IN SEARCH OF HUMAN RATIONALITY

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Historical Perceptions of Human Rationality

- “Animal spirits” (John Maynard Keynes)
  - Economic activity and market prices are driven in part by waves of optimism and pessimism
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- 1960s-90s: The golden era of rationality
  - Rational expectations (John Muth, Robert Lucas)
  - Efficient financial markets (Eugene Fama)
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- 1960s-90s: The golden era of rationality
  - Rational expectations (John Muth, Robert Lucas)
  - Efficient financial markets (Eugene Fama)

- 1990s-2000s: Growth of behavioral finance and economics
  - Highlights human irrationality
  - “The end of behavioral finance” (Richard Thaler)
What Does Rationality Mean?

- Rationality means two things:
  1. When they receive new information, agents *update their beliefs correctly*, in the manner described by Bayes’ law.
  2. Given their beliefs, agents *make optimal choices*.
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• Behavioral finance questions both pillars of rationality

• Behavioral finance argues that asset prices are often “wrong” as a result of human mistakes
Strengths of Behavioral Finance

• Human beings are clearly not 100% rational automata
  – We all make mistakes now and then
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• Bringing evidence from psychology into finance and economics
  – Psychology documents the mistakes that people tend to make
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• Bringing evidence from *psychology* into finance and economics
  – Psychology documents the mistakes that people tend to make

• Ability to propose explanations for various puzzling phenomena
Weaknesses of Behavioral Finance

• Lack of discipline
  – Roughly half of financial market anomalies are “explained” by *overreaction* and half by *underreaction* (Fama, 1998)
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  - Scientific hypotheses must be testable
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  ⇒ Models match evidence qualitatively but not quantitatively
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• Even if individuals make mistakes . . .
  – They learn from them, otherwise they gradually die out
  – 99% of the trading volume on the NYSE is done by institutions
  ⇒ Asset prices can be right even if most people are irrational
Behavioral “Proofs” of Irrationality: Example 1

- **Fact:** 80% of people claim to be drivers of above-average ability
  ⇒ Conclusion: People are *overconfident* in their abilities
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- **Example:** Speed vs safety
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• **Example:** Speed vs safety
  – Jožko drives fast. To him, a good driver is a fast driver. He rates his own driving ability high because he is fast.
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  – Marienka drives slowly. To her, a good driver is a careful driver. She rates her own driving ability high because she is careful.
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  - Marienka drives slowly. To her, a good driver is a careful driver. She rates her own driving ability high because she is careful.
  - Both Jožko and Marienka think of themselves as above-average drivers, and they are both right! **Neither is overconfident.**
Behavioral “Proofs” of Irrationality: Example 2

- **Fact:** People tend to reject the fair gamble “win $110, lose $100”
- Rabin (2000) shows that if such people maximize utility, they would also reject “win $20,000,000, lose $1,000”, which is implausible

⇒ Conclusion: People are not rational utility-maximizers
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• But there are many reasons why experimental subjects may reject “win $110, lose $100”

  – They are usually college students on limited budgets
  – They may not want to look like gamblers in front of their peers
  – They may not have time for an extra trip to the ATM machine
  – etc.
• **Fact:** Researchers have found **anomalies** in financial markets
Behavioral “Proofs” of Irrationality: Example 3

- **Fact:** Researchers have found **anomalies** in financial markets.
- Many “anomalies” weaken or disappear when measured differently.
  - **Example:** Low post-IPO stock returns.
    - *Brav and Gompers, Journal of Finance, 1997*
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- Many apparent anomalies can be explained with rational models
  - Rational models are parsimonious; fewer degrees of freedom
Rational Explanations for Apparently Irrational Phenomena

• **Examples** from my recent work:

  – Valuations of young firms

  – Stock returns around IPO waves

  – The Nasdaq “bubble” in the late 1990s

  – Stock price “bubbles” during technological revolutions

  – Firm profitability after an IPO
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  – Stock price “bubbles” during technological revolutions  

  – Firm profitability after an IPO  
Rational IPO Waves

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Journal of Finance, 2005
IPO Waves

- Number of firms going public (IPOs) changes over time:
The Puzzle

- **Puzzling fact:** Stock market returns tend to be
  - *High before* IPO waves
  - *Low after* IPO waves
• **Puzzling fact:** Stock market returns tend to be
  – *High before* IPO waves
  – *Low after* IPO waves

• Behavioral explanation:
  Many firms go public when the stock market is overvalued
  – So the stock issuers know that the market is overvalued, but the stock buyers don’t? Is this plausible?
What We Do

- We develop a fully rational model of optimal IPO timing
  - Entrepreneurs solve for the optimal time to go public
  - Time-varying risk aversion $\Rightarrow$ Time-varying expected return
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  – We test all predictions empirically by analyzing IPO data in 1960–2002, and find strong support for all predictions
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• The model can also be plausibly *calibrated*
Intuition

• Many firms go public after expected market return falls
  – Because they can raise capital for investment more cheaply
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  \textit{IPO waves tend to be preceded by drops in discount rates} \( (r \downarrow) \)
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  \[
  \frac{P}{D} = \frac{1}{r - g}
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• Before IPO waves, \(r \downarrow \implies P \uparrow\),
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• Before IPO waves, \( r \downarrow \Rightarrow P \uparrow \),
  \( \Rightarrow \) IPO waves are \textit{preceded} by \textit{high} market returns

• After IPO waves, expected return \( r \) is low (because it went down),
  \( \Rightarrow \) IPO waves are \textit{followed} by \textit{low} market returns
Was There a Nasdaq Bubble in the Late 1990s?

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The Puzzle

Graph showing the index level for Nasdaq and Dow from 1995 to 2004.
• Behavioral explanation: Stocks overvalued due to irrationality
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• Is it obvious that stock prices exceeded their fundamental values? Not necessarily.
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Bubble?

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- Is it obvious that stock prices exceeded their fundamental values? Not necessarily.
  (i) Uncertainty about average profitability increases firm value
  (ii) This uncertainty was high in the late 1990s
  (i)+(ii) → Fundamental values were high in the late 1990s
• Behavioral explanation: Stocks overvalued due to irrationality.

• Is it obvious that stock prices exceeded their fundamental values? Not necessarily.
  
  (i) *Uncertainty* about average profitability *increases* firm value.
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• We calibrate a valuation model that includes this uncertainty.
Bubble?

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• Find: Stock prices can be rationalized with plausible uncertainty

⇒ Valuations were not necessarily irrational
Why Does Uncertainty about Profitability Increase Firm Value?

- Gordon growth model:

  When $g$ is known: \[
  \frac{P}{D} = \frac{1}{r - g}
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Why Does Uncertainty about Profitability Increase Firm Value?

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  When $g$ is known: \[ \frac{P}{D} = \frac{1}{r - g} \]

  When $g$ is unknown: \[ \frac{P}{D} = \mathbb{E}\left(\frac{1}{r - g}\right) \]

  - Note: $1/(r - g)$ is convex in $g$
  \[ \Rightarrow \frac{P}{D} \text{ increases with uncertainty about } g \]
Why Does Uncertainty about Profitability Increase Firm Value?

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  When $g$ is known:
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  – Note: $1/(r - g)$ is convex in $g$
  \[\Rightarrow \] $P/D$ increases with uncertainty about $g$

- Same intuition holds in our model, with $M/B$ in place of $P/D$
Why Was Uncertainty about Profitability High in the Late 1990s?

• Technological revolution; “new era”
• Tech stock profitability was highly volatile
• Tech stock prices were highly volatile
Panel A. Return volatility

- NYSE/Amex
- Nasdaq

Panel B. Difference between return volatilities of Nasdaq and NYSE/Amex
Why Was Uncertainty about Profitability High in the Late 1990s?

• Technological revolution; “new era”
• Tech stock profitability was highly volatile
• Tech stock prices were highly volatile
• Anecdotal evidence
  “...the projections of revenue growth were, by and large, wild guesses.”
  *Investment Dealers Digest, 23 October 2000.*

  “Internet firms’ highly unpredictable growth rates make historical information less useful.”
  *TIAA-CREF Investment Forum, March 2001.*

  “...being wrong isn’t very costly, and being right has a high payoff... With Amazon, we believe the payoff for being right is high.”
  *Bill Miller, portfolio manager of the Legg Mason Value Trust, in Barron’s, 15 Nov 1999.*
• Profitability has an uncertain mean, with standard deviation $\sigma$
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- We derive an explicit formula for the market value $M$:

$$M = f(\sigma, \ldots)$$

- Note: $M$ increases if uncertainty $\sigma$ increases
Model and Calibration

- Profitability has an uncertain mean, with standard deviation $\sigma$.
- We derive an explicit formula for the market value $M$:
  \[ M = f(\sigma, \ldots) \]
  - Note: $M$ increases if uncertainty $\sigma$ increases.
- We calibrate the model to the circumstances of March 2000.
- We ask: How uncertain did we have to be about the growth rates of Nasdaq firms to justify their valuations?
  - That is, how large must $\sigma$ be to equate the model-implied $M$ with the observed $\hat{M}$?
  - Implied uncertainty: $\hat{\sigma}$ such that $\hat{M} = f(\hat{\sigma}, \ldots)$.
How Can We Judge Whether Uncertainty is Plausible?

• In the model, stock return volatility $V$ also increases with $\sigma$:

$$M = f(\sigma, \ldots)$$

$$V = g(\sigma, \ldots)$$
How Can We Judge Whether Uncertainty is Plausible?

- In the model, stock return volatility $V$ also increases with $\sigma$:

$$M = f(\sigma, \ldots) \quad (1)$$
$$V = g(\sigma, \ldots) \quad (2)$$

1. Compute $\hat{\sigma}$ that fits equation (1) (i.e., implied uncertainty)
2. Compute $V = g(\hat{\sigma}, \ldots)$ from equation (2)
3. Compare the model-implied $V$ with the observed $\hat{V}$
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• We find that model-implied $V$’s are close to the observed ones!

$\Rightarrow$ Uncertainty $\hat{\sigma}$ that is needed to match the level of stock prices also matches the volatility of prices
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  $\Rightarrow$ Uncertainty $\hat{\sigma}$ that is needed to match the level of stock prices also matches the volatility of prices

• Firms with the highest stock market valuations also had the most volatile returns: Not a coincidence!
  – These are firms with the most uncertain growth rates
Why Did the “Bubble” Burst?

- Nasdaq profitability dropped like a stone after 2000
Conclusions Regarding the Nasdaq “Bubble”

• Stock prices in the late 1990s were not necessarily irrational *ex ante*

• Uncertainty about average future profitability can rationalize both
  – The high *level* of tech stock prices, even at the peak
  – The high *volatility* of tech stock prices in the late 1990s

• Firms with the highest stock market valuations also had the most volatile returns
  – These are firms with the most uncertain growth rates
Technological Revolutions and Stock Prices

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Working paper, 2008
“Technological revolutions and financial bubbles seem to go hand in hand.”

“Every previous technological revolution has created a speculative bubble... With each wave of technology, share prices soared and later fell...”

(The Economist, September 21, 2000)

- Stocks tend to exhibit “bubbles” during technological revolutions
  - Prices rise and then fall, especially for innovative firms
  - Return volatility is high, especially for innovative firms
- Examples: Internet, biotech, electronics, electricity, automobiles
“Technological revolutions and financial bubbles seem to go hand in hand.”

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• Behavioral explanation: irrationality
  – Investors get too excited about the new technology
  – Is this plausible? Do they never learn?

• We propose a rational explanation
Our Story

- New technologies have **highly uncertain** future productivity
  - This uncertainty makes stock returns highly volatile
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• Initially, this uncertainty is mostly **idiosyncratic**
  – Because the new technology is first developed on a small scale
Our Story

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- In *technological revolutions*, new technologies are widely adopted
- For those technologies that are widely adopted, the uncertainty gradually changes from idiosyncratic to **systematic**
  - As a result, discount rates rise and stock prices fall
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• In *technological revolutions*, new technologies are widely adopted
• For those technologies that are widely adopted, the uncertainty gradually changes from idiosyncratic to **systematic**
  – As a result, discount rates rise and stock prices fall
• The “bubble” is observable *ex post* but unpredictable *ex ante*
  – We know *ex post* that a technological revolution took place, but investors did not know that *ex ante*
Our model

• We develop a general equilibrium model with a representative agent

• Two sectors: the “new economy” and the “old economy”
  – Old economy: *Large-scale* production using *old* technology
  – New economy: *Small-scale* production using *new* technology
Our model

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- The representative agent
  1. Sets up the new economy to learn about the new technology
  2. Learns by observing the productivity of the new economy
  3. Decides when to adopt the new technology on a large scale

- Large-scale adoption = *technological revolution*
Some Theoretical Results

**Proposition 1:** It is not optimal to adopt the new technology at a large scale immediately after it is invented.

- Because its productivity is uncertain and agent is risk averse.
Provision 1: It is not optimal to adopt the new technology at a large scale immediately after it is invented.

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Provision 2: It is optimal to adopt the new technology at a later time if we learn that it is sufficiently productive.
Some Theoretical Results

Proposition 1: It is not optimal to adopt the new technology at a large scale immediately after it is invented.

- Because its productivity is uncertain and agent is risk averse

Proposition 2: It is optimal to adopt the new technology at a later time if we learn that it is sufficiently productive.

Proposition 3: It is optimal to set up the new economy to begin learning about the new technology immediately after it is invented.

- Because learning provides a valuable option
Model Predictions for M/B and Volatility in Simulations.

(A) Revolution: Market to Book Ratios

(B) No Revolution: Market to Book Ratios

(C) Revolution: Stock Return Volatility

(D) No Revolution: Stock Return Volatility
Testing the Model

• The model makes many additional testable predictions
  – about changes in the level of stock prices
  – about changes in the volatility of stock prices
  – about changes in systematic risk (beta)
  – about changes in productivity
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  – about changes in the level of stock prices
  – about changes in the volatility of stock prices
  – about changes in systematic risk (beta)
  – about changes in productivity

• We test these predictions empirically for . . .
  – the Internet revolution (1990s through early 2000s)
  – the railroad revolution (1830s-1860s)

• We find strong empirical support for the model’s predictions
Summary

• Many puzzling phenomena can be explained rationally
  – Premature to abandon rationality as the pillar of economics
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• What should behavioral economics do?
  – Produce clear *testable predictions*
  – Empirically *distinguish* its explanations from alternatives
  – Quantify effects, *calibrate* models
  – Take evidence from *psychology* more seriously
Summary

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• The rational and behavioral paradigms will continue clashing
  ⇒ Economics has an exciting future!