
Bias	Conservatism + representativeness	Overconfidence + self-attribution	Gradual info diffusion
Agents	Representative	Informed + uninformed	Newswatchers + momentum traders
Momentum	Underreaction to single news (conservatism)	Self-attribution reinforces initial overreaction	Trend-chasing by momentum traders
Reversal	Overreaction to streaks corrects	Public information eventually corrects	Overshoot from momentum trading corrects
Distinctive prediction	Stronger after earnings streaks	Selective events predict same-sign drift	Stronger for low-coverage stocks

→ All three models generate momentum and reversals from different psychological primitives—but each makes distinctive cross-sectional predictions that can be tested.

All Three Models Require Limits to Arbitrage but Differ on Agent Structure

Points of agreement

1. All three generate both momentum and reversals from a *single* mechanism
2. All require limits to arbitrage for the patterns to survive in equilibrium
3. All locate the source of mispricing in beliefs—how investors process information

Points of divergence

1. BSV and DHS use a *representative* agent; Hong-Stein uses heterogeneous agents
2. BSV and DHS are about *individual biases*; Hong-Stein is about *market structure*
3. None of these models involves preferences—they are purely about distorted beliefs

→ The belief channel explains much—but can *preferences* also generate anomalies? That is the question for Section 4.

Prospect Theory and Asset Prices

The Disposition Effect Generates Momentum in Equilibrium

The mechanism

Recall the disposition effect: investors are reluctant to sell losers (to avoid realising a loss) and too eager to sell winners (to lock in a gain).

Grinblatt and Han (2005) show this creates underreaction:

- Good news → disposition investors sell too soon → price rises *less* than it should
- Bad news → disposition investors hold on → price falls *less* than it should

The price gradually catches up → momentum.

The empirical test

The *capital gains overhang*—how far the current price sits above or below the average purchase price—measures the strength of the disposition effect for each stock.

- Capital gains overhang subsumes past returns as a predictor of future returns
- Once it is controlled for, return-based momentum disappears

Momentum is not a separate anomaly—it is the disposition effect showing up in prices.

→ Momentum may not be about distorted beliefs at all—it may be about reference-dependent preferences that slow price adjustment.

Disposition-Driven Underreaction Concentrates at Earnings Announcements

The disposition channel for drift

Frazzini (2006): if the disposition effect slows price adjustment, post-announcement drift should be largest when capital gains and news have the same sign.

Data: stock-level capital gains overhang from mutual fund holdings (FIFO cost basis), 1980–2002.

Key findings

- Post-announcement drift is largest when news and capital gains have the same sign
- Mutual fund managers exhibit the disposition effect: PGR − PLR = 3%
  (PGR = proportion of gains realised; PLR = proportion of losses realised)
- Bottom-quintile funds: PGR − PLR = 8%—comparable to retail investors

Selling into good news and holding through bad news both slow price adjustment.

→ Even professional fund managers display the disposition effect—it is not confined to retail investors.

Loss Aversion and Prior Outcomes Jointly Explain the Equity Premium

Prospect theory and the equity premium

Barberis et al. (2001): Lucas-tree economy where investors feel loss aversion over portfolio gains/losses, with sensitivity varying with prior outcomes ("house money effect").

After gains → less loss-averse → lower discount rate → prices rise further. After losses → the reverse.

What the model achieves

- Equity premium ≈ 5%
- Return volatility ≈ 24%
- Low return-consumption correlation (0.15)
- Amplifies dividend shocks into excess volatility

Critical insight: loss aversion alone is insufficient—without prior-outcome dependence, the P/D ratio is constant and returns are i.i.d.

→ Prospect theory can explain the aggregate equity premium—but it requires the "house money effect" to generate time-varying risk aversion.

Prospect Theory Explains Fourteen of Twenty-Three Stock Market Anomalies

A comprehensive test

Cao et al. (2021): three-date economy with full cumulative PT (loss aversion + diminishing sensitivity + probability weighting) plus narrow framing and prior gains/losses.

14 of 23 anomalies explained—including momentum, idiosyncratic volatility, failure probability, and ROA.

What PT gets right—and wrong

- Average absolute pricing error matches the Carhart 4-factor model
- Common mechanism: low-alpha stocks have higher volatility, more skewness, more negative capital gains overhang
- The 7 failures (including value) concentrate returns around *earnings announcements*

The failures suggest that where PT falls short, beliefs—not preferences—drive the anomaly.

→ PT preferences explain most anomalies—but the value premium and other announcement-driven patterns require belief-based models (BSV, DHS).

Beliefs and Preferences Are Complementary Channels for Mispricing

The belief channel (Section 3)

- Conservatism, representativeness, overconfidence, self-attribution, gradual diffusion
- Generates: momentum, reversals, post-announcement drift, value premium
- Particularly strong around earnings announcements

The preference channel (Section 4)

- Loss aversion, disposition effect, narrow framing, probability weighting
- Generates: momentum (via disposition), equity premium, 14/23 cross-sectional anomalies
- Operates through portfolio decisions

→ Neither channel alone is sufficient. Beliefs explain announcement-driven anomalies; preferences explain portfolio-level patterns. A complete account of market anomalies requires both.

Sentiment and Anomaly Survival

When Investors Are Optimistic, Speculative Stocks Get Overpriced

Measuring market-wide sentiment

Baker and Wurgler (2006) build a sentiment index from six indicators of speculative appetite (IPO activity, trading volume, fund discounts, etc.).

When sentiment is high, investors are eager to speculate; when low, they are cautious.

What happens next

- After high sentiment: the riskiest, most speculative stocks (small, young, volatile, unprofitable) earn low subsequent returns—they were overpriced
- After low sentiment: these same stocks earn high returns—they were underpriced by cautious investors

The same stock characteristics predict opposite returns depending on the mood of the market.

→ Sentiment doesn't just add noise—it systematically distorts the prices of the most subjective, hard-to-value stocks.

Anomaly Profits Come from Overpriced Stocks That Cannot Be Shorted

The asymmetry

Stambaugh et al. (2012) split 11 anomaly strategies into their "buy" side (underpriced stocks) and "sell" side (overpriced stocks), then check which side drives the profits.

All 11 anomalies are stronger after high sentiment—the combined strategy earns about 0.7%/month more when sentiment is high.

It is almost entirely the sell side

- The overpriced stocks drive the anomaly: they earn very negative returns after high sentiment, as their overpricing corrects
- The underpriced stocks are barely affected by sentiment
- Why? There is no constraint on buying underpriced stocks, but short-sale constraints prevent traders from correcting overpricing

→ Anomalies are primarily about overpricing that cannot be arbitraged away—not underpricing. This links directly back to limits to arbitrage.

Investors Extrapolate Past Returns—and the Market Punishes Them for It

What investors expect

Greenwood and Shleifer (2014) combine six major investor surveys (1963–2011) and find a single, consistent pattern:

- When past returns have been high, investors expect high future returns
- When past returns have been low, investors expect low future returns

In short: investors extrapolate recent performance.

What actually happens

The opposite. Investor optimism negatively predicts future returns:

- When surveys show peak optimism, subsequent returns are low
- When surveys show peak pessimism, subsequent returns are high
- If expectations were rational, optimism and future returns should move *together*—they do not

→ Investors systematically expect high returns precisely when returns are about to be low. Extrapolation is one of the most robust findings in behavioural finance.

Analysts Overreact to Genuinely Informative Signals—Not to Noise

The puzzle

Analysts who forecast high long-term earnings growth for a stock tend to be too optimistic: those stocks subsequently underperform by 13.6%/yr relative to stocks with low growth forecasts.

But the optimistic analysts are not *completely* wrong—high-forecast stocks *do* have somewhat better fundamentals. The problem is that analysts overreact to the signal.

Diagnostic expectations

Bordalo et al. (2019): representativeness causes analysts to react about twice as strongly as warranted to new information.

- The overreaction is larger when the signal is more informative (high earnings persistence, high volatility)
- Analysts revise forecasts *downward* for optimistic stocks even after positive earnings surprises

→ Overreaction is grounded in real information—investors are not responding to noise, but they are responding too strongly. This is representativeness at work.

Anomaly Returns Shrink after Academics Publish Them—but Do Not Disappear

The natural experiment

McLean and Pontiff (2016) track 97 anomalies across three periods:

1. **In-sample:** the period the paper studied
2. **Post-sample, pre-publication:** after the sample ends but before the paper is published
3. **Post-publication:** after investors can read the paper

What happens to the returns?

- Returns decline 26% between periods 1 and 2—this is the upper bound on data mining (the anomaly was partly a statistical artefact)
- Returns decline a further 32% after publication—this is arbitrageurs reading the research and trading on it
- Total post-publication decay: 58%

But significant returns remain—anomalies weaken, they do not vanish.

→ Academic publication is itself a natural experiment: it reveals how much of the anomaly was real and how much the market learns from research.

Anomaly Returns Arrive When News Corrects Biased Expectations

A simple test: when do returns arrive?

Engelberg et al. (2018) ask: do anomaly returns come evenly across all days, or do they concentrate on days when firms release information?

If anomalies reflect risk, returns should be spread evenly. If they reflect mispricing, returns should spike when news arrives and corrects biased beliefs.

The answer is stark

- Anomaly returns are 6× higher on earnings announcement days than on other days
- Analyst forecasts are systematically wrong in the direction the anomaly predicts—and corrected when earnings are announced

A risk-based explanation would require risk to be 6× higher on earnings days—implausible.

→ Returns arrive precisely when new information corrects biased beliefs. This is what mispricing looks like.

Conclusions

Key Takeaways across Eight Themes

Theme	Key mechanism	Signature finding
Anomaly landscape	Value, momentum, reversals across asset classes	5–12% long-short returns globally
Limits to arbitrage	PBA, short-sale constraints, noise trader risk	Reg SHO causally reduces anomalies by 72 bps/m
BSV model	Conservatism + representativeness	Short-run momentum, long-run reversal from regime beliefs
DHS model	Overconfidence + self-attribution	Selective events predict same-sign drift
Hong-Stein model	Gradual diffusion + momentum trading	Momentum 60% stronger for low-coverage stocks
Prospect theory	Disposition effect, loss aversion	14/23 anomalies; failures at announcements
Sentiment	Baker-Wurgler index, short-leg amplification	All 11 anomalies stronger after high sentiment
Survival	Publication decay, earnings-day concentration	58% post-publication decay; 6× earnings-day returns

Anomalies Are Real, Persistent, and Behavioural

1. Anomalies are real—value, momentum, and dozens more survive out-of-sample and across asset classes
2. Limits to arbitrage sustain mispricing—short-sale constraints and noise trader risk prevent correction
3. Three canonical models (BSV, DHS, Hong-Stein) explain momentum and reversals from different psychological primitives—all belief-based
4. Prospect theory shapes prices—the disposition effect generates momentum; loss aversion explains the equity premium
5. Sentiment and extrapolation move markets—but publication and arbitrage gradually erode anomaly returns

→ The question is not whether investors are rational or irrational—it is understanding which biases leave systematic traces in prices, and why arbitrage does not eliminate them.

Closing Quiz

Interactive quiz on Vevox

Test your understanding of:
Limits to arbitrage, BSV, DHS, Hong-Stein,
prospect theory, and anomaly survival

Please open Vevox and enter the session code

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