# Panic on Wall Street

*Introduction to behavioral finance*

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dxFeed

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**Definition (Efficient Market Hypothesis)**

Real-world financial markets *are* efficient.

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  - Irrational investors are eliminated by arbitrageurs
- Empirical
  - *(Reaction to information)*
    News arrive $\Longrightarrow$ price quickly and correctly adjusts
  - *(Non-reaction to non-information)*
    No news about fundamentals $\Longrightarrow$ no significant price movements

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- *"Physical reality":*
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  - Momentum and other factors are consistent predictors
  - Flash Crash (reaction to non-news)

# Flash Crash

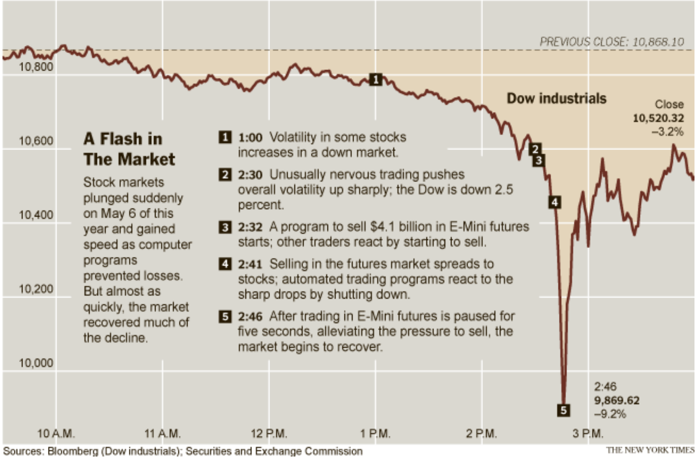


Figure 1: A trillion-dollar drop around 2:30 p.m. EST on May 6, 2010

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  - systematically fail in absorbing new information

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  - nonlinearity kicks in

# Other effects

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Figure 2: The Economist, November 1997

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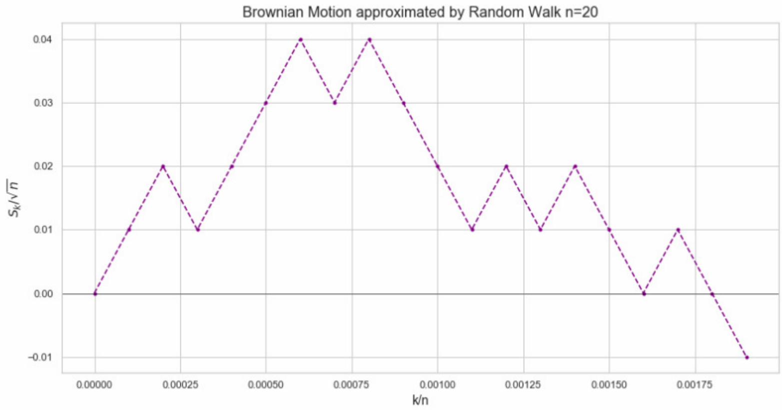
- *Derive* quantifiable conclusions using mathematics
- *Test* conclusions on real (possibly, simulated) data

# Random walk, brownian motion

- Random walk *converges* to brownian motion:



# Sornette, Andersen (2002)

- Option pricing (Black, Scholes, Merton (1973)):

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$$\frac{dB}{B} = \mu dt + \sigma dW_t$$

- Adding price jumps:

$$\frac{dB}{B} = \mu dt + \sigma dW_t - \kappa dj$$

# Sornette, Andersen (2002)

- *No-arbitrage* condition leads to

$$B(t) = \alpha^{\alpha} \frac{1}{\left(\mu_0(t_c - t) - \frac{\sigma_0}{B_0^m} W_t\right)^{\alpha}}$$

$$\alpha = \frac{1}{m-1}, t_c = \frac{y_0}{(m-1)\mu_0}$$

- Simplified version:

$$B(t) = \frac{\alpha^{\alpha}}{(1 - W_t)^{\alpha}}$$

# Original result

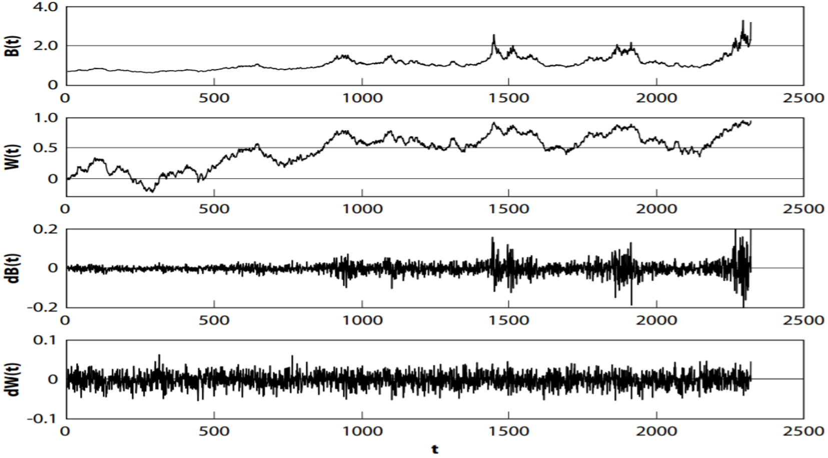


Figure 3: Bubble price and its' components. Source: [Sornette, Andersen (2002)]

# Reproducing in R

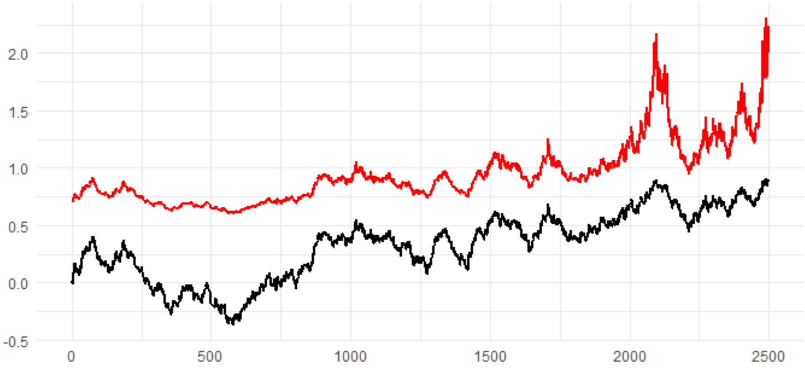


Figure 4: Brownian motion $W_t$ (black), price bubble $B(t)$ (red)

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- In general, given a set $D$ of $\alpha_H$ heads and $\alpha_T$ tails

$$P(D|\theta) = \theta^{\alpha_H} (1-\theta)^{\alpha_T}$$

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- Take $D = \{5\,Heads\}$, then $\hat{\theta} = 1$ — a coin with two heads...?

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- Formula (Reverend Thomas Bayes, 1702–1761):

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# Bayesian estimates

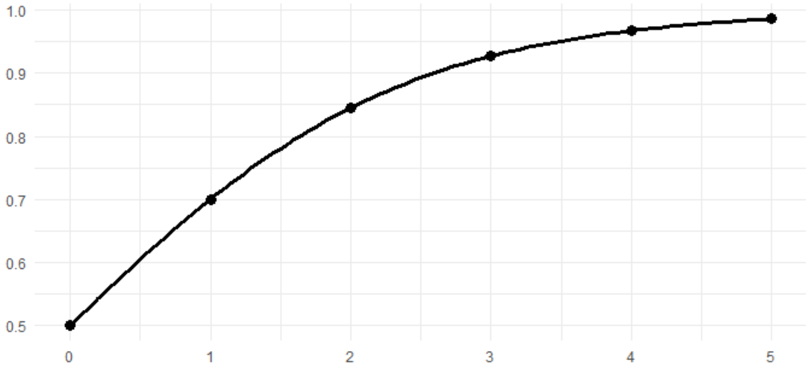


Figure 5: How a true Bayesian would answer

# Bayesian estimates

| Roll | Outcome | History | Estimate |
|---|---|---|---|
| 0 | | | 50% |
| 1 | H | H | 70% |
| 2 | H | HH | 84.5% |
| 3 | H | HHH | 92.7% |
| 4 | H | HHHH | 96.7% |
| 5 | H | HHHHH | 98.6% |
| 6 | T | HHHHHT | 96.7% |

Table 1: Coin-tossing experiment, bayesian answers

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- Edwards (1968): excess conservatism, *underreaction*
- Kahneman, Tversky (1974): representativeness heuristic, *overreaction*

# Background

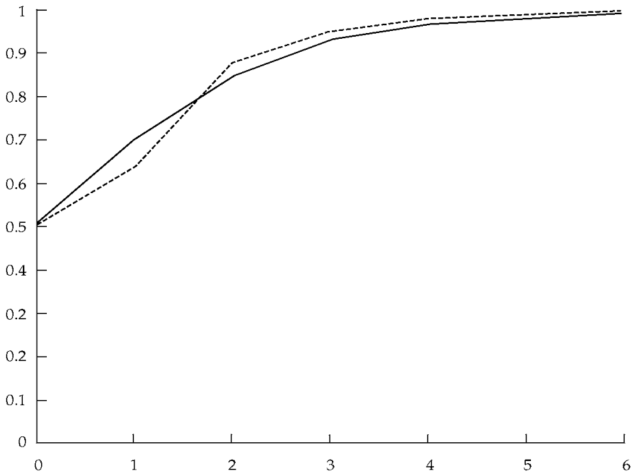
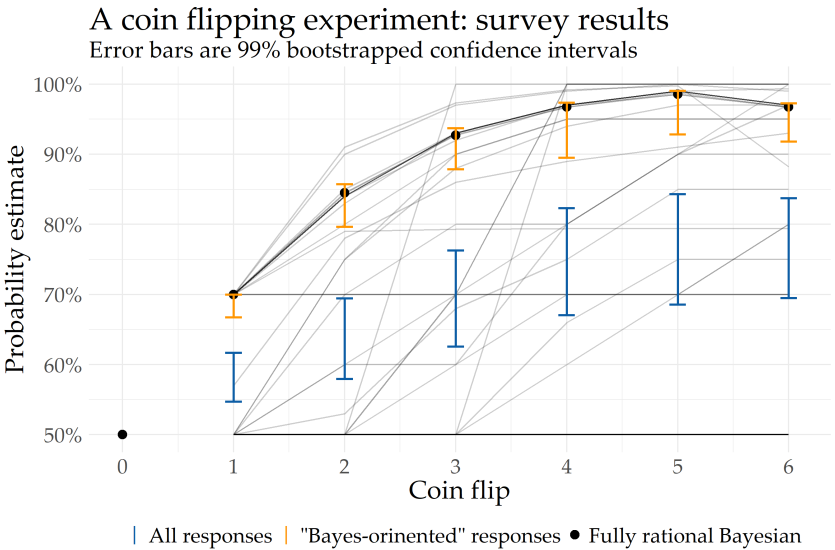



Figure 6: Bayesian (solid) and average response (dashed). Source: [Shleifer, 2000]

# Our results

- Total respondents: 43
- Group 1: non-Bayesian congregation (all answers $\leqslant 50\%$)
- Group 1a: non-Bayesian after first throw (all answers $= 70\%$)
- Group 2: MLE-infuenced (there is at least one 100% answer)
- Group 3: "I can feel it" and informed Bayesians

# Our results


A coin flipping experiment: survey results
Error bars are 99% bootstrapped confidence intervals
Probability estimate
100%
90%
80%
70%
60%
50%
0
1
2
3
4
5
6
Coin flip
All responses
"Bayes-orinented" responses
Fully rational Bayesian

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- Here $y_t$ is either $+y$ or $-y$, i.e. positive or negative shock

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- M2 is similar, with $\pi_H$ instead of $\pi_L$

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- Regime switching between M1 and M2 is also Markovian

$$
\begin{array}{ccc}
 & s_{t+1} = 1 & s_{t+1} = 2 \\
s_t = 1 & 1 - \lambda_1 & \lambda_1 \\
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- $\lambda_1$ and $\lambda_2$ are small, $\lambda_1 + \lambda_2 < 1$, $\lambda_1 < \lambda_2$ (on average, M1 is more likely)

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## Proposition

*Under some conditions on $\pi_L, \pi_H, \lambda_1, \lambda_2$, the price exhibits both under- and overreaction to $N_t$.*

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- Pick two portfolios: "winners" and "losers"
- Calculate difference in performance $r_+^n - r_-^n$ for $n = 1, 2, 3, 4$ years
- It *decreases monotonically:*

| | |
|---|---|
| $r_+^1 - r_-^1$ | 0.0391 |
| $r_+^2 - r_-^2$ | 0.0131 |
| $r_+^3 - r_-^3$ | −0.0072 |
| $r_+^4 - r_-^4$ | −0.0309 |

Figure 7: Difference between portfolios. Source: [Shleifer, 2000]

# Reproducing in R

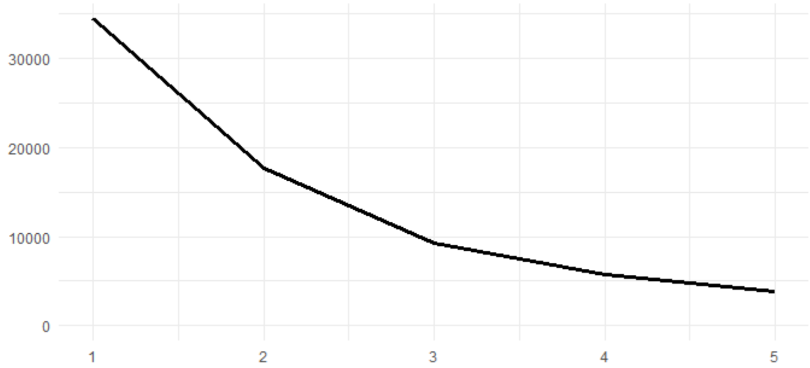


Figure 8: Difference between portfolios decays with $n$

# Takeaway

Key concepts and ideas:

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- Behavioral effects in finance
- Price-driven crash model [Sornette, Andersen (2002)]
- Model of investor sentiment [Barberis et al. (1998)]

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Don't panic and become a Bayesian!

Thanks!

# References


- Sornette, D.; Andersen, J. V. (2002). *A Nonlinear Super-Exponential Rational Model of Speculative Financial Bubbles.* International Journal of Modern Physics C, Volume 13, Issue 02, pp. 171–187.
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