

New Research in Behavioral Finance

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Overview

- ◆ two major paradigms in finance:

“Rational agent” framework

- ◆ all market participants are rational

Behavioral finance

- ◆ some market participants are less than fully rational

Overview

- ◆ in finance, rationality means two things
 - sensible *beliefs* (update properly when new information arrives)
 - sensible *decision-making* under risk
- ◆ behavioral finance studies:
 - less than fully rational beliefs
 - less than fully rational decision-making under risk
- ◆ for guidance on *how* people deviate from rationality, we draw on research in psychology
 - psychology of beliefs
 - e.g. overconfidence, representativeness
 - psychology of decision-making under risk
 - e.g. prospect theory, ambiguity aversion

Overview

Applications

- ◆ asset pricing
 - the aggregate stock market, the cross-section of stock returns, the formation of bubbles
- ◆ investor behavior
 - the portfolios that investors hold, their trading activity over time
- ◆ corporate finance
 - security issuance, capital structure, investment decisions, M&A activity

Methodology

- ◆ start with a psychological principle, derive the predictions, then test them
- ◆ start with a puzzling fact, propose a psychology-based hypothesis, then test it

Overview

- ◆ behavioral finance has existed as a field for decades, but the past 15 years have been particularly active
 - research in the field is having influence in academia, business, and government
- ◆ “rational agent” framework strongholds
 - U. Chicago, MIT Sloan, Wharton
- ◆ schools with significant behavioral finance presence
 - Yale U., Harvard U., Princeton U.

Overview

- ◆ in this talk, we look at one classic idea in behavioral finance
 - representativeness
- ◆ and at three new ideas
 - probability weighting
 - mutual fund flows
 - realization utility

Representativeness

- ◆ people draw overly strong inferences from small samples of data (Kahneman and Tversky, 1974)
 - in particular, they extrapolate recent trends too far into the future
- ◆ e.g. belief in “hot hand” in basketball

Table 2.1 Probability of Making a Shot Conditioned on the Outcome of Previous Shots for Nine Members of the 76ers

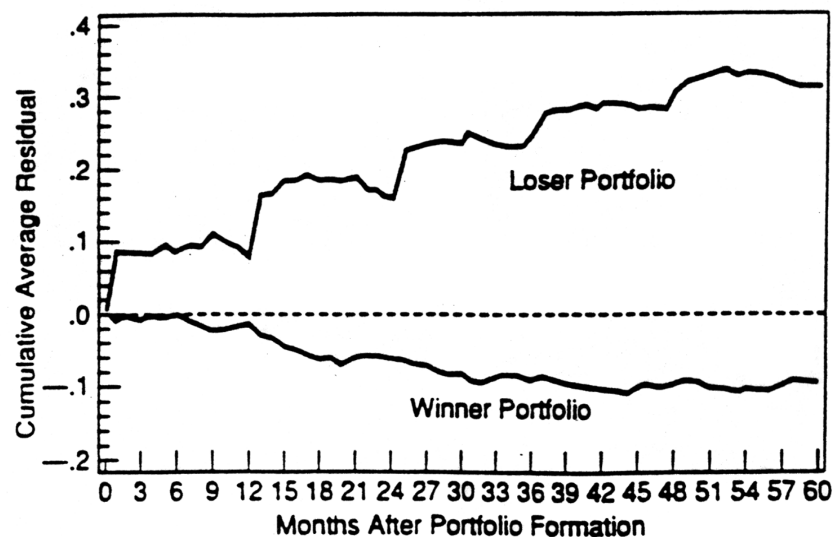
Player	$P(x ooo)$	$P(x oo)$	$P(x o)$	$P(x)$	$P(x x)$	$P(x xx)$	$P(x xxx)$	r
C. Richardson	.50	.47	.56	.50	.49	.50	.48	-.02
J. Erving	.52	.51	.51	.52	.53	.52	.48	.02
L. Hollins	.50	.49	.46	.46	.46	.46	.32	.00
M. Cheeks	.77	.60	.60	.56	.55	.54	.59	-.04
C. Jones	.50	.48	.47	.47	.45	.43	.27	-.02
A. Toney	.52	.53	.51	.46	.43	.40	.34	-.08
B. Jones	.61	.58	.58	.54	.53	.47	.53	-.05
S. Mix	.70	.56	.52	.52	.51	.48	.36	-.02
D. Dawkins	.88	.73	.71	.62	.57	.58	.51	-.14
Mean =	.56	.53	.54	.52	.51	.50	.46	-.04

NOTE: x = a hit; o = a miss. r = the correlation between the outcomes of consecutive shots

Representativeness

Application: *long-run mean reversion*

- ◆ representativeness predicts long-run mean reversion in stock returns
- ◆ De Bondt and Thaler (1985) confirm this prediction
 - a portfolio of stocks with poor (good) performance over the previous three years subsequently performs well (poorly)



- ◆ representativeness may also be an important psychological driver of momentum, and of bubbles

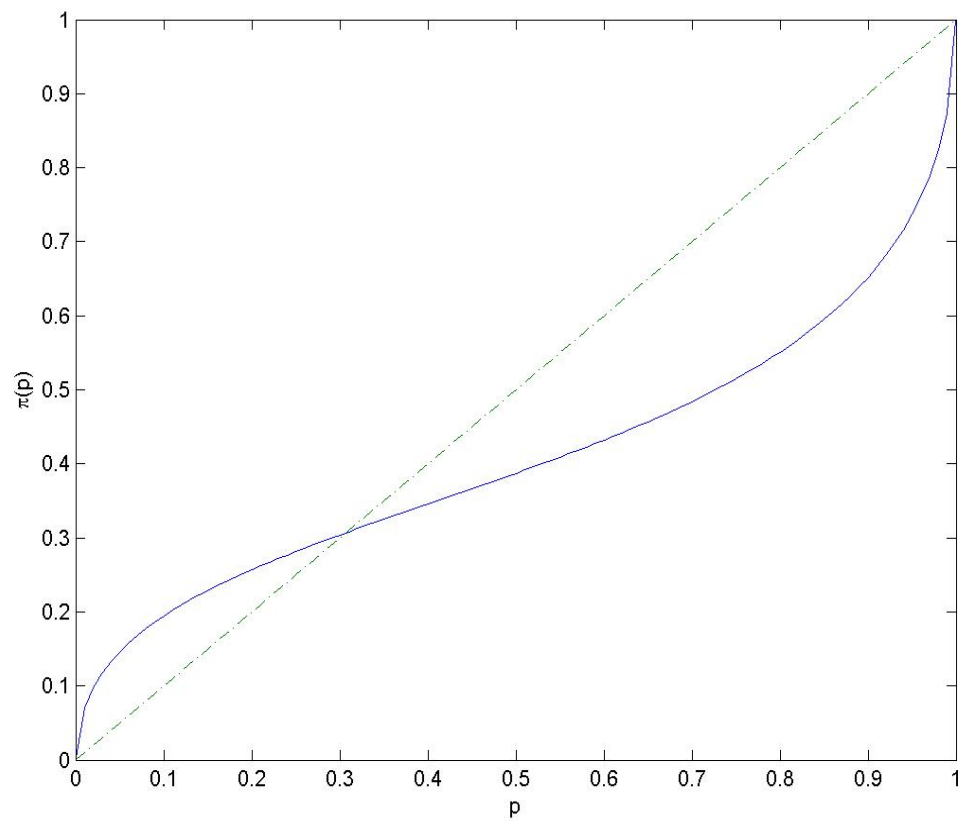
Probability weighting

- ◆ a rational decision-maker should evaluate risk in the following way
 - consider the different possible future outcomes
 - decide how good or bad each outcome will make him feel
 - weight each outcome by its probability, p
 - the “Expected Utility” framework
- ◆ to repeat: a rational decision-maker should assign a weight of p to an outcome that will occur with probability p

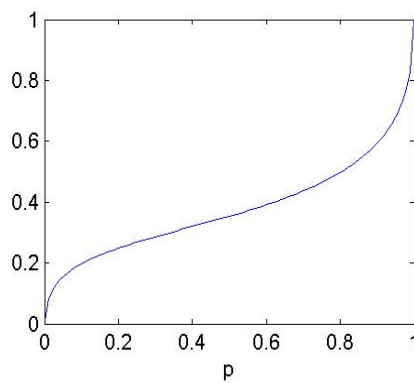
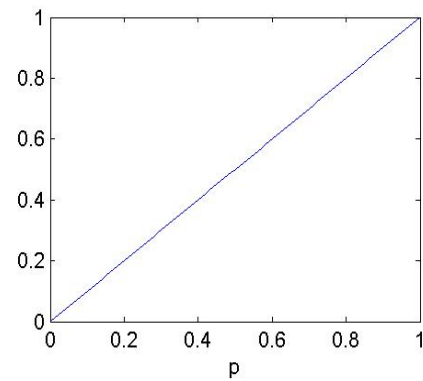
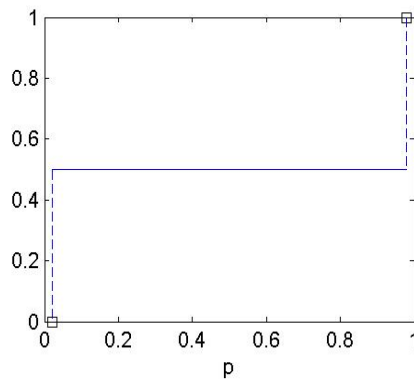
Probability weighting

- ◆ unfortunately, this may not be a good description of how people *actually* think about risk
- ◆ based on a large amount of experimental evidence, Kahneman and Tversky (1979) argue that the brain weights probabilities in a *nonlinear* way
 - “probability weighting”
 - in particular, the brain overweights low probabilities
- ◆ this captures the simultaneous demand people have for both lotteries and insurance
 - people prefer $(\$5000, 0.001)$ to \$5 and also prefer -\$5 to $(-\$5000, 0.001)$
- ◆ transformed probabilities are *decision weights*, not beliefs
- ◆ probability weighting is an element of Kahneman and Tversky’s (1979) “prospect theory” model of how people think about risk
 - loss aversion is another well-known element

Probability weighting



Probability weighting



Probability weighting

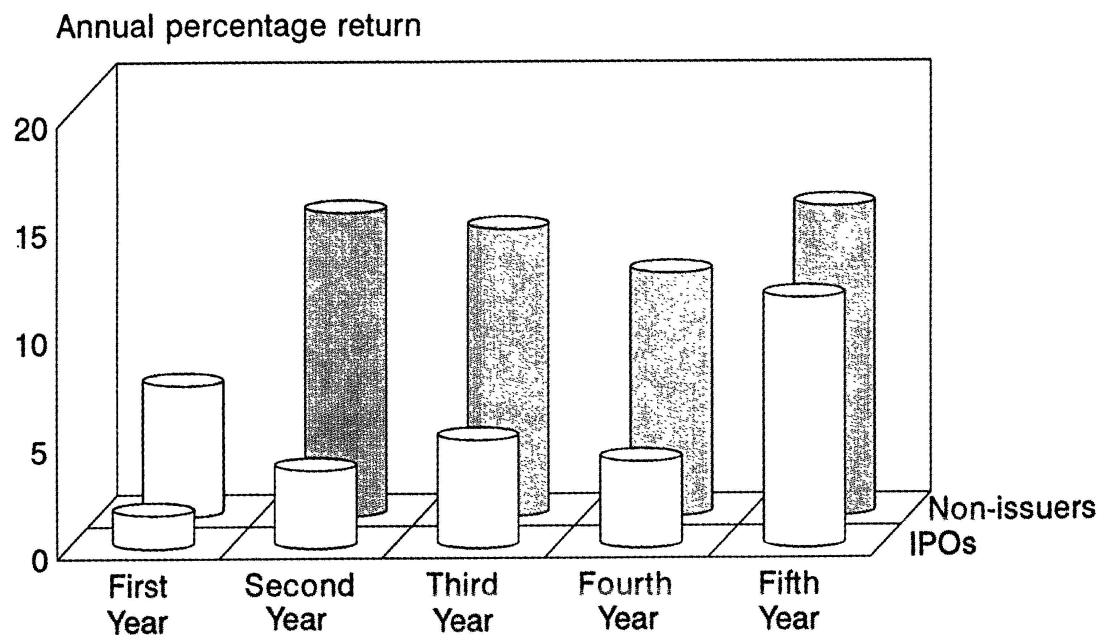
What predictions does probability weighting make about financial markets?

- ◆ probability weighting predicts that a security's *own skewness* will be priced
 - positively skewed assets will be overpriced and will earn low average returns
 - negatively skewed assets will be underpriced and will earn high average returns
 - Barberis and Huang (2008), “Stocks as lotteries...”
- ◆ by taking a significant position in a positively skewed asset, you give yourself a small chance of making a lot of money
 - probability weighting means that this small chance is highly valued

Probability weighting

Applications

- ◆ the low average return on IPO stocks in the 5 years after issue
 - the 5 year post-issue return distribution is highly positively skewed



- Green and Hwang (2012) show that IPOs predicted to be more positively skewed have lower long-run returns

Probability weighting

Applications, ctd.

- ◆ option pricing
 - stock options predicted to have more positively skewed returns have lower *average* returns (Boyer and Vorkink, 2011)
- ◆ the volatility anomaly
 - stocks with high idiosyncratic volatility have low average returns (Ang et al., 2006)
 - but these stocks are also positively skewed (Boyer, Mitton, Vorkink, 2010)
- ◆ under-diversification
 - undiversified households hold stocks that are more highly skewed than the average stock (Mitton and Vorkink, 2007)

Probability weighting

- ◆ can we also test the initial prediction?
 - that more positively skewed assets have lower average returns
- ◆ Boyer, Mitton, and Vorkink (2010) use a regression model to predict skewness
 - use past idiosyncratic volatility, past idiosyncratic skewness, past return, and past turnover as predictor variables
 - they find support for the prediction
- ◆ Zhang (2005) and Conrad, Dittmar, and Ghysels (2011) also confirm the prediction using other measures of skewness

Probability weighting

Summary

- ◆ almost all economic models of the stock market assume that investors evaluate risk according to the Expected Utility framework
 - but the predictions of these models have received little empirical support
 - e.g. the CAPM, the CCAPM
- ◆ a model of the stock market in which investors process risk according to prospect theory seems to do better
 - and probability weighting plays a key role

Mutual fund flows

- ◆ a recent literature argues that we can make sense of stock price movements by thinking about mutual fund flows
- ◆ three empirical facts about fund flows:
 - returns this period positively predict flows next period
 - flows are positively serially correlated
 - when they receive new flows, fund managers allocate a substantial fraction of them to *existing* positions
- ◆ this leads to a new interpretation of a number of phenomena
 - Lou (2009)

Mutual fund flows

Momentum

- ◆ if a stock does well, the funds that hold it do well
 - this brings new flows to the funds
 - these flows push the stock up further

The “smart money effect”

- ◆ fund flows this period predict returns next period
 - this used to be seen a sign of investor intelligence
 - but may simply be a consequence of fund flows

Fund performance persistence

- ◆ performance this period positively predicts performance next period
 - this used to be seen as a sign of managerial skill
 - but may simply be a consequence of fund flows

Mutual fund flows

- ◆ Lou (2009) shows that this framework can help us predict future stock returns
- ◆ given a stock:
 - look at which funds are holding it, and record the returns of these funds
 - this allows us to predict flows to these funds
 - and hence to predict the demand pressure that will hit each stock
- ◆ Lou (2009) shows that this “expected demand pressure” variable strongly predicts returns:

Table VI (A): Monthly Portfolio Returns in Year 1

Decile	Qtr 1			Qtr 1-4		
	excess	alpha 3f	alpha 4f	excess	alpha 3f	alpha 4f
1	0.38% (1.08)	-0.50% (-3.37)	-0.25% (-1.88)	0.53% (1.56)	-0.40% (-3.02)	-0.13% (-1.04)
10	1.21% (3.33)	0.43% (3.64)	0.27% (2.20)	0.97% (2.76)	0.18% (1.66)	0.24% (1.76)
10 - 1	0.84%*** (3.96)	0.93%*** (4.15)	0.53%** (2.51)	0.44%*** (2.63)	0.58%*** (3.30)	0.37%** (2.26)

Realization utility

- ◆ individual investors prefer to sell stocks trading at a *gain* relative to purchase price, rather than at a loss
 - the “disposition effect”
 - originally documented in a large database of trading activity of clients of a discount brokerage firm (Odean, 1998)
- ◆ when an investor in Odean’s sample sells a stock, categorize each stock in her portfolio as one of:
 - “realized gain”, “realized loss”, “paper gain”, “paper loss”
- ◆ sum up across all investors over the entire sample, and compute:

$$PGR = \frac{\#realized\ gains}{\#realized\ gains + \#paper\ gains}$$

$$PLR = \frac{\#realized\ losses}{\#realized\ losses + \#paper\ losses}$$

- ◆ the disposition effect is the finding that $PGR > PLR$

Realization utility

- ◆ the disposition effect:
 - is present in all the major databases we have on individual investor trading behavior
 - holds for mutual fund managers as well; and also in the housing market
 - is a possible driver of momentum in stock returns
- ◆ but it remains a puzzle
 - it is hard to find rational explanations for it
 - e.g. it does *not* represent informed trading
- ◆ one psychological driver may be “realization utility”
 - investors feel a burst of pleasure (pain) when they sell an asset at a gain (loss)
 - people often think about their investing history as a series of investing episodes
 - selling a stock at a gain creates a positive new investing episode
 - Barberis and Xiong (2012)

Realization utility

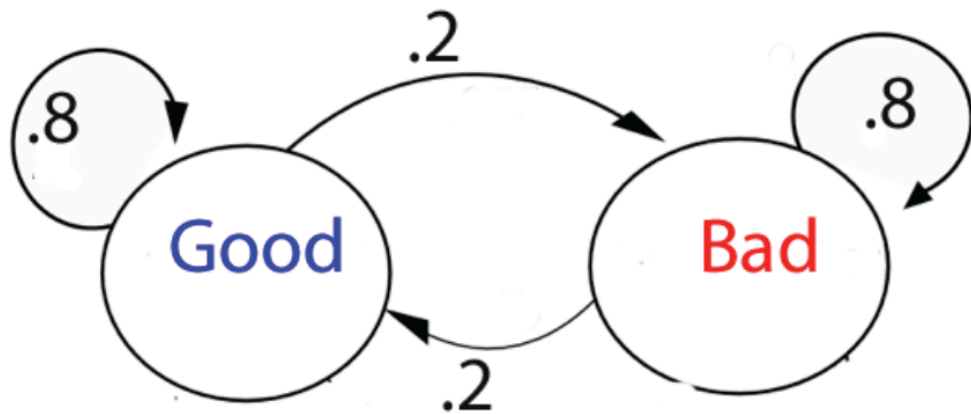
- ◆ one recent study uses *neural* evidence to test the realization utility hypothesis
 - Frydman, Barberis, Camerer, Bossaerts, Rangel (2011)
- ◆ 28 Caltech students and employees traded stocks in an experimental stock market while we monitored their brain activity using an fMRI scanner
 - functional Magnetic Resonance Imaging

Realization utility

- ◆ three stocks: A, B, and C
 - at each moment, each stock is either in a “good” state or a “bad” state
 - if in a good state, it goes up with probability 0.55 and down with probability 0.45
 - if in a bad state, it goes up with probability 0.45 and down with probability 0.55
 - at each price update, a stock stays in the same state with probability 0.8 and switches with probability 0.2
 - subjects are not told the states of the three stocks, but can try to infer them from the price updates they observe

Realization utility

[Stock price process]



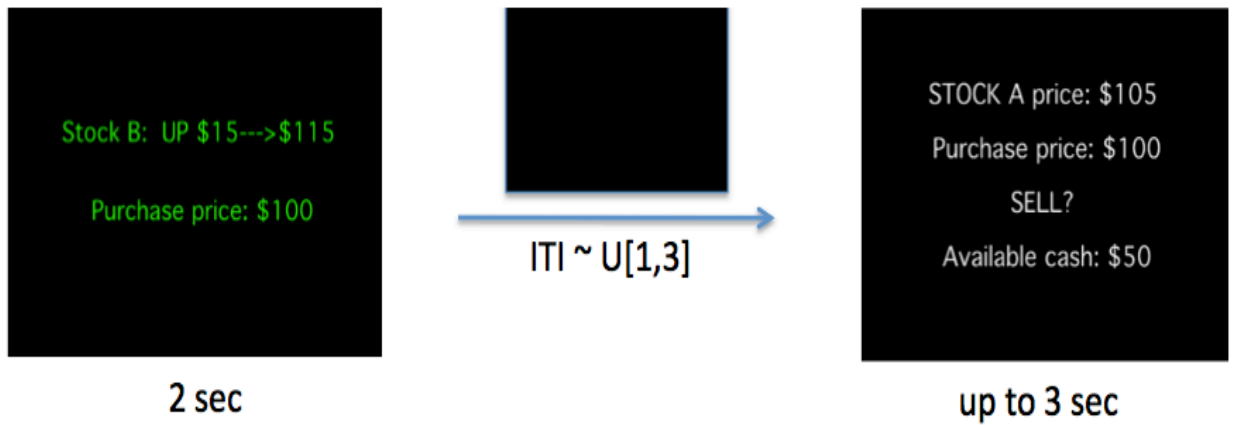
Realization utility

- ◆ each subject starts with \$350
 - he can hold either 0 shares or 1 share of each stock
 - there are 216 trials
 - in each trial, he sees a price update screen for a randomly chosen stock
 - and then, a decision screen for a randomly chosen stock
 - here, he can buy a share if he doesn't currently own the stock
 - or sell his share if he does
 - a stock's price changes only when a price update screen is shown

- ◆ note that, from a subject's perspective, each stock is positively autocorrelated
 - a rational trader should therefore exhibit the *opposite* of the disposition effect

Realization utility

[Price update and decision screens]



Realization utility

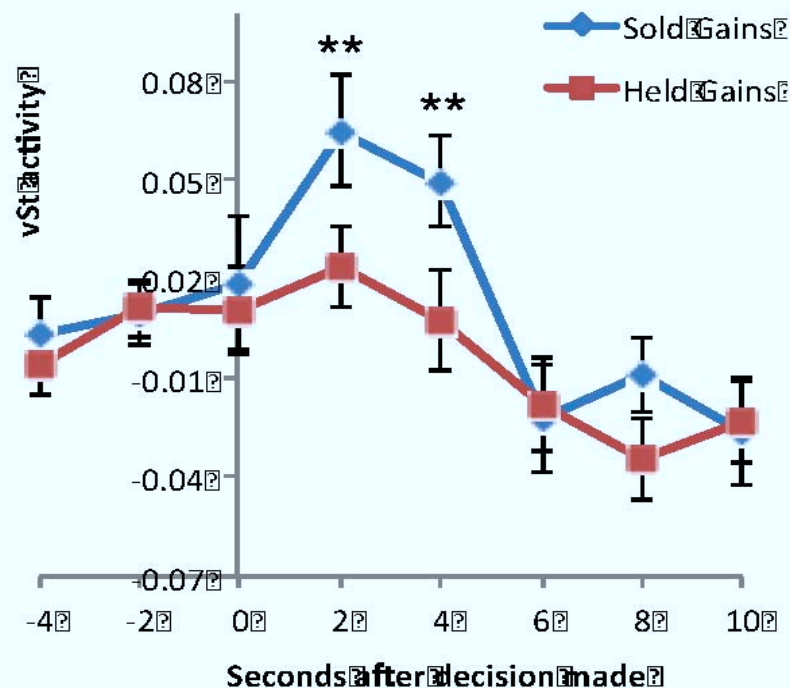
- ◆ we find that, on average, our subjects exhibit a strong disposition effect
 - this is a mistake in our setting
- ◆ we then use the neural data to test some predictions of the realization utility hypothesis

Realization utility

- ◆ a specific area of the brain, the ventral striatum (vStr) is widely believed to encode “hedonic value,” or subjective feelings of pleasure
- ◆ realization utility says that people experience a burst of pleasure when they sell an asset at a gain
- ◆ under this theory, then, neural activity in the vStr should spike up around the moment where a subject issues a command to sell a stock at a gain
 - as compared to when he issues a command to *hold* a stock with a similar embedded gain

Realization utility

- ◆ we plot a time series of neural activity in the vStr around the time at which a subject issues a command to sell a stock at a gain
 - and compare it to activity in the vStr around the time at which he issues a command to hold a stock with a gain
- ◆ the results confirm our prediction:



Summary

- ◆ behavioral finance interprets some financial phenomena as the result of less than fully rational behavior on the part of some participants
- ◆ in this talk, we looked at one classic idea in the field
 - representativeness
- ◆ and at three new ideas
 - probability weighting
 - mutual fund flows
 - realization utility