#### The Economics of FinTech, Lecture 6

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Overview

Background of Robo-Advising

3 Kelly Criterion and Goal Based Investing

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### Background of Robo-Advising

- As estimated by the U.S. News & World Report (October 5, 2017), as of October 2017 robo-advisors had \$224 billion in assets under management. For example, Vanguard Group and Charles Schwab Corporation had about \$83 billion and \$19 billion in assets under management related to robo-advising in September 2017, respectively (Forbes Magazine, September 12, 2017).
- See https://personal.vanguard.com/us/FundsInvQuestionnaire
- The differences between traditional advising and robo-advising
  - A robo-advisor must effectively identify clients' risk profile based on simple inputs of clients, as the clients may have no idea about utility functions.
  - A robo-advisor must provide recommendations that are consistent with the common investment wisdom.

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#### Examples of robo-advising

- Kelly criterion: Consider log utility; assume homogeneous risk profile; dynamic; time horizon may be relevant for models with stochastic volatility or stochastic returns.
- Goal based investing: Consider the probability of achieving goals; heterogeneous risk profile; dynamic; time horizon may be relevant.
- Dynamic mean variance: Extending mean variance to a dynamics setting; heterogeneous risk profile; dynamic; time horizon may be relevant for models with stochastic volatility or stochastic returns.
- Black-Litterman model: Single period mean variance with Bayesian estimation; heterogeneous risk profile; one period, not dynamic; time horizon is irrelevant.

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- The difficulty of investment (My cousin's husband story, Shiller story)
- A game with equal odds: winning 50% of wager with 55% probability or losing 50% of wager with 45% probability. The expected payoff is 1.5\*0.55+0.5\*0.45=1.05>1, i.e. 5% expected profit per play.

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- Starting with \$10,000, what percentage of money would you like to use to play for 100 times?
- If you choose 100%, then after 100 rounds of the game, the mean wealth is over 10,000 \*  $(1.05)^{100} > 1,300,000$ .

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- But the median wealth is around \$1.3!
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- Why? Because the distribution is skewed to the right, due to the multiplicative nature of investment.
- Mean is much larger than median

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- Kelly criterion, using the logarithm utility to choose the best fraction of the wealth, i.e. max the median.
- See https:
  //www.forbes.com/sites/startswithabang/2017/05/23/
  how-physicists-used-science-to-beat-the-odds-at-roulette/
  #344526093c39
- See https://en.wikipedia.org/wiki/Breaking\_Vegas
- Merton, any power utility function. Nobel prize 1997.

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