Market efficiency implies publicly available information should be factored into stock prices

- Trading anomalies we have surveyed **are based on publicly available information**
- These anomalies **should not be exploitable according to EMH**
- In this lecture, we examine **3 alternative explanations**

Explanation	Notes
Trading costs	Anomalies surveyed are not exploitable in practice due to market and trading frictions
Behavioral economics	Market participants make decisions using heuristics that result in different behavior from fully rational agents
Alpha decay	Anomalies were costly to exploit during the time period of their backtest. Due to advances in information technology, they are now easily exploitable. This has resulted in strategies 'decaying'

Introduction	Discussion of market neutral strategies					Microeconomic Explanations						Out of sample performance		
	Overview	Seasonality	Asset Expansion Spread	Analyst Revisions Momentum	Post Earnings Announcement Drift	Trading and institutional frictions	Behavioral Economics: Anchoring	Mental accounting	Overconfidence	Availability		Overfitting	Alpha decay	Alpha or Risk?

There are 5 components of trading costs when implementing market neutral equity strategies

1. Bid-ask spread
2. Trading commissions
3. Short borrow costs
4. Financing
5. Market impact

Commissions may not be a large portion of trading costs

- Commissions for equity trades negotiated with prime brokers are usually a function of AUM, strategy turnover and planned leverage.
- There may be different commissions rates for different markets (e.g. USA, EU) and different equity implementations (cash, swaps)
- Note: We only pay trading commissions on turnover, not portfolio holdings

Top 10 Prime Brokers Servicing Hedge Funds, Preqin May 2017

Prime Broker	No. of known hedge funds serviced Preqin May 2017 Special Report on Hedge Fund Service Providers	Publicly disclosed commissions and fees, US exchange traded equities
Goldman Sachs	3051	N/A
Morgan Stanley Prime Brokerage	2712	N/A
JP Morgan	1968	N/A
Credit Suisse Prime Fund Services	1306	N/A
UBS Prime Services	1105	N/A
Deutsche Bank Global Prime Finance	1111	N/A
Bank of America Merrill Lynch	929	N/A
Citi Prime Finance	679	N/A
Barclays	599	N/A
Interactive Brokers	588	Around 1.1 basis points

Sources:
http://docs.preqin.com/reports/Preqin-Special-Report-Hedge-Fund-Service-Providers-May-2017.pdf
https://investors.interactivebrokers.com/download/investors/3Q17-InvestorPresentation.pdf

Short borrow costs are also a function of selected trading universe

Trading universe	Short borrow cost (3Q 2018)
General collateral	35 bps
S&P 500	60 bps (equal weighted)
Russell 1000	82 bps (equal weighted)
Russell 3000	163 bps (equal weighted)

Source: Bloomberg, IHS Markit

Financing rates are only applicable with use of leverage

- Prime brokerage financing rates are generally tied either LIBOR + spread or Fed Funds + spread
- Spread charged by prime broker will likely vary by client AUM, and is usually not publicly disclosed
- Indicative rates of around BM + 0.3% for interactive brokers
- However, financing costs may not be valid reason for quantitative strategies not working, since we can chose not to use leverage

Introduction to market impact

- Market impact refers to how act of trading itself affects shape of supply and demand curves for that instrument
- Price impact is a cost for traders, which they need to control in order to optimize execution
- Short term one day mean reversion is often a result of market impact due to market-on-close (MOC) orders on previous day
- Market impact is likely largest cost of trading, dwarfing commissions, bid-ask spreads, etc
- Market impact is also of concern to securities regulators, because it affects price stability
- It is also the main source of liquidity risk, and is the primary reason for not being able to execute a transaction at the current quoted price

Source: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294498

Market impact may depend most on participation rate and volatility

$$MI = c\sigma\left(\frac{V_{trade}}{\bar{V}}\right)^{\delta}$$

- A commonly used formula for market impact is given, where:
  - c is numerical constant estimated from sample statistics
  - Ratio in braces is participation rate
  - Sigma is daily volatility of stock
  - Exponent is typically between 0.4 and 0.7

Source: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294498

The square root law is often used in academia and the financial industry

$$MI = c\sigma\sqrt{\frac{V_{trade}}{\overline{V}}}$$

- A widely used variant is the "square root impact law", which is strongly supported by the empirical data (e.g. Grinold and Kahn '00)
- This is also consistent with traders' "rule of thumb" where "*transaction cost of volume equal to average one day's volume is roughly one day's price volatility*" (Gatheral '10)

Source: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294498

Recent research has also focused on the impact of trade duration on market impact

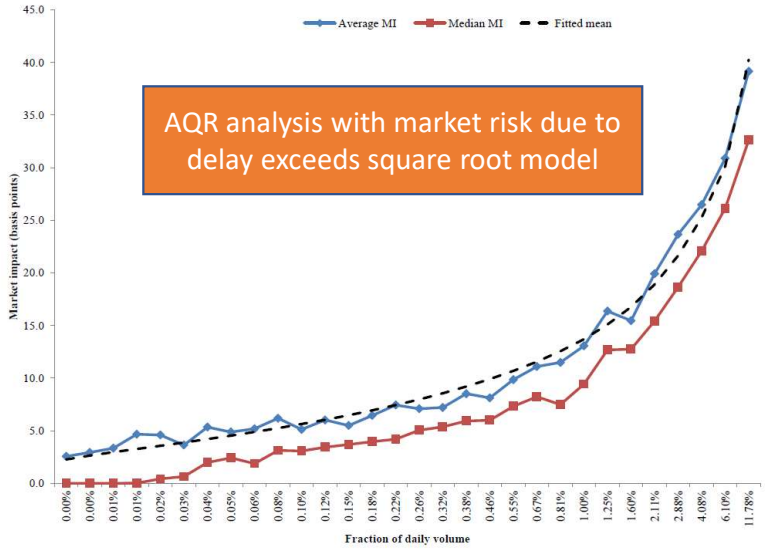
- Trade duration refers to spreading a trade out over a longer period of time, versus executing at a fast rate
- For e.g., in case of a VWAP algorithm, the 'meta-order' is sliced into numerous child orders which are spread over the daily's expected volume profile
- We can unify concepts of execution duration and execution rate by referring to instantaneous participation rate (targeting target size versus average volume at that point of the day)
- Longer execution duration:
  - On one hand, market impact can be reduced by dividing an intended transaction into smaller orders in separate time intervals because instantaneous participation rate is lower
  - On the other hand, information in our executed trades or partial meta order may be used by other market participants
- Some research has shown that for reasonable trading rates (e.g. 1% to 25% of ADV), market impact can be modelled without trade duration (Gatheral '10)

Source: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294498

Spreading out execution duration also increases the risk of market risk

Figure 4
Market Impact by Fraction of Trading Volume

This table shows average Market Impact (MI). We sort all trades in our datasets in 30 bins based on their fraction of daily volume and compute average and median market impact for each bucket. This table includes all available developed market equity transactions (cash equities and equity swaps) in our data between August 1998 and December 2011. Market Impact is in basis points.



AQR analysis with market risk due to delay exceeds square root model

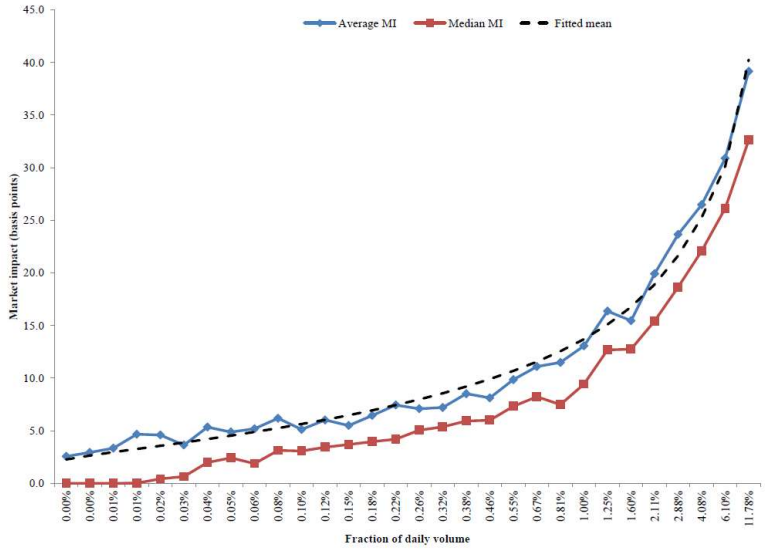
- Participation rate (% ADV traded) in turn depends on following:
  - Choice of trading universe
  - Strategy turnover
  - Portfolio AUM
- Assuming US $1bn AUM, trading universe of S&P 500 and strategy turnover equal to the seasonality strategy from class 3, total market impact costs estimated at 25 bps / year using the curve from Figure 4

Source: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294498

Most have found a square root relationship between participation rate and market impact

Figure 4
Market Impact by Fraction of Trading Volume

This table shows average Market Impact (MI). We sort all trades in our datasets in 30 bins based on their fraction of daily volume and compute average and median market impact for each bucket. This table includes all available developed market equity transactions (cash equities and equity swaps) in our data between August 1998 and December 2011. Market Impact is in basis points.



Source: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294498

- Participation rate (% ADV traded) in turn depends on following:
  - Choice of trading universe
  - Strategy turnover
  - Portfolio AUM
- Assuming US $1bn AUM, trading universe of S&P 500 and strategy turnover equal to the seasonality strategy from lecture 1, total market impact costs estimated at 25 bps / year using the curve from Figure 4

Interpreting asset pricing anomalies with behavioral economics

- Behavioral economics examine **human decision making under bounded rationality**
- This includes **the relationship with financial market inefficiencies**
- The field is starting to mature, with economist Richard Thaler winning the **2017 Nobel Prize for Economic Sciences for his contributions to behavioral economics** and his "**pioneering work in establishing that people are predictably irrational in ways that defy economic theory**"
- Nevertheless, there is considerable debate on validity of behavioral explanations for market anomalies, and **scholars of the field may still be searching for a unified theory**

Non-exhaustive list of common behavioral heuristics

In a behavioral world, decision makers respond to costly information gathering and costly cognition, limited time as well as biological stress by making decisions via **heuristics**

Behavioral heuristic	Notes
Anchoring	Decision making relative to a reference frame rather than based on total utility
Mental accounting	Separating assets into discrete sets and making independent decision on each rather than from portfolio perspective
Overconfidence	Estimating a higher precision for estimates than underlying base rate
Availability	Using readily and easily recallable examples to evaluate concepts or decisions involving entire sets / classes
etc ..	

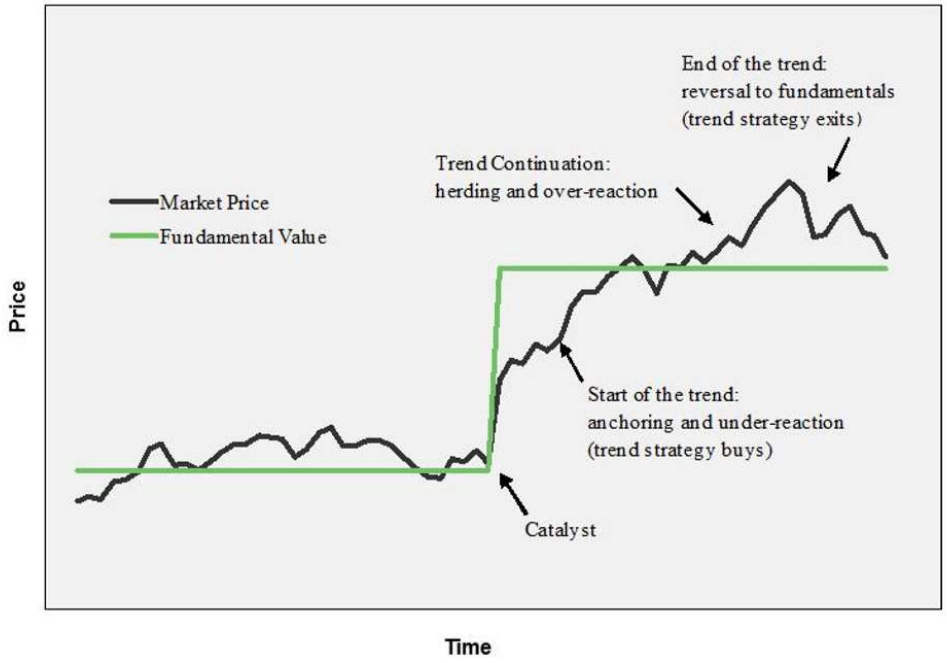
- In this class, we will show how each of the 4 behavioral heuristic listed above may individually explain specific stock return anomalies, including those previously discussed
- The list above is not exhaustive; note that one ongoing criticism of behavioral finance is the need for a unified theory to 'link' the various psychological traits

Psychological biases and market anomalies: a survey

- Investor under-reaction, Prospect theory and mental accounting
  - Momentum in stock prices, strongest amongst small stocks and stocks with low analyst coverage
  - Post earnings announcement drift
- Mental accounting
  - Mean reversion in futures prices
- Overconfidence
  - Mean reversion in prices (Odean 1998), and the size effect
- Availability
  - Link between media attention and stock returns (Barber & Odean 2008)
  - Accrual anomaly
  - Pairs Trading

Momentum strategies can arise from investor underreaction to news

Figure 1. Stylized Plot of the Lifecycle of a Trend.



Source: http://pages.stern.nyu.edu/~lpederse/papers/DemystifyingManagedFutures.pdf

- Investor underreaction occurs when stock prices do not adjust to new fundamentals instantly, but do so over time
- This leads to momentum in stock prices
- Momentum strategies discussed in this course include:
  - "12 months – 1 month" momentum
  - Analyst forecast revisions
  - Post earnings announcement drift

Investor underreaction, prospect theory and anchoring

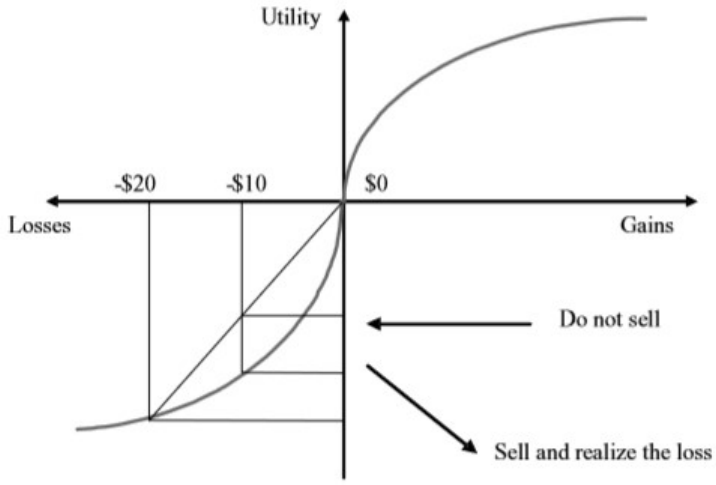


Figure 1. Prospect theory, mental accounting, and the disposition effect: Realize a loss. Assume that an investor purchased one share at $50 and the price is now $40. Suppose that in the next month, the price could go either up $10 or down $10 (with equal probability). The investor must choose between selling the stock now and realizing a paper loss of $10, or keeping the stock in his portfolio. This figure shows the utility gain (loss) of the two alternatives.

Source: Figure 1, FRAZZINI, A. (2006), The Disposition Effect and Underreaction to News. The Journal of Finance, 61: 2017-2046

- In prospect theory, investors derive utility from "gains/losses relative to anchor point", rather than from total wealth
- In addition, marginal gains in utility are highest around 0
- Consequently, investors tend to sell their winning positions quickly, while holding on to losing positions
- For 'rational investor', it would be irrelevant whether position is currently making money or not; what is relevant would be stock's expected returns

Prospect theory and selling gains too quickly, holding on to losses too long

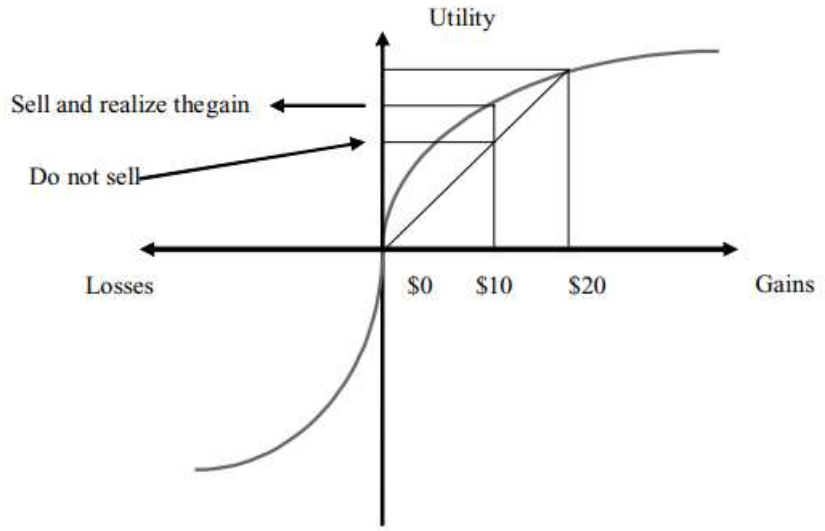


Figure 2. Prospect theory, mental accounting, and the disposition effect: Realize a gain. Assume that an investor purchased one share at $50 and the price is now $60. Suppose that in the next month the price could go either up $10 or down $10 (with equal probability). The investor must choose between selling the stock now and realizing a paper gain of $10, or keeping the stock in his portfolio. This figure shows the utility gain (loss) of the two alternatives.

Source: Figure 2, FRAZZINI, A. (2006), The Disposition Effect and Underreaction to News. The Journal of Finance, 61: 2017-2046

Academic research documents the disposition effect even amongst professional traders

- Locke and Mann (2000) analyze the trading behavior of professional futures traders and find that all traders hold losers longer than winners; the least successful traders hold losers the longest, while the most successful traders hold losers for the least time

- Conval and Shumway (2005) report evidence of loss aversion among professional market markets at the Chicago Board of Trade

- Wermers (2003) show that managers of underperforming funds appear reluctant to sell their losing stocks

Mutual Funds realize gains more frequently than losses, with the effect most pronounced amongst poorly performing mutual funds

Table III

Proportion of Gains Realized to the Aggregate Proportion of Losses Realized, Mutual Funds (1980–2002)

This table compares the aggregate proportion of gains realized (PGR) to the aggregate proportion of losses realized (PLR). PGR (# of shares) is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains. PLR (# of shares) is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. PGR ($ value) is the dollar value of realized gains divided by the dollar value of realized gains plus the dollar value of paper (unrealized) gains. PLR ($ value) is the dollar value of realized losses divided by the dollar value of realized losses plus the dollar value of paper (unrealized) losses. Realized gains, paper gains, realized losses, and paper losses are aggregates across funds from 1980 to 2002. PGR and PLR are reported for the full sample and across mutual funds ranked by the previous year's return. The *t*-statistics test the null hypothesis that the difference in proportions is equal to zero; 5% statistical significance is indicated in bold.

	Fund Return in the Previous Year (Quintiles)					
	1 (Low)	2	3	4	5 (High)	All
# of shares						
PLR	0.112	0.122	0.137	0.158	0.169	0.145
PGR	0.193	0.182	0.188	0.179	0.198	0.176
PGR − *PLR*	**0.081**	**0.060**	**0.051**	**0.021**	**0.029**	**0.031**
t-stat	(24.0)	(25.5)	(23.0)	(17.0)	(10.0)	(43.6)
$ Value						
PLR	0.120	0.138	0.150	0.157	0.154	0.149
PGR	0.183	0.179	0.192	0.188	0.164	0.172
PGR − *PLR*	**0.063**	**0.041**	**0.042**	**0.031**	**0.010**	**0.023**
t-stat	(19.0)	(22.5)	(21.0)	(16.0)	(9.0)	(33.6)

Source: Table III, FRAZZINI, A. (2006), The Disposition Effect and Underreaction to News. The Journal of Finance, 61: 2017-2046

Using SEC mandated mutual funds N30D filings from 1980 to 2002, Frazzini '06 reconstructs mutual funds holdings over time, as well as the cost basis of each mutual fund using FIFO accounting

In the table, aggregate proportion of gains realized (PGR) = realized gains / (realized gains + unrealized gains), with a similar definition for PGL for losses

Table shows even professional money managers are 'anchored' to their cost basis

Why does the disposition effect lead to investor underreaction and stock price momentum?

Case 1: Investors net long

	Good news released for stock	**Bad news released for stock**
Investors have unrealized capital gains	Investors realize capital gains too quickly (under-react to positive news) This in turn leads to positive post announcement drift	-
Investors have unrealized capital losses	-	Investors reluctant to realize losses (under-react to negative news) This in turn leads to negative post-announcement drift

Why does the disposition effect lead to investor underreaction and stock price momentum?

Case 2: Investors net short

	Good news released for stock	**Bad news released for stock**
Investors have unrealized capital gains	-	Investors realize capital gains too quickly (under-react to negative news) This in turn leads to negative post announcement drift
Investors have unrealized capital losses	Investors reluctant to realize losses (under-react to positive news) This in turn leads to positive post-announcement drift	-

Investor behavior can be affected by mental accounting

- Mental accounting refers to the tendency of separating money into different accounts, and make decisions for each account in isolation

- As a result, decision makers do not take a portfolio approach

- Thaler (‘83) gives the following example: "**A few years ago I gave a talk to a group of executives in Switzerland. After the conference my wife and I spent a week visiting the area. At that time the Swiss franc was at an all-time high relative to the US dollar, so the usual high prices in Switzerland were astronomical. My wife and I comforted ourselves that I had received a fee for the talk that would easily cover the outrageous prices for hotels and meals. Had I received the same fee a week earlier for a talk in New York though, the vacation would have been much less enjoyable.**"

Coval and Shumway ('05) study the effects of mental accounting among CBOT proprietary traders

- Coval and Shumway study proprietary traders who account for over 95% of all trades on the Chicago Board of Trade (CBOT) daily
- Each trades on the order of US$ 200 million worth of contracts per day
- Dataset covers every transaction made by these market makers in T-Bonds over a 1 year period, which is over 5 million transacctions
- Each trader is a full-time proprietary trader trading for her own account, and who are not trading to satisfy hedging needs
- CBOT market makers have clear incentives encouraging them to evaluate performance on a daily basis
  1. They receive and review statements at the end of each trading day detailing performance during the day
  2. Most trades are unwound by the end of the day, and traders seldom retain significant positions overnight.
  3. PNL can therefore be attributed to trades executed on that day
  4. Market makers' focus is on reading the order flow, which only conveys short lived signals that carry little advantage from one day to the next
  5. Hence, statements received at close can be viewed as a 'report card' on their day at work

Source: https://deepblue.lib.umich.edu/bitstream/handle/2027.42/115930/jofi723.pdf?sequence=1&isAllowed=y

Competing behavioral hypotheses

- If traders are averse to losses incurred at the daily horizon, they will take fewer risks as they become profitable

- If traders view past trading profits as overly representative of future trading opportunities, or if they are more willing to assume risk when gambling with the 'house's money', they will take greater risks as their profits grow

Dataset covers 426 local traders at CBOT's treasury bond futures pit over 236 full trading days in 1998

Table I
Summary Statistics

This table reports a number of summary statistics for the sample. The sample consists of the trading experience of 426 local traders at the CBOT's Treasury Bond Futures pit over 236 full trading days during 1998. Summary statistics using raw trader data are reported for all trader days. Trader data is normalized by trader for summary statistics of traders with profitable and losing mornings.

Panel A: Statistics by Trader-Day

	Morning			Afternoon		
Variable	Mean	Median	St. Dev.	Mean	Median	St. Dev.
All Trader-Days ($N = 82{,}595$) Raw Data						
Profits	1808.33	750.00	171848.13	661.78	187.50	113964.28
Number of trades	116.62	88.00	105.37	73.25	52.00	72.95
Average trade size	10.03	4.84	19.17	9.35	4.53	18.27
Total dollar risk	9641.46	1150.00	57540.27	10876.76	1242.83	75133.82
Price-setting trades	0.202	0.000	0.514	0.327	0.000	0.643
Traders with Profitable Mornings ($N = 55{,}877$) Normalized by Trader						
Profits	0.467	0.276	0.574	0.095	0.067	0.733
Number of trades	−0.035	−0.159	0.986	−0.066	−0.234	0.980
Average trade size	−0.063	−0.222	0.967	−0.046	−0.213	0.989
Total dollar risk	−0.122	−0.317	0.776	−0.100	−0.335	0.801
Price-setting trades	−0.009	−0.188	0.601	−0.017	−0.128	0.467
Traders with Losing Mornings ($N = 26{,}718$) Normalized by Trader						
Profits	−0.563	−0.273	0.727	0.082	0.067	0.915
Number of trades	0.066	−0.065	1.013	0.124	−0.036	1.016
Average trade size	0.119	−0.081	1.040	0.086	−0.114	1.006
Total dollar risk	0.180	−0.146	0.993	0.141	−0.205	0.997
Price-setting trades	0.018	−0.171	0.619	0.036	−0.116	0.526

Panel B: Statistics by Day

Variable	Mean	St. Dev.	Minimum	Maximum
Afternoon price changes	621.8703	215.383	195.00	1582.00
Fraction with morning losses	0.3238	0.049	0.20	0.50
Fraction of loss-averse traders with losses	0.3305	0.055	0.19	0.50
Fraction of price-setting traders with losses	0.3230	0.051	0.19	0.49

Source: Table 1, https://deepblue.lib.umich.edu/bitstream/handle/2027.42/115930/jofi723.pdf?sequence=1&isAllowed=y

Traders who incurred a loss in the morning trading session are more likely to take greater risks in the afternoon session

Table II

Morning Profits and Afternoon Risk-Taking

This table reports the results of a number of different regressions relating morning profits to afternoon risk-taking by locals at the CBOT. All regressions have the basic form,

$$\mathrm{RISK}^{\wedge}_{i,t} = \alpha + \beta_{\pi}\pi^{\mathrm{M}}_{i,t} + \beta_{I}\left|\mathrm{INV}^{\mathrm{M}}_{i,t}\right| + \beta_{\pi I}\pi^{\mathrm{M}}_{i,t}\cdot\left|\mathrm{INV}^{\mathrm{M}}_{i,t}\right| + \beta_{R}\mathrm{RISK}^{\mathrm{M}}_{i,t} + \varepsilon_{i,t}.$$

The t-statistics are in parentheses. Risk is measured in three different ways, as the number of afternoon trades, the average size of afternoon trades, or the cumulative risk-weighted inventory of each trader. All variables that depend on measures of inventory are Winsorized at the 1 and 99% levels. The standard errors of the fixed-effects PCSE results are allowed to be heteroskedastic and concurrently correlated across locals. In Panel D, only the top (i.e., most profitable) X% of all traders on a given day are included in the regression, where X is the fraction of traders with losses on that day. In Panels A–C, the sample contains 82,595 local-days. In Panel D the sample contains 65,061 local-days.

Method	α	β_{π}	β_{I}	$\beta_{\pi I}$	β_{R}
Panel A: Dependent Variable: Afternoon Number of Trades					
Pooled OLS	0.0187	−0.1349	0.0313	0.056	0.2361
	(4.88)	(−23.38)	(7.26)	(12.99)	(61.66)
FM by trader	0.0315	−0.1173	0.0511	0.058	0.2182
	(2.35)	(−4.62)	(2.35)	(7.49)	(25.7)
FM by date	−0.0143	−0.1874	0.0378	0.0588	0.1499
	(−0.49)	(−27.89)	(7.27)	(10.33)	(23.3)
Fixed effects PCSE	–	−0.1362	0.03395	0.0547	0.2106
	–	(−17.90)	(5.44)	(11.36)	(12.07)
Panel B: Dependent Variable: Afternoon Average Trade Size					
Pooled OLS	0.0098	−0.0691	0.0606	0.0203	0.2159
	(2.53)	(−11.95)	(13.67)	(4.69)	(54.89)
FM by trader	−0.0045	−0.1013	0.0421	0.0227	0.2056
	(−0.27)	(−3.44)	(1.41)	(2.75)	(23.79)
FM by date	0.0095	−0.1076	0.0582	0.0290	0.1726
	(0.65)	(−11.86)	(9.31)	(3.83)	(27.58)
Fixed effects PCSE	–	−0.7061	0.0594	0.0189	0.1964
	–	(−11.16)	(11.70)	(4.18)	(31.28)
Panel C: Dependent Variable: Afternoon Total Dollar Risk					
Pooled OLS	0.0000	−0.0079	0.5802	0.0134	0.3001
	(0.02)	(−3.00)	(195.70)	(6.80)	(98.2)
FM by trader	0.0015	−0.0107	0.6208	0.0170	0.2555
	(1.55)	(−2.41)	(60.93)	(4.27)	(29.81)
FM by date	−0.0007	−0.0161	0.5812	0.0235	0.2868
	(−0.12)	(−3.91)	(63.97)	(4.75)	(39.98)
Fixed effects PCSE	–	−0.0091	0.5794	0.0139	0.2990
	–	(−2.77)	(157.09)	(6.34)	(70.17)
Panel D: Dependent Variable: Afternoon Total Dollar Risk Matched Percentiles of Winners and Losers					
Pooled OLS	−0.0003	−0.0078	0.5925	0.0139	0.2933
	(−0.17)	(−2.83)	(181.63)	(6.75)	(87.31)
FM by trader	−0.0001	−0.0095	0.6342	0.017	0.2501
	(−0.1)	(−2.1)	(61.62)	(4.31)	(28.65)
FM by date	−0.0014	−0.0151	0.593	0.0232	0.2811
	(−0.22)	(−3.57)	(65.03)	(4.64)	(38.8)
Fixed effects PCSE	–	−0.0085	0.5913	0.0143	0.2927
	–	(−2.58)	(147.79)	(6.38)	(63.92)

Source: Table 2, https://deepblue.lib.umich.edu/bitstream/handle/2027.42/115930/jofi723.pdf?sequence=1&isAllowed=y

Inverse relationship between trader profitability and risk taking appear concentrated in the bottom third of traders

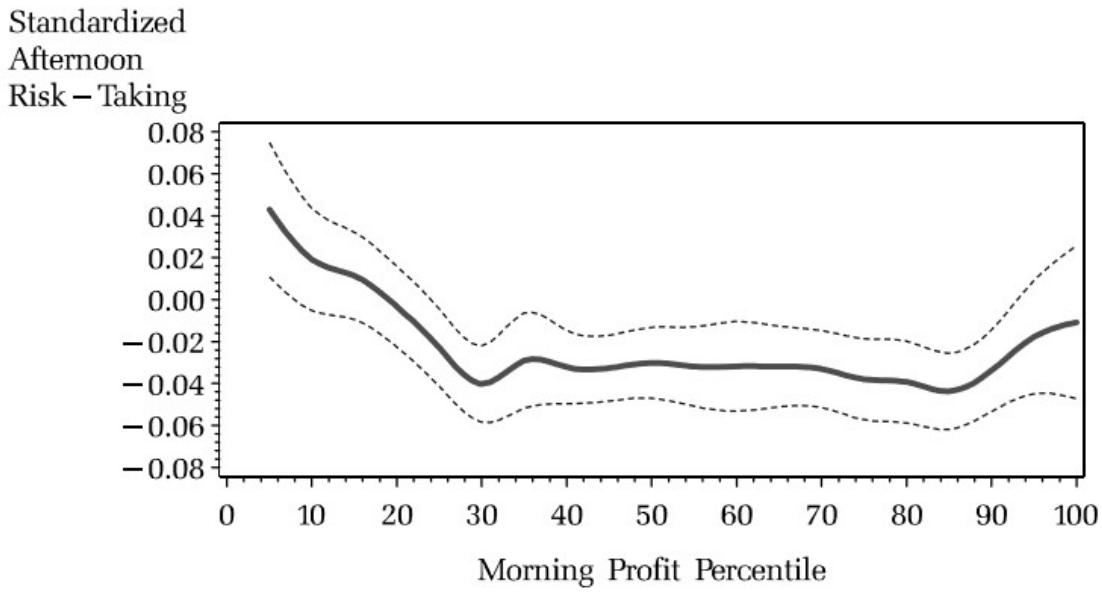


Figure 1. Morning profit percentile and afternoon risk-taking. This figure plots the time-series averages of 236 daily cross-sectional semiparametric regressions of afternoon total dollar risk on morning profit percentile. The regressions are kernel-smoothed and the dashed lines reflect two standard error bands of the time series-averaged regressions.

Source: Figure 1, https://deepblue.lib.umich.edu/bitstream/handle/2027.42/115930/jofi723.pdf?sequence=1&isAllowed=y

Prices set by traders who had losses in the mornings are also more likely to mean revert

Table VII

Price Reversals

This table reports the average price reversals that follow the price-setting trades placed by the traders in our sample. Price reversals are measured as the fraction of the price-setting trade's price change that is reversed during the next 5 minutes. The price-setting trades are divided according to the price path sequence leading up to the trade. The first column identifies the price path sequence of the last four trades, with C denoting a continuation and R denoting a reversal. For example, if one of our traders places the final trade in the sequence 25-24-25-26, this would be included in the category RC. Price-setting trades are further divided according to whether the trade resulted in an expanded or contracted inventory for the trader and whether or not the trader experienced a morning loss. Differences between the price reversals that follow price-setting trades of traders with morning losses and those with no morning loss are recorded in columns 4 and 7. The t-statistics are in parentheses.

Five-Minute Price Changes in Ticks

	Contracting			Expanding		
Price Path	Loss	No Loss	Diff.	Loss	No Loss	Diff.
CC	2.0000	2.0211	−0.0211	3.5411	1.5040	2.0371
	(3.3)	(5.7)	(0.0)	(4.4)	(2.2)	(1.9)
RC	2.0365	1.8333	0.2032	2.5165	1.9667	0.5498
	(16.1)	(21.0)	(1.3)	(15.5)	(22.6)	(3.0)
CR	0.8141	0.6806	0.1334	0.8211	0.6883	0.1328
	(9.2)	(10.4)	(1.2)	(7.0)	(11.2)	(1.0)
RR	0.6640	0.7350	−0.0710	0.8461	0.6950	0.1510
	(19.7)	(27.2)	(−1.6)	(20.3)	(28.9)	(3.1)
Average	0.8035	0.8166	−0.0131	1.0122	0.7967	0.2155
	(25.7)	(33.8)	(−0.3)	(25.4)	(35.6)	(4.7)

Source: Table 7, https://deepblue.lib.umich.edu/bitstream/handle/2027.42/115930/jofi723.pdf?sequence=1&isAllowed=y

Mental accounting and mean reversion

- Table VII shows that prices set by traders with morning losses are reversed much more dramatically than those set by traders with morning gains
- Average trader with morning losses place around 25% more price setting trades than trader with morning gains
- Traders with morning losses experience price reversals that are 27% larger than reversals of other traders
- Trades of losing traders have only a temporary impact on prices, other traders in the pit appear to regard them as noise trades and trade against them
- The differences are only pronounced for traders expanding their positions
- Limits to arbitrage do not appear to delay the elimination of behaviorally induced mispricing in this market

Overconfidence may also influence trades by market participants

- It is difficult to reconcile observed trading volume in equity markets with trading by rational investors
- Theoretical models predict overconfident investors trade excessively
- Barber and Odean (’01) test this prediction by partitioning investors on gender in an attempt to separate into those more and those less prone to over confidence
- This is based on psychological research showing men are more overconfident than women

Source: http://faculty.haas.berkeley.edu/odean/Papers/gender/BoysWillBeBoys.pdf

"Psychologists find that in areas such as finance, men are more overconfident than women"

- Lundeberg, Fox and Puncochar '94 find that men are generally more overconfident than women, although gender differences in overconfidence are highly task dependent
- In a survey conducted by Gallup for PaineWebber between 1998 and 2000, respondents were asked
  - "What overall rate of return do you expect to get on your portfolio in the NEXT twelve months?"
  - "Thinking about the stock market more generally, what overall rate of return do you think the stock market will provide investors during the coming twelve months?"
  - On average, both men and women expected their own portfolios to outperform the market. However, men expected to outperform by 2.8 percent while women expected to outperform by 2.1%

Barber and Odean test the following 2 hypotheses

- H1: Men trade more than women
- H2: By trading more, men hurt their performance more than do women

Data and methodology

TABLE I

DESCRIPTIVE STATISTICS FOR DEMOGRAPHICS OF FEMALE AND MALE HOUSEHOLDS

	All households			Married households			Single households		
Variable	Women	Men	Difference (women–men)	Women	Men	Difference (women–men)	Women	Men	Difference (women—men)
Panel A: Infobase data									
Number of households	8,005	29,659	NA	4,894	19,741	NA	2,306	6,326	NA
Percentage married	68.0	75.7	−7.7						
Percentage with children	25.2	32.2	−7.0	33.6	40.4	−6.8	10.6	10.5	0.1
Mean age	50.9	50.3	0.6	49.9	51.1	−1.2	53.0	48.2	4.8
Median age	48.0	48.0	0.0	48.0	48.0	0.0	50.0	46.0	4.0
Mean income ($000)	73.0	75.6	−2.6	81.2	79.6	1.6	56.7	62.8	−6.1
% with income > $125,000	11.2	11.7	−0.5	14.2	13.0	1.2	5.9	7.4	−1.5
Panel B: Self-reported data									
Number of households	2,637	11,226		1,707	7,700		652	2,184	
Net worth ($000)									
90th Percentile	500.0	500.0	0.0	500.0	500.0	0.0	350.0	450.0	−100.0
75th Percentile	200.0	250.0	−50.0	250.0	250.0	0.0	175.0	200.0	−25.0
Median	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
25th Percentile	60.0	74.5	−14.5	62.5	74.5	−12.0	40.0	62.0	−22.0
10th Percentile	27.0	37.0	−10.0	35.0	37.0	−2.0	20.0	35.0	−15.0
Equity to net worth (%)									
Mean	13.3	13.2	0.1	12.9	12.9	0.0	14.4	14.3	0.1
Median	6.7	6.7	0.0	6.3	6.6	−0.3	7.9	7.4	0.5
Investment experience (%)									
None	5.4	3.4	2.0	4.7	3.4	1.3	7.4	3.0	4.4
Limited	46.8	34.1	12.7	44.9	34.2	10.7	52.6	33.3	19.3
Good	39.1	48.5	−9.4	40.8	48.5	−7.7	33.3	48.8	−15.5
Extensive	8.7	14.0	−5.3	9.6	13.9	−4.3	6.7	14.9	−8.2

The sample consists of households with common stock investment at a large discount brokerage firm for which we are able to identify the gender of the person who opened the household's first account. Data on marital status, children, age, and income are from Infobase Inc. as of June 1997. Self-reported data are information supplied to the discount brokerage firm at the time the account is opened by the person on opening the account. Income is reported within eight ranges, where the top range is greater than $125,000. We calculate means using the midpoint of each range and $125,000 for the top range. Equity to Net Worth (%) is the proportion of the market value of common stock investment at this discount brokerage firm as of January 1991 to total self-reported net worth when the household opened its first account at this brokerage. Those households with a proportion equity to net worth greater than 100 percent are deleted when calculating means and medians. Number of observations for each variable is slightly less than the number of reported households.

Source: Table 1, http://faculty.haas.berkeley.edu/odean/Papers/gender/BoysWillBeBoys.pdf

- Primary data set is information from a large discount brokerage firm on the investments of 78,000 households for 6 years ending Dec 1996
- Authors focus on the common stock investments of the 38,664 households for which they are able to identify gender of the person who opened the account

Total trading costs paid by each investor is computed to estimate the effect of 'over trading'

Total trading costs = bid-ask spread component of transactions costs + commissions

Where bid-ask spread component of transactions costs for sales and purchases are respectively:

$$spr_{d_s} = \left(\frac{P^{cl}_{d_s}}{P^{s}_{d_s}} - 1\right), \text{ and } spr_{d_b} = -\left(\frac{P^{cl}_{d_b}}{P^{b}_{d_b}} - 1\right).$$

Commissions are calculated to be the dollar value of the commission paid scaled by total principal value of the transaction

Average purchase costs an investor 0.31% while average sale costs an investor 0.69% in bid-ask spread

Value weighted average purchase cost 0.77% in commissions while the average sale cost 0.66%

Portfolio's traded by men show nearly 3 pct pts higher monthy turnover

TABLE II

POSITION VALUE, TURNOVER, AND RETURN PERFORMANCE OF COMMON STOCK INVESTMENTS OF FEMALE AND MALE HOUSEHOLDS: FEBRUARY 1991 TO JANUARY 1997

	All households			Married households			Single households		
	Women	Men	Difference (women–men)	Women	Men	Difference (women–men)	Women	Men	Difference (women–men)
Number of households	8,005	29,659	NA	4,894	19,741	NA	2,306	6,326	NA
Panel A: Position Value and Turnover									
Mean [median] beginning position value ($)	18,371 [7,387]	21,975 [8,218]	−3,604*** [−831]***	17,754 [7,410]	22,293 [8,175]	−4,539*** [−765]***	19,654 [7,491]	20,161 [8,097]	−507*** [−606]***
Mean [median] monthly turnover (%)	4.40 [1.74]	6.41 [2.94]	−2.01*** [−1.20]***	4.41 [1.79]	6.11 [2.81]	−1.70*** [1.02]***	4.22 [1.55]	7.05 [3.32]	−2.83*** [−1.77]***
Panel B: Performance									
Own-benchmark monthly abnormal gross return (%)	−0.041*** (−2.84)	−0.069*** (−3.66)	0.028*** (2.43)	−0.050*** (−2.89)	−0.068*** (−3.67)	0.018 (1.28)	−0.029* (−1.64)	−0.074*** (−3.60)	0.045*** (2.53)
Own-benchmark monthly abnormal net return (%)	−0.143*** (−9.70)	−0.221*** (−10.83)	0.078*** (6.35)	−0.154*** (−9.10)	−0.214*** (−10.48)	0.060*** (3.95)	−0.121*** (−6.68)	−0.242*** (−11.15)	0.120*** (6.68)

***, **, * indicate significant at the 1, 5, and 10 percent level, respectively. Tests for differences in medians are based on a Wilcoxon sign-rank test statistic.

Households are classified as female or male based on the gender of the person who opened the account. Beginning position value is the market value of common stocks held in the first month that the household appears during our sample period. Mean monthly turnover is the average of sales and purchase turnover. [Median values are in brackets.] Own-benchmark abnormal returns are the average household percentage monthly abnormal return calculated as the realized monthly return for a household less the return that would have been earned if the household had held the beginning-of-year portfolio for the entire year (i.e., the twelve months beginning February 1). *T*-statistics for abnormal returns are in parentheses and are calculated using time-series standard errors across months.

Source: Table 2, http://faculty.haas.berkeley.edu/odean/Papers/gender/BoysWillBeBoys.pdf

"Own-benchmark" refers to performance if start of year portfolio was held for entire year without rebalancing

Relative turnover and return results from summary statistics are robust to controls in cross sectional regressions

TABLE III

CROSS-SECTIONAL REGRESSIONS OF TURNOVER, OWN-BENCHMARK ABNORMAL RETURN, BETA, AND SIZE: FEBRUARY 1991 TO JANUARY 1997

Dependent variable	Mean monthly turnover (%)	Own-benchmark abnormal net return	Portfolio volatility	Individual volatility	Beta	Size coefficient
Intercept	6.269***	−0.321***	11.466***	11.658***	1.226+	0.776***
		(−11.47)	(58.85)	(70.98)	(11.44)	(22.16)
Single	0.483***	0.002	0.320***	0.330***	0.020**	0.079***
	(4.24)	(0.14)	(3.40)	(4.17)	(2.12)	(4.65)
Woman	−1.461***	0.058***	−0.689***	−0.682***	−0.037***	−0.136***
	(−12.76)	(4.27)	(−7.27)	(−8.54)	(−3.91)	(−8.00)
Single × woman	−0.733***	0.027	−0.439**	−0.540***	−0.029	−0.138***
	(−3.38)	(1.08)	(−2.45)	(−3.57)	(−1.60)	(−4.30)
Age/10	−0.311***	0.002***	−0.536***	−0.393***	−0.027***	−0.055***
	(−9.26)	(4.23)	(−19.31)	(−16.78)	(−9.55)	(−11.00)
Children	−0.037	0.008	−0.014	−0.051	−0.002	−0.008
	(−0.40)	(0.76)	(−0.19)	(−0.79)	(−0.22)	(−0.61)
Income /1000	−0.002	0.0002	0.0003	0.001	0.003	0.001
	(−1.30)	(1.33)	(0.22)	(1.38)	(2.49)**	(0.31)
Income dummy	−0.0003	0.027	0.011	0.012	−0.008	−0.018
	(−0.24)	(1.54)	(0.10)	(0.11)	(−0.68)	(−0.82)
Adj. R^2 (%)	1.53	0.20	2.11	1.95	0.59	1.19

***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.
+ indicates significantly different from one at the 1 percent level.

Each regression is estimated using data from 26,618 households. The dependent variables are the mean monthly percentage turnover for each household, the mean monthly own-benchmark abnormal net return for each household, the portfolio volatility for each household, the average volatility of the individual common stocks held by each household, estimated beta exposure for each household, and estimated size exposure for each household. Own-benchmark abnormal net returns are calculated as the realized monthly return for a household less the return that would have been earned if the household had held the beginning-of-year portfolio for the entire year. Portfolio volatility is the standard deviation of each household's monthly portfolio returns. Individual volatility is the average standard deviation of monthly returns over the previous three years for each stock in a household's portfolio. The average is weighted equally across months and by position size within months. The estimated exposures are the coefficient estimates on the independent variables from time-series regressions of the gross household excess return on the market excess return ($R_{mt} - R_{ft}$) and a zero-investment size portfolio (SMB_t). Single is a dummy variable that takes a value of one if the primary account holder (PAH) is single. Woman is a dummy variable that takes a value of one if the primary account holder is a woman. Age is the age of the PAH. Children is a dummy variable that takes a value of one if the household has children. Income is the income of the household and has a maximum value of $125,000. When Income is at this maximum, Income dummy takes on a value of one. (t-statistics are in parentheses.)

Source: Table 3, http://faculty.haas.berkeley.edu/odean/Papers/gender/BoysWillBeBoys.pdf

Estimated dummy variable on gender is highly significant (t = -12.76) in column 2 of Table III

This indicates monthly turnover in married women's accounts is 146 b.p. less than married men's

Differential on returns are robust to a risk based explanation

TABLE IV

RISK EXPOSURES AND RISK-ADJUSTED RETURNS OF COMMON STOCK INVESTMENTS OF FEMALE AND MALE HOUSEHOLDS: FEBRUARY 1991 TO JANUARY 1997

	All households			Married households			Single households		
	Women	Men	Difference (women–men)	Women	Men	Difference (women–men)	Women	Men	Difference (women–men)
Number of households	8,005	29,659	NA	4,894	19,741	NA	2,306	6,326	NA
Panel A: Gross average household percentage monthly returns									
Two-factor model intercept	−0.044	−0.083	0.039	−0.051	−0.082	0.031	−0.036	−0.099	0.063
Two-factor model coefficient estimate on $(R_{mt} - R_{ft})$	1.050***	1.081***	−0.031**	1.053***	1.075***	0.022*	1.035***	1.088***	0.053***
Two-factor model coefficient estimate on SMB_t	0.360***	0.519***	−0.159***	0.380***	0.490***	0.109***	0.307***	0.582***	0.275***
Adjusted R^2	93.8	92.0	65.3	93.4	92.1	52.8	94.4	91.5	70.6
Panel B: Net average household percentage monthly returns									
Two-factor model intercept	−0.162*	−0.253**	0.091***	−0.171**	−0.245**	0.074**	−0.142**	−0.285**	0.143***

***, **, * indicate significant at the 1, 5, and 10 percent level, respectively.

Households are classified as female or male based on the gender of the person who opened the account. Households are classified as married or single based on the marital status of the head of household. Coefficient and intercept estimates for the two-factor model are those from a time-series regression of the gross (net) average household excess return on the market excess return $(R_{mt} - R_{ft})$ and a zero-investment size portfolio (SMB_t): $(RM_t^{gr} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + \epsilon_{it}$.

Source: Table 4, http://faculty.haas.berkeley.edu/odean/Papers/gender/BoysWillBeBoys.pdf

Differences between gender portfolios are clear using 'net returns' but not 'gross returns', indicating overtrading and trading costs play a role in explaining differences

“Availability” and the buying behavior of individual and institutional investors

- The “availability heuristic” is a decision making shortcut that relies on immediately and conveniently recallable information

- In Tversky & Kahneman's first examination of availability heuristics, subjects were asked, "**If a random word is taken from an English text, is it more likely that the word starts with a K, or that K is the third letter?" They argue that English-speaking people would immediately think of many words that begin with the letter "K" (kangaroo, kitchen, kale), but that it would take a more concentrated effort to think of any words in which "K" is the third letter (acknowledge, ask). Results indicated that participants overestimated the number of words that began with the letter "K" and underestimated the number of words that had "K" as the third letter. Tversky and Kahneman concluded that people answer questions like these by comparing the availability of the two categories and assessing how easily they can recall these instances. In other words, it is easier to think of words that begin with "K", more than words with "K" as the third letter. Thus, people judge words beginning with a "K" to be a more common occurrence. In reality, however, a typical text contains twice as many words that have "K" as the third letter than "K" as the first letter. There are three times more words with "K" in the third position than words that begin with "K".**[8]

Availability implies that stocks with more media attention may see greater investor interest

- Barber and Odean ('05) find that individual investors are net buyers of attention grabbing stocks
  - Stocks in the news
  - Stocks experiencing high abnormal trading volume
  - Stocks with extreme one day returns
- Attention-based buying results from the difficulty that investors have searching the thousands of stocks they can potentially buy
- Stocks bought by individual investors on high-attention days tend to underperform those sold by those investors

Source: http://finpko.faculty.ku.edu/myssi/FIN938/Barber%20%26%20Odean.all%20that%20glitters.WP_2005.pdf

Barber and Odean ('05) track investor behavior via the following 4 datasets

- Investor trading data from a large discount brokerage firm, including trading and position records for the investments of 78,000 households from Jan 91 to Dec 96.
- Sampled households were required to have an open account with the discount brokerage during 1991
- Average buy trade was $11,205 and average sell trade was $13,707

- Information from a smaller discount brokerage firm
- Firm emphasizes high quality trade execution and is likely to appeal to more sophisticated and active investors
- Includes daily trading records from Jan 96 to Jun 99
- Includes 14667 accounts
- Average buy trade of $55,077 and average sell trade of $55,999

- Information from a large retail brokerage firm on investments of households for the 30 months ending in June 1999
- 665,533 investors with at least one common stock trade during sample period
- Average buy trade of $14,209 and average sell trade of $21,169

- Data compiled by the Plexus Group including daily trading records for 43 institutional money managers from Jan 93 to Mar 96
- Managers are classified as momentum, value and diversified
- Average trade sizes between $500,000 to $1 million

Less than 1% of retail investors engaging in short selling; position entry is overwhelmingly via long positions

Stocks experiencing 'attention grabbing events' are selected in 3 ways

Volume Sorts

On days where a stock experiences abnormally heavy volume, it is likely that investors are paying more attention to it than usual

Abnormal trading volume = Vit / ADV (i,t, 252)

Stocks are grouped into 10 deciles using abnormal trading volume

Return Sorts

Investors are likely to notice when stocks have extreme one day returns. Such returns will often be associated with news about the firm

Stocks are assigned to 10 deciles based on t-1 returns in CRSP. Decile 1 and 10 (lowest and highest returns respectively) are further split into 2 vingtiles

News Sorts

Firms that are in the news are more likely to catch investors' attention than those which are not

Using daily news feed from Dow Jones News Service, partition stocks into those for which there is a news story that day and those for which there is no news. On average, 91% of stock-days have no news

Buy-sell imbalance is further computed for each partition of stock

$$BSI_{pt} = \frac{\sum_{i=1}^{n_{pt}} NB_{it} - \sum_{i=1}^{n_{pt}} NS_{it}}{\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NS_{it}} \qquad (3)$$

where n_{pt} is the number of stocks in partition p on day t, NB_{it} the number of purchases of stock i on day t, and NS_{it} the number of sales of stock i on day t. We calculate the time series mean of the daily buy-sell imbalance (BSI_{pt}) for the days that we have trading data for each investor type. Note that throughout the paper our measure of buy-sell imbalance considers only executed trades; limit orders are counted if and when they execute. If there are fewer than five trades in a partition on a particular day, that day is excluded from the time series average for that partition. We also calculate buy-sell imbalances based on the value rather than number of trades by substituting in the value of the stock i bought (or sold) on day t for NB_{it} (or NS_{it}) in equation 3. Note that while total buys and sells increase as volume increases, on a value weighted basis, aggregate buys and sells will increase equally. Thus aggregate value weighted (executed) buy-sell imbalance remains zero as abnormal volume increases, and how the buy-sell imbalance of a particular investor group changes with volume is an empirical question.

Source: http://finpko.faculty.ku.edu/myssi/FIN938/Barber%20%26%20Odean.all%20that%20glitters.WP_2005.pdf

BSI for stocks grouped by abnormal volume

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1 (lowest volume)	-18.15	-16.28	-25.26	-21.26	-20.49	-22.70	14.68	13.74	34.57	33.99	12.52	17.10
	(0.98)	(1.37)	(2.11)	(1.60)	(3.41)	(3.88)	(1.76)	(2.26)	(5.54)	(6.45)	(2.42)	(2.91)
2	-8.90	-11.32	-18.78	-20.63	-10.31	-11.02	12.13	11.09	15.20	13.63	14.87	15.06
	(0.65)	(0.98)	(1.23)	(1.30)	(2.30)	(2.47)	(1.07)	(1.44)	(2.35)	(2.91)	(1.62)	(1.97)
3	-6.23	-9.49	-15.16	-19.59	-6.95	-7.76	11.38	10.35	10.95	8.43	15.83	11.84
	(0.52)	(0.84)	(1.18)	(1.18)	(1.47)	(1.90)	(0.85)	(1.15)	(1.49)	(1.93)	(1.28)	(1.65)
4	-2.76	-8.70	-10.11	-20.07	-4.92	-5.91	12.19	11.89	10.02	4.37	14.92	8.23
	(0.45)	(0.73)	(0.99)	(1.29)	(1.17)	(1.56)	(0.81)	(1.07)	(1.23)	(1.61)	(1.09)	(1.50)
5	-0.76	-7.24	-4.82	-17.38	-4.06	-6.80	12.62	12.24	10.90	6.51	13.41	3.97
	(0.42)	(0.67)	(1.03)	(1.37)	(0.77)	(1.34)	(0.72)	(0.94)	(1.10)	(1.38)	(0.96)	(1.28)
6	1.65	-7.33	0.23	-16.23	-1.86	-3.33	13.54	13.95	8.73	0.31	12.58	3.31
	(0.42)	(0.64)	(1.01)	(1.17)	(0.81)	(1.05)	(0.70)	(0.92)	(1.03)	(1.32)	(0.90)	(1.23)
7	5.45	-2.87	6.69	-13.80	-0.05	-2.58	12.47	13.17	7.25	-0.61	10.99	-0.61
	(0.43)	(0.63)	(1.03)	(1.19)	(0.74)	(0.96)	(0.65)	(0.85)	(0.97)	(1.28)	(0.82)	(1.11)
8	9.20	-1.10	13.53	-7.92	1.43	-2.11	11.60	12.11	8.93	1.30	10.80	-0.19
	(0.41)	(0.62)	(1.14)	(1.16)	(0.79)	(0.86)	(0.64)	(0.87)	(0.95)	(1.25)	(0.84)	(1.21)
9	13.62	2.86	19.82	-2.02	5.78	1.36	11.33	8.90	7.83	1.09	11.11	3.47
	(0.43)	(0.62)	(1.27)	(1.21)	(0.62)	(0.91)	(0.62)	(0.93)	(1.01)	(1.40)	(0.89)	(1.32)
10a	17.72	6.97	22.25	2.62	8.90	3.67	10.84	7.57	7.72	6.38	11.04	5.58
	(0.51)	(0.75)	(1.46)	(1.24)	(0.83)	(1.07)	(0.81)	(1.22)	(1.46)	(2.04)	(1.20)	(1.93)
10b (highest volume)	29.50	17.67	19.34	2.02	17.31	11.78	6.72	-0.55	4.83	4.15	8.12	7.23
	(0.49)	(0.73)	(1.71)	(1.84)	(0.98)	(1.03)	(0.82)	(1.34)	(1.79)	(2.44)	(1.37)	(2.22)

Source: http://finpko.faculty.ku.edu/myssi/FIN938/Barber%20%26%20Odean.all%20that%20glitters.WP_2005.pdf

BSI for stocks grouped by extreme returns

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1a (Negative Return)	29.4 (0.61)	29.1 (0.87)	25.79 (1.60)	22.89 (1.43)	17.32 (1.04)	14.9 (1.43)	-21.03 (1.32)	-30.45 (1.83)	17.26 (3.13)	20.09 (3.41)	10.91 (2.43)	18.08 (2.88)
1b	19.2 (0.54)	16.2 (0.82)	17.86 (1.43)	11.46 (1.57)	11.2 (1.04)	8.58 (1.46)	-6.43 (1.05)	-19.21 (1.56)	14.03 (2.33)	15.62 (2.72)	13.82 (1.75)	15.31 (2.37)
2	13.7 (0.42)	8.8 (0.64)	13.73 (1.17)	5.47 (1.00)	8.65 (0.74)	3.51 (1.20)	-0.62 (0.73)	-14.58 (1.04)	11.19 (1.27)	11.01 (1.73)	14.18 (1.04)	10.47 (2.33)
3	8.9 (0.45)	3.1 (0.63)	6.60 (1.18)	-5.01 (1.09)	3.77 (0.76)	1.23 (1.23)	5.10 (0.71)	-3.72 (0.96)	10.23 (1.06)	7.68 (1.44)	12.30 (0.92)	4.75 (1.29)
4	3.9 (0.45)	-3.3 (0.64)	1.72 (1.06)	-10.98 (1.07)	1.69 (0.84)	-2.75 (1.31)	8.91 (0.76)	4.64 (1.00)	7.98 (0.99)	2.22 (1.34)	11.68 (0.90)	3.04 (1.26)
5	4.1 (0.41)	-3.6 (0.61)	-4.37 (0.95)	-14.36 (0.88)	-0.6 (0.89)	-3.68 (1.40)	9.84 (0.86)	7.02 (1.24)	9.20 (1.29)	3.69 (1.74)	11.56 (1.11)	2.62 (1.63)
6	3.7 (0.42)	-4.2 (0.62)	-3.95 (1.00)	-14.98 (0.95)	-0.99 (0.82)	-3.68 (1.38)	11.07 (0.93)	8.97 (1.28)	9.03 (1.81)	3.52 (2.22)	18.12 (1.34)	9.62 (1.92)
7	2.0 (0.44)	-7 (0.64)	-0.07 (0.91)	-15.23 (1.12)	-1.77 (0.82)	-3.29 (1.28)	15.56 (0.75)	16.36 (0.99)	10.61 (1.18)	1.77 (1.55)	15.39 (0.96)	4.18 (1.36)
8	1.8 (0.42)	-8.6 (0.62)	2.21 (0.84)	-15.85 (0.98)	-1.53 (0.82)	-4.0 (1.27)	19.31 (0.74)	25.22 (0.99)	7.92 (1.06)	0.96 (1.45)	14.00 (0.88)	1.10 (1.30)
9	6.7 (0.43)	-4.8 (0.62)	6.54 (0.88)	-12.80 (1.08)	0.55 (0.73)	-0.79 (1.13)	22.69 (0.69)	32.44 (0.93)	4.30 (1.21)	-6.06 (1.66)	12.99 (1.02)	-1.70 (1.55)
10a	13.4 (0.51)	3.2 (0.78)	6.58 (0.90)	-11.24 (1.17)	1.17 (0.96)	-2.93 (1.41)	24.04 (0.93)	34.75 (1.37)	-4.16 (2.14)	-12.66 (2.57)	10.23 (1.58)	-3.98 (2.24)
10b (Positive Return)	24 (0.52)	11.1 (0.81)	9.01 (0.91)	-7.93 (1.11)	3.8 (0.84)	-3.59 (1.20)	21.50 (1.28)	36.37 (1.74)	-17.32 (3.14)	-16.83 (3.41)	7.57 (2.30)	-0.60 (2.81)

Source: http://finpko.faculty.ku.edu/myssi/FIN938/Barber%20%26%20Odean.all%20that%20glitters.WP_2005.pdf

BSI for stocks grouped by news event

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
Partition	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
Panel A: All Days												
News	9.35	0.07	16.17	-2.36	6.76	1.87	13.38	14.00	6.36	-0.24	6.21	2.26
	(0.72)	(0.86)	(1.29)	(1.32)	(0.48)	(0.72)	(1.33)	(1.71)	(1.59)	(2.05)	(1.11)	(1.50)
No News	2.70	-5.62	-1.84	-14.59	-0.66	-4.87	12.20	10.43	10.96	3.62	7.26	1.24
	(0.43)	(0.63)	(0.87)	(0.87)	(0.58)	(1.23)	(1.11)	(1.16)	(1.37)	(1.49)	(0.97)	(0.84)
Panel B: Positive Return Days												
News	1.74	-9.25	14.07	-7.74	1.14	-3.13	22.70	31.95	5.87	-1.01	7.80	3.92
	(0.94)	(1.07)	(1.04)	(1.25)	(0.64)	(0.95)	(1.50)	(2.10)	(1.94)	(2.65)	(1.31)	(2.00)
No News	-2.51	-14.31	1.76	-13.90	-4.49	-8.41	22.39	25.64	14.20	6.67	8.95	6.66
	(0.54)	(0.79)	(0.88)	(1.00)	(0.79)	(1.40)	(1.31)	(1.46)	(1.51)	(1.74)	(1.05)	(1.05)
Panel C: Negative Return Days												
News	17.39	10.91	15.59	3.17	13.77	9.32	3.94	-7.39	4.29	-2.41	4.72	2.24
	(0.83)	(1.12	(1.58)	(1.43)	(0.71)	(1.08)	(1.43)	(2.11)	(2.09)	(2.77)	(1.30)	(2.25)
No News	8.86	3.85	-3.38	-13.57	4.35	1.29	0.68	-8.60	6.92	1.60	5.58	-4.11
	(0.53)	(0.81)	(0.88)	(0.85)	(0.77)	(1.42)	(1.25)	(1.46)	(1.52)	(1.89)	(1.03)	(1.23)
Panel C: Zero Return Days												
News	1.41	-5.90	-0.44	-8.74	1.58	-1.22	14.12	15.16	11.37	9.59	5.21	1.62
	(1.76)	(2.31)	(0.94)	(1.45)	(2.25)	(2.68)	(2.35)	(3.19)	(3.44)	(4.35)	(2.47)	(3.68)
No News	-0.95	-6.40	-14.49	-18.24	-3.27	-7.95	14.60	12.86	10.65	2.42	8.36	-0.17
	(0.68)	(1.13)	(1.06)	(1.08)	(1.35)	(2.04)	(1.38)	(1.81)	(1.73)	(2.49)	(1.27)	(1.84)

Source: http://finpko.faculty.ku.edu/myssi/FIN938/Barber%20%26%20Odean.all%20that%20glitters.WP_2005.pdf

Stocks that are bought due to 'high attention reasons' underperform

Sorting on the Current Day's Abnormal Trading Volume —Combined (2/91 to 6/99)

Abnormal Volume Sort Decile	Market-adjusted Return	*t-statistic*	Four-factor Alpha	*t-statistic*
1 (Lo)	0.037	0.080	0.029	0.060
2	-0.063	-0.300	-0.036	-0.150
3	0.170	1.010	0.100	0.570
4	0.271	2.040	0.319	2.370
5	-0.020	-0.160	0.026	0.210
6	0.093	0.890	0.064	0.610
7	0.062	0.630	0.075	0.760
8	0.026	0.250	0.043	0.390
9	-0.176	-1.440	-0.195	-1.450
10 (High)	-0.683	-4.130	-0.690	-3.830

Panel B. Difference in Percentage Return to Purchase and Sales Portfolios formed after Sorting on the Previous Day's Return—Combined (2/91 to 6/99)

Return Sort Decile	Market-adjusted Return	*t-statistic*	Four-factor Alpha	*t-statistic*
1 (Negative Return)	-0.338	-1.950	-0.332	-1.770
2	-0.150	-1.420	-0.104	-0.910
3	0.012	0.120	0.010	0.090
4	0.218	1.960	0.250	2.290
5	0.146	0.970	0.178	1.090
6	0.204	1.540	0.267	1.970
7	0.198	2.150	0.209	2.320
8	0.067	0.670	0.079	0.820
9	-0.105	-1.010	-0.116	-1.180
10 (Positive Return)	-0.427	-3.370	-0.510	-3.790

Source: http://finpko.faculty.ku.edu/myssi/FIN938/Barber%20%26%20Odean.all%20that%20glitters.WP_2005.pdf

Attention based buying patterns do not generate superior returns

- Individual investors display attention based buying behavior, while institutional investors do not
- There is strong empirical support for the conclusion that when investors purchasing decisions are influenced by attention, the stocks they buy will subsequently underperform those that they sell

More examples of trading that may be related to "availability"

TECH INDUSTRY

Pets.com latest high-profile dot-com disaster

The online pet store known for its popular sock puppet spokesdog is shutting down its retail operations and laying off 255 employees.

Pets.com is shutting down its retail operations and laying off hundreds of employees, the company said Tuesday.

The Amazon.com-backed company was the leading online pet store and was known for its wildly popular sock puppet spokesdog. The San Francisco-based company said it would sell off its assets, including its catchy URL and the rights to the sock puppet icon.

"I am deeply saddened by this event," chief executive Julie Wainwright said in a statement.

The company said in a notice on its Web site that it will continue taking orders until 11 a.m. PT Thursday. Pets.com plans to shut down its Web site that day, although it may delay the closure depending on its order volume, company spokesman John Cummings said.

Some of the layoffs will be effective Tuesday, but Cummings said he did not know when the other employees would lose their jobs.

Source: CNET.com, January 2, 2002

(15 to 16 years later …)

Bloomberg

Markets

Long Island Iced Tea Soars After Changing Its Name to Long Blockchain

By Arie Shapira and Kailey Leinz

December 21, 2017, 10:06 PM GMT+8 *Updated on December 22, 2017, 6:17 AM GMT+8*

Bitcoin: What's Coming in the Year Ahead

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There's a new leader in the sweepstakes for the zaniest name change in the crypto craze.

Long Island Iced Tea Corp. shares rose as much as 289 percent after the unprofitable Hicksville, New York-based company rebranded itself Long Blockchain Corp. It's the latest in a near-daily phenomenon sweeping the

Source: Bloomberg.com, December 21, 2017

Which of the 3 behavioral heuristics surveyed may play a role in explaining the anomalies surveyed in class 3?

	Anchoring	Availability	Mental Accounting	Overconfidence
Seasonality				
Asset expansion				
Post earnings announcement drift			?	
Analyst forecast revisions				