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People Analytics

Introduction to People Analytics

Professors Cade Massey, Matthew Bidwell, and Martine Haas

People Analytics

- The use of data and analytic tools to inform decisions about how to manage people

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Goals for the Course

Professors Cade Massey, Matthew Bidwell, and Martine Haas

Goals for the Course

- By the end of this course, you should understand:
  - The range of areas where analytics are being used to improve how people are managed
  - Conceptual underpinnings of major people decisions
  - Basics of where to find appropriate data and how to set up analyses
  - Outlines of more sophisticated approaches to analyzing data
  - Major pitfalls and best practices in people analytics

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Course Outline and Overview

Professors Cade Massey, Matthew Bidwell, and Martine Haas

Course Outline

	Application Areas	Issues
Module 1	Performance evaluation	Chance variations vs. true difference
Module 2	Staffing	Assessing causality
Module 3	Collaboration	Measuring outcomes
Module 4	Talent Management Future directions	Building a people analytics capability

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People Analytics

People Analytics in Practice

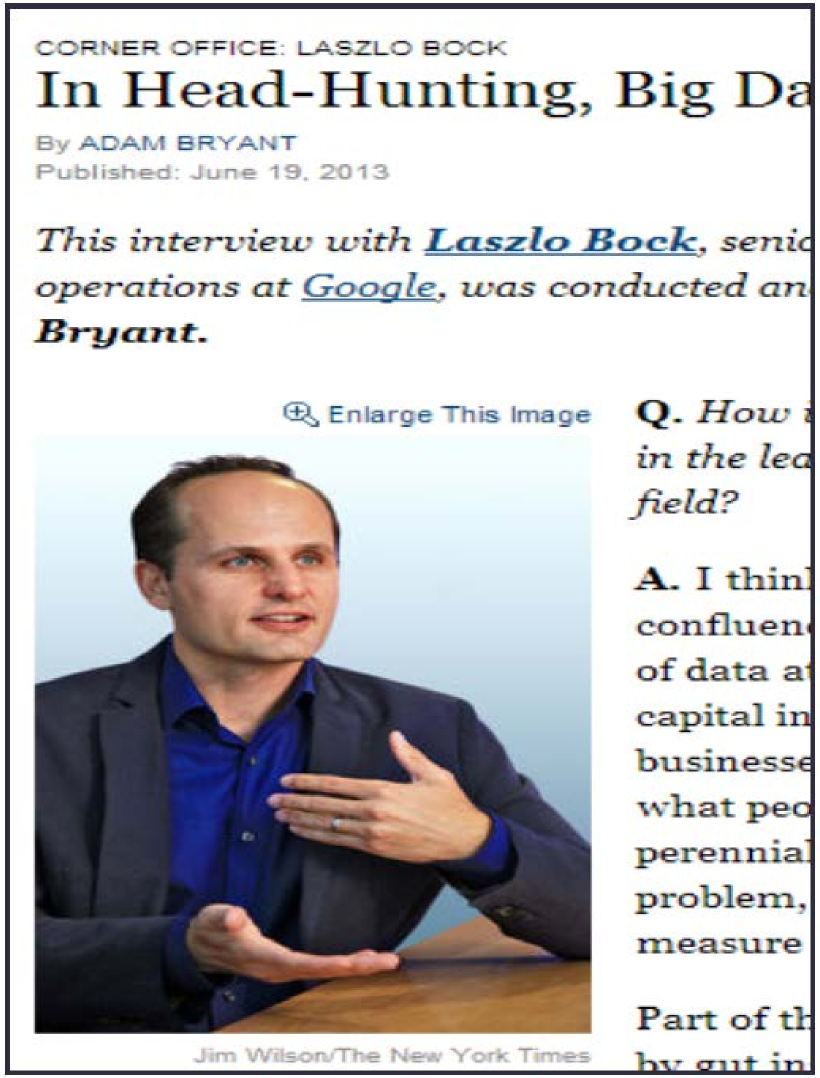
Professor Cade Massey

People Analytics in Practice

- Rigorously tracks the performance of all teachers, comparing it to evaluations when they were hired
- Helps refine the most productive steps in the hiring process, where to allocate more resources, etc.

TEACH FOR AMERICA

People Analytics in Practice


CORNER OFFICE: LASZLO BOCK

In Head-Hunting, Big Da

By ADAM BRYANT
Published: June 19, 2013

*This interview with **Laszlo Bock**, senio operations at Google, was conducted an **Bryant.***

Enlarge This Image

Jim Wilson/The New York Times

***Q.** How i in the lea field?*

A. I thinl confluen of data a capital in business what peo perennial problem, measure

Part of th by gut in

- Systematically tracked interview predictions about new hires to figure out how good they were at it
- Answer: Not very
- So dramatically reduced the # of interviewers

People Analytics in Practice

- Believes a 1% increase in retention can save $75-100m/year
- 3-year study: Changing jobs increases employee “stickiness”
- Increased internal postings of open jobs from <50% to >80%

CREDIT SUISSE

Many, Many Others

- Firms in technology, financial services, telecommunications, automotive, consumer packaged goods, energy, not-for-profit…
- …are finding:
  - Better levers for retaining key employees
  - More diagnostic methods for hiring
  - Who their most valuable employees are
  - How to compose the most productive teams
  - Etc.

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Performance Evaluation: The Challenge of Noisy Data

Professor Cade Massey

Part 1A – Performance Evaluation

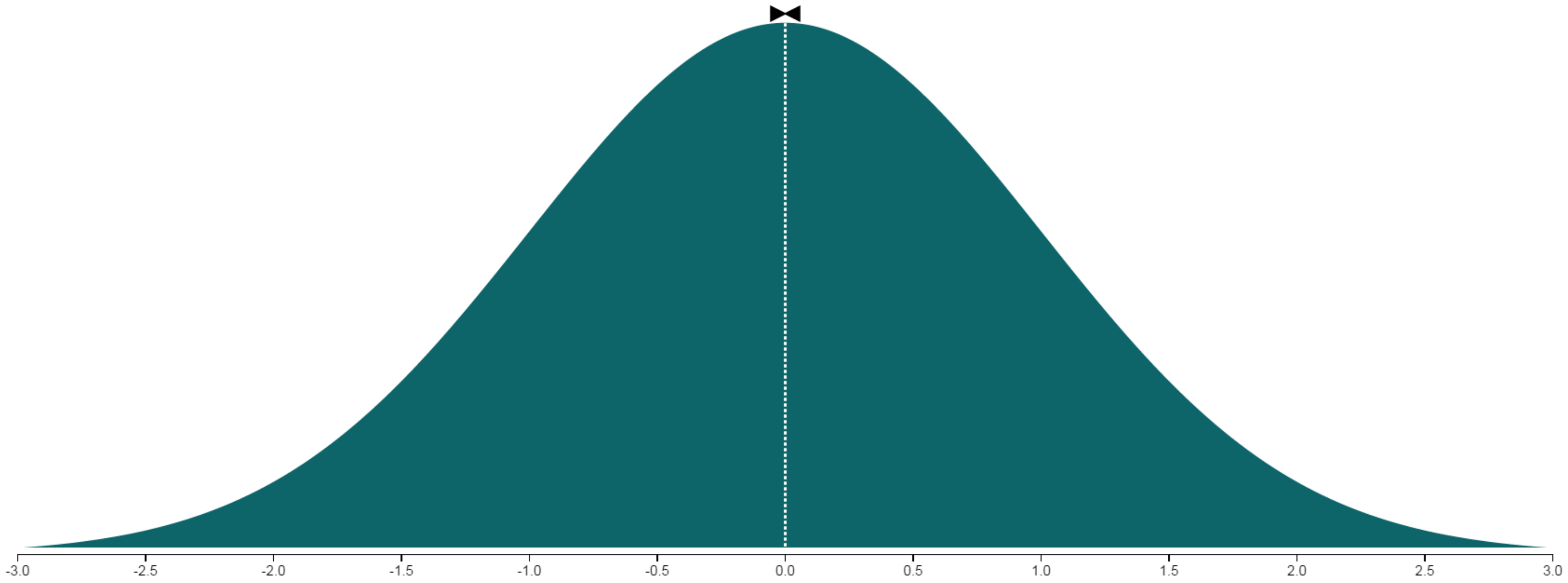
- Purpose of performance evaluation
  - Feedback
  - Rewards / punishment
- Performance valuation, not talent management. Tough to compare employees if not in identical situations.
- Helpful starting place, for this lecture (and often for life): <u>Begin</u> by assuming all employees are equal ability

Noise

- The fundamental challenge in performance evaluation is that performance measures are noisy
- I.e., outcomes are imperfectly related to employee effort

Noise

- For any given level of effort, a range of outcomes can occur due to factors outside the employee’s control
  - Competitors, team members, her boss, the economy, etc.
  - The challenge: Separating skill from luck

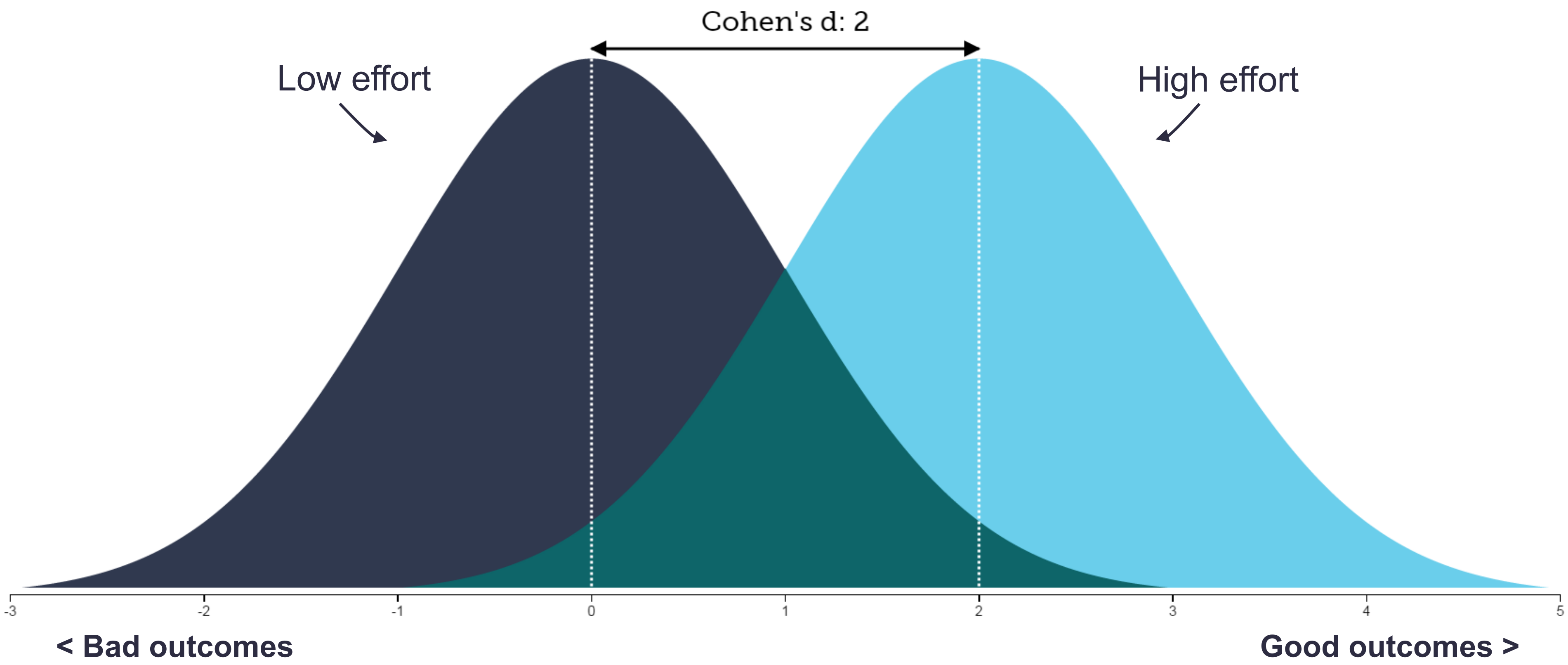


"The distinction between ascertaining skill and luck shows up all the time," he added. "Who do you give your money to for investing? How much do you pay a certain employee? It's everywhere. It isn't just about sports. It's about life."

— JOHN HUIZINGA
UNIVERSITY OF CHICAGO ECONOMIST

Noise

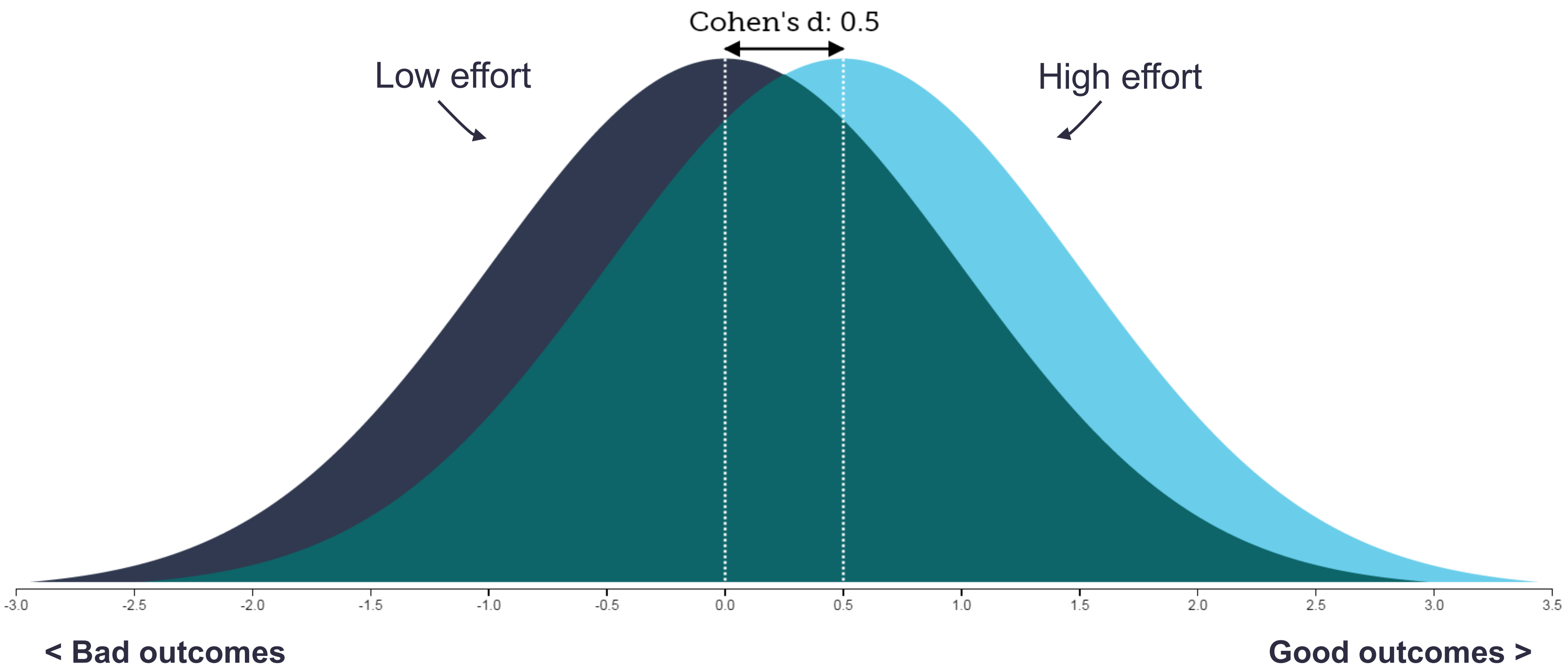
- In some environments this isn't so hard…



dataviz: rpsychologist.com

Noise

- … but in others it's brutal



dataviz: rpsychologist.com

Module Plan

- Extended example
- Four key issues:
  - Regression to the mean
  - Sample size
  - Signal independence
  - Process vs. Outcome
- Summary

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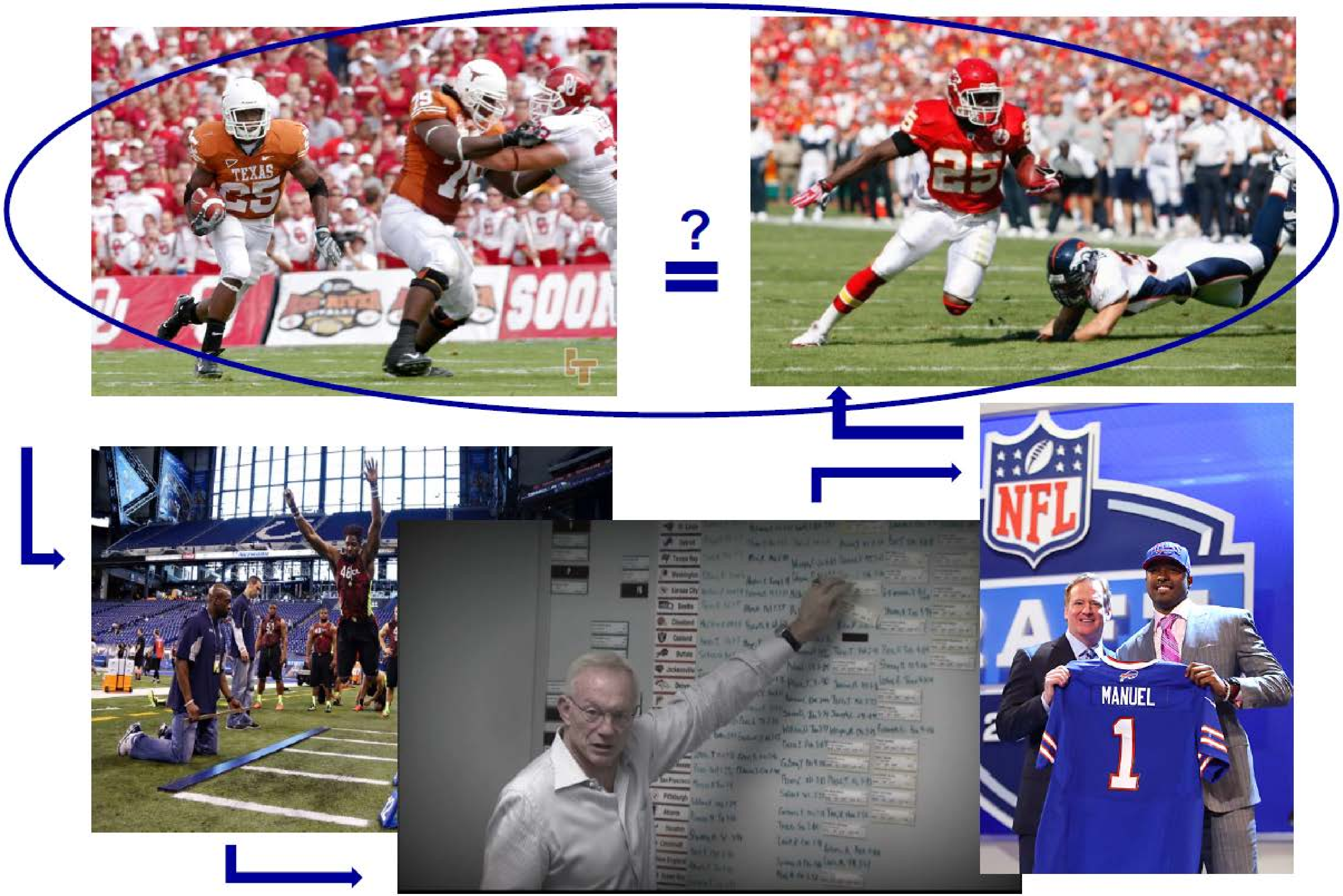
Chance vs. Skill: The NFL Draft

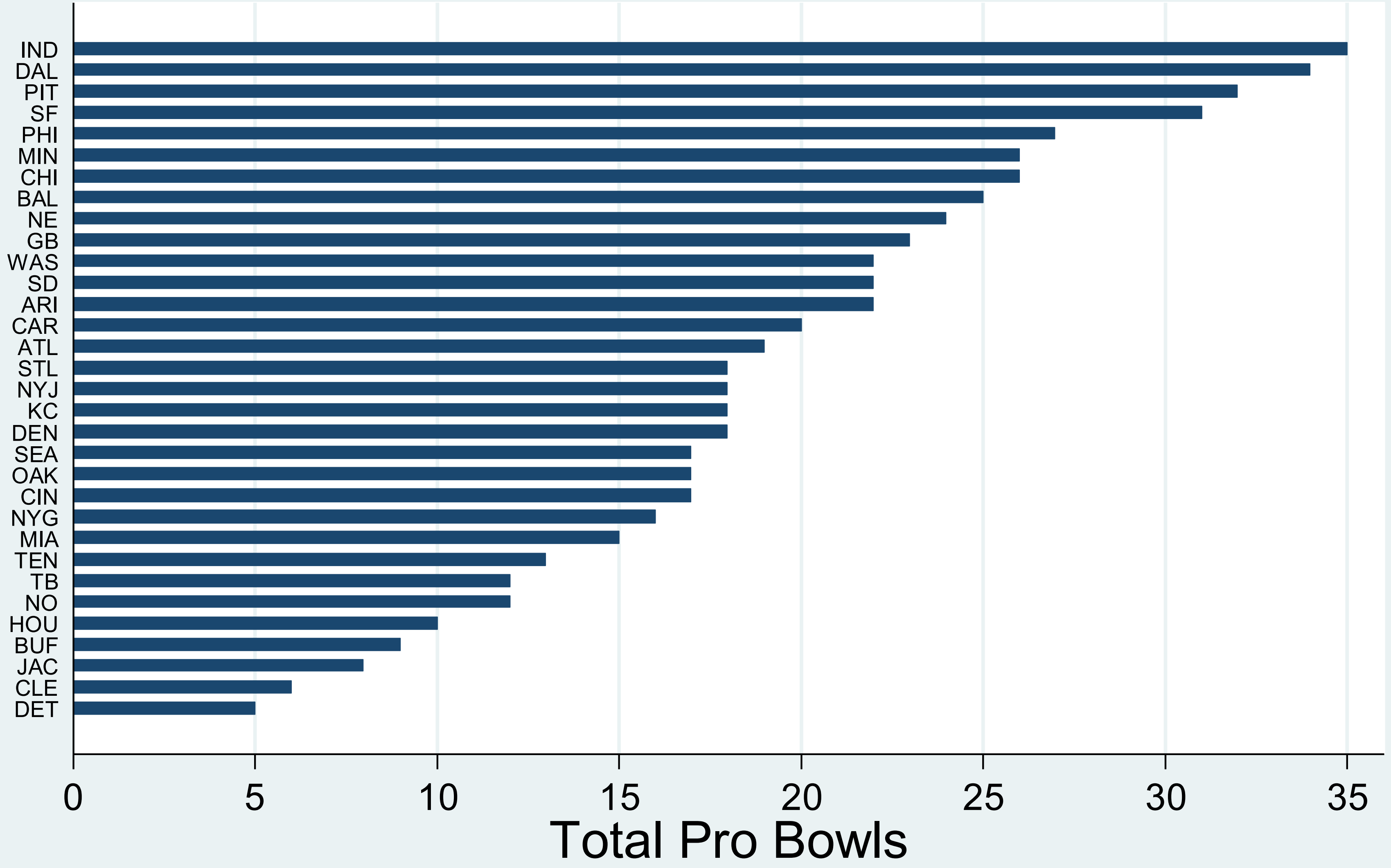
Professor Cade Massey

Module Plan

- **Extended example**
- Four key issues:
  - Regression to the mean
  - Sample size
  - Signal independence
  - Process vs. Outcome
- Summary


TEXAS
NFL
MANUEL
1

Pro Bowls by DRAFTING TEAM



1997-2007 drafts, through the 2009 season.

NFL Draft

Updated: April 21, 2010, 4:44 PM ET

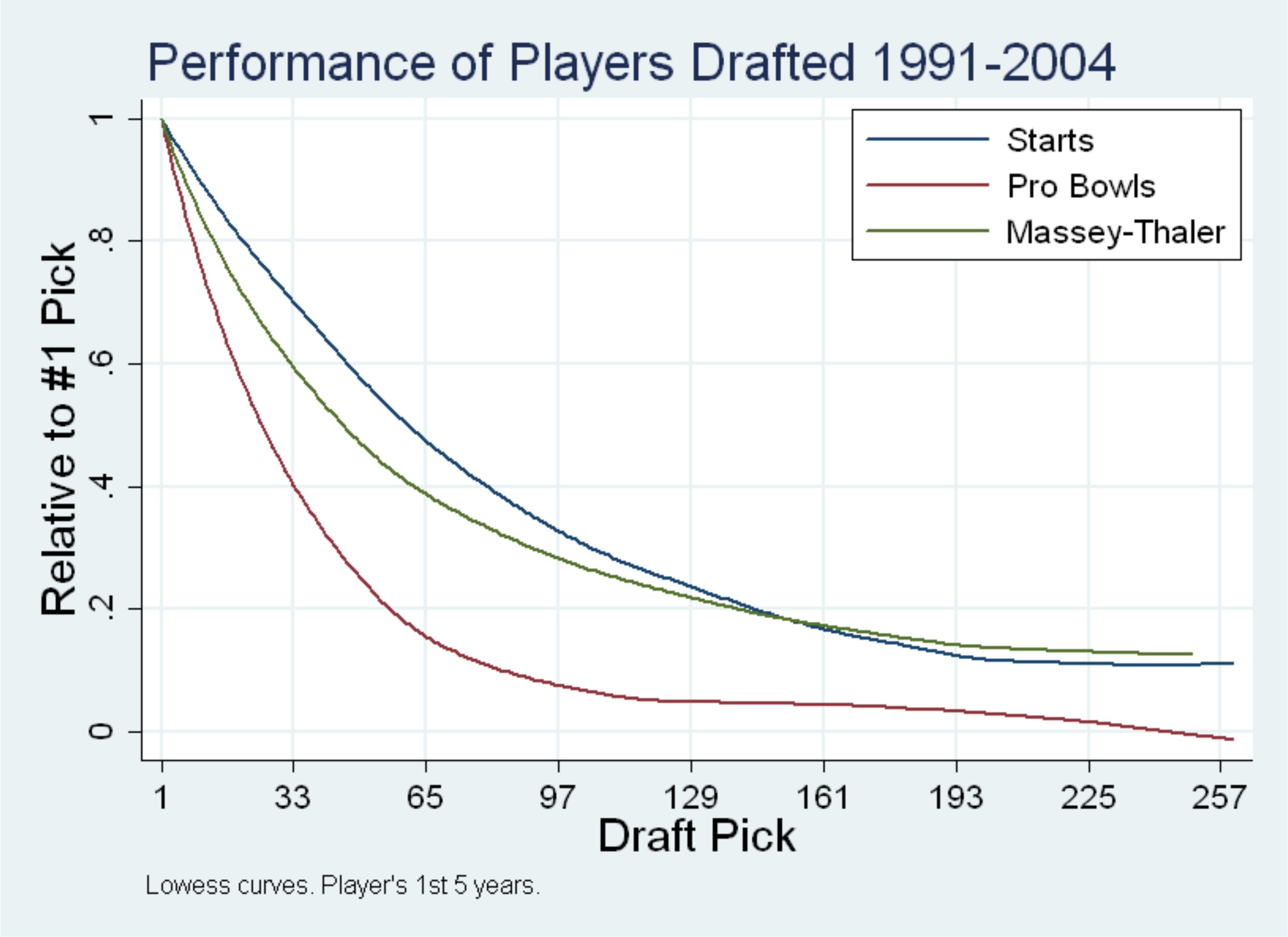
Not feeling the NFL draft

By Rick Reilly
ESPN.com
Archive

- "**Indianapolis Colts**…not just with Peyton Manning… Dwight Freeney, Edgerrin James and Reggie Wayne were **genius picks**, too."
- "The **Cleveland Browns**…screwed the Chihuahua. Their run of No. 1 picks from 1999 to 2002 is the single **worst stretch of drafting** since the Iraqi Republican Guard. Were they using an Ouija board?"

Reason for Skepticism

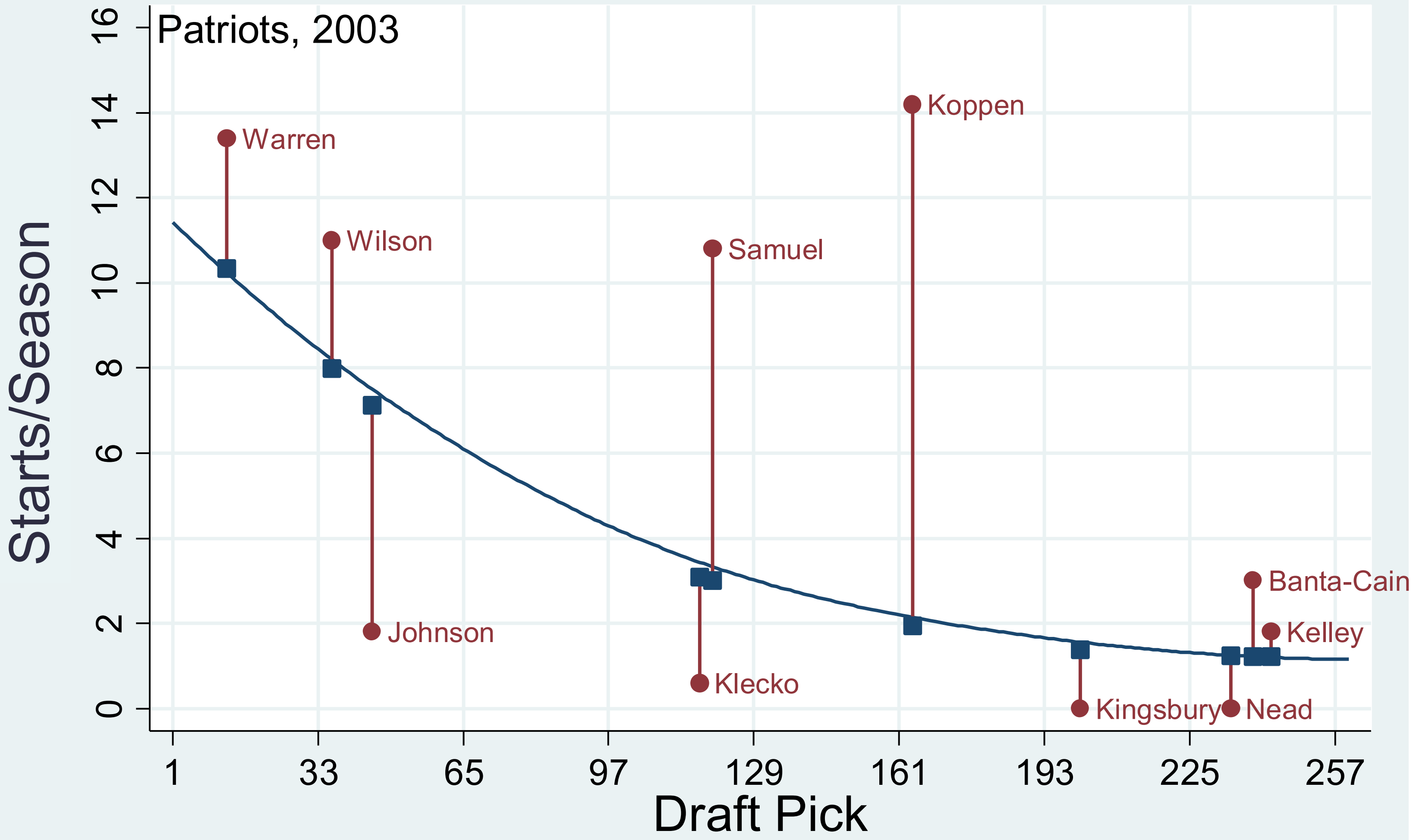
- Massey & Thaler (2013)
  - Overconfidence in the NFL draft
- Baron & Hershey (1988)
  - Outcome bias
- Rabin (2002)
  - Law of Small Numbers
  - Less difference in skill than people believe
    - This <u>fictitious variation</u> is “the most important economic consequence of the law of small numbers”


Performance of Players Drafted 1991-2004
Starts
Pro Bowls
Massey-Thaler
Relative to #1 Pick
0
.2
.4
.6
.8
1
1
33
65
97
129
161
193
225
257
Draft Pick
Lowess curves. Player's 1st 5 years.

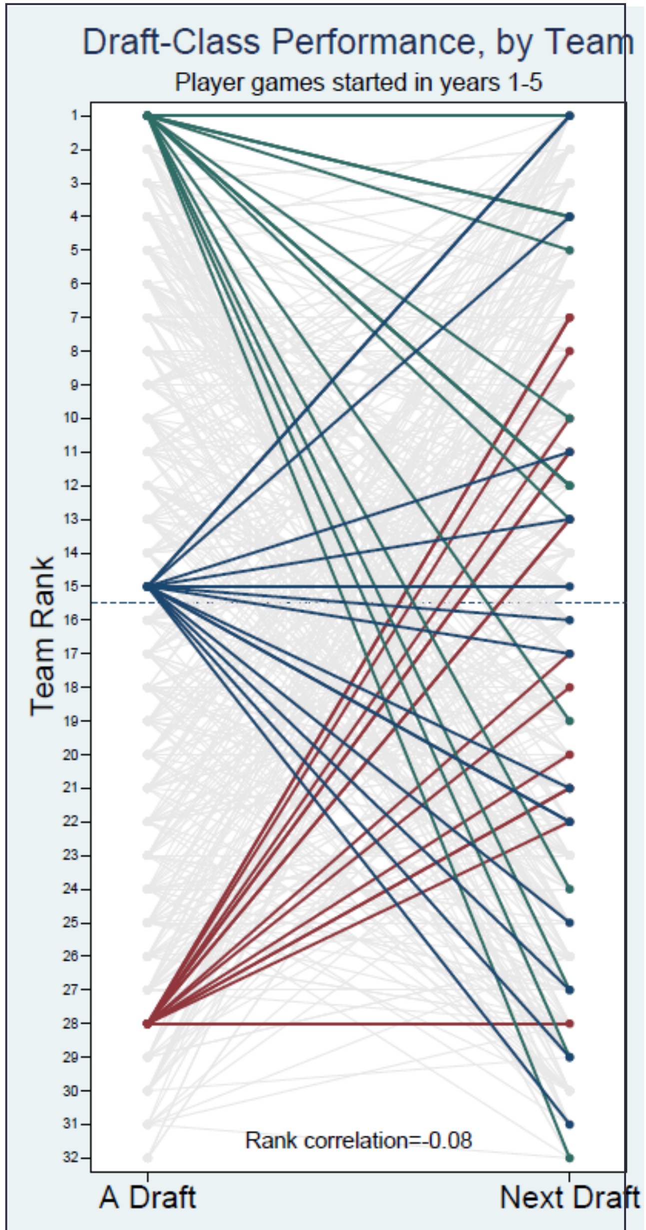
Skill and Chance in the Draft

- Clearly there is skill involved
- But are there differences in skill?
- Are some teams better than others at picking players?

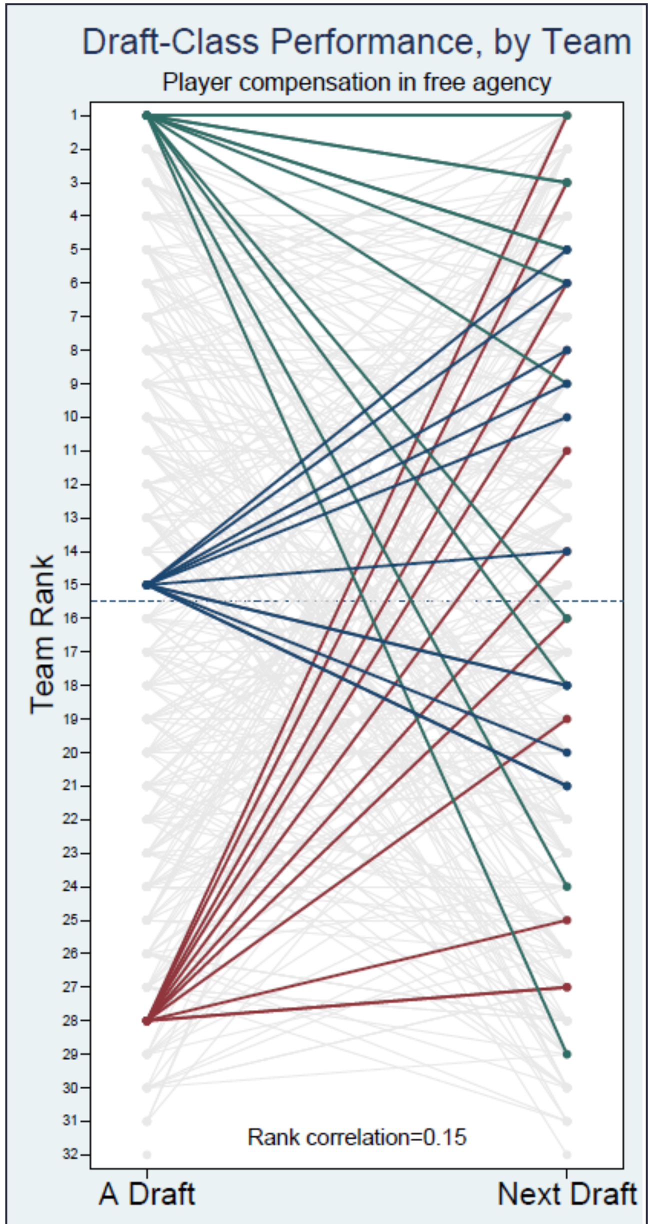
Draft-pick Performance vs. Expectation



Performance evaluated over player's 1st 5 years.



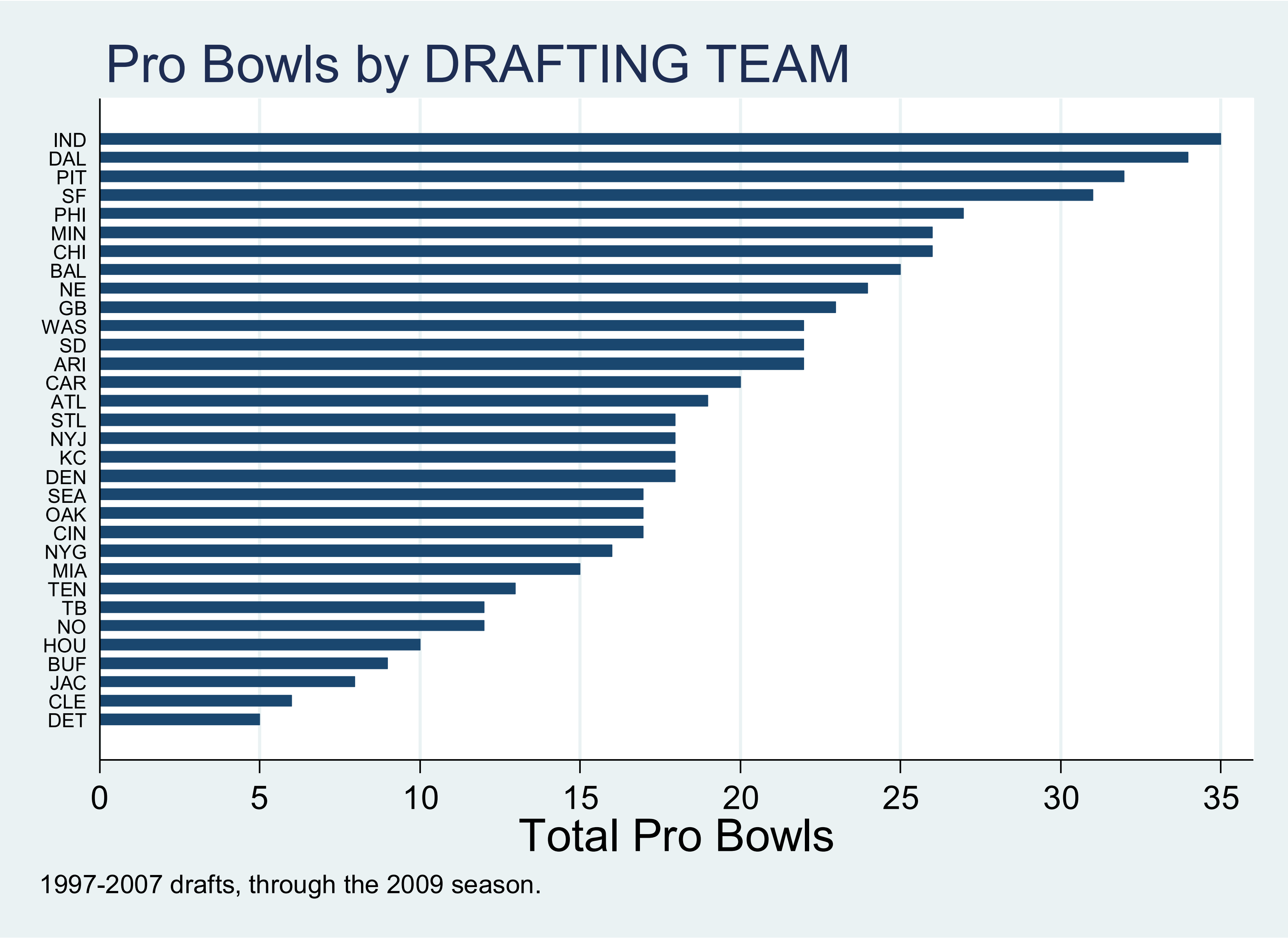
1991-2006 drafts, 1991-2008 seasons. Versus expected for pick #.



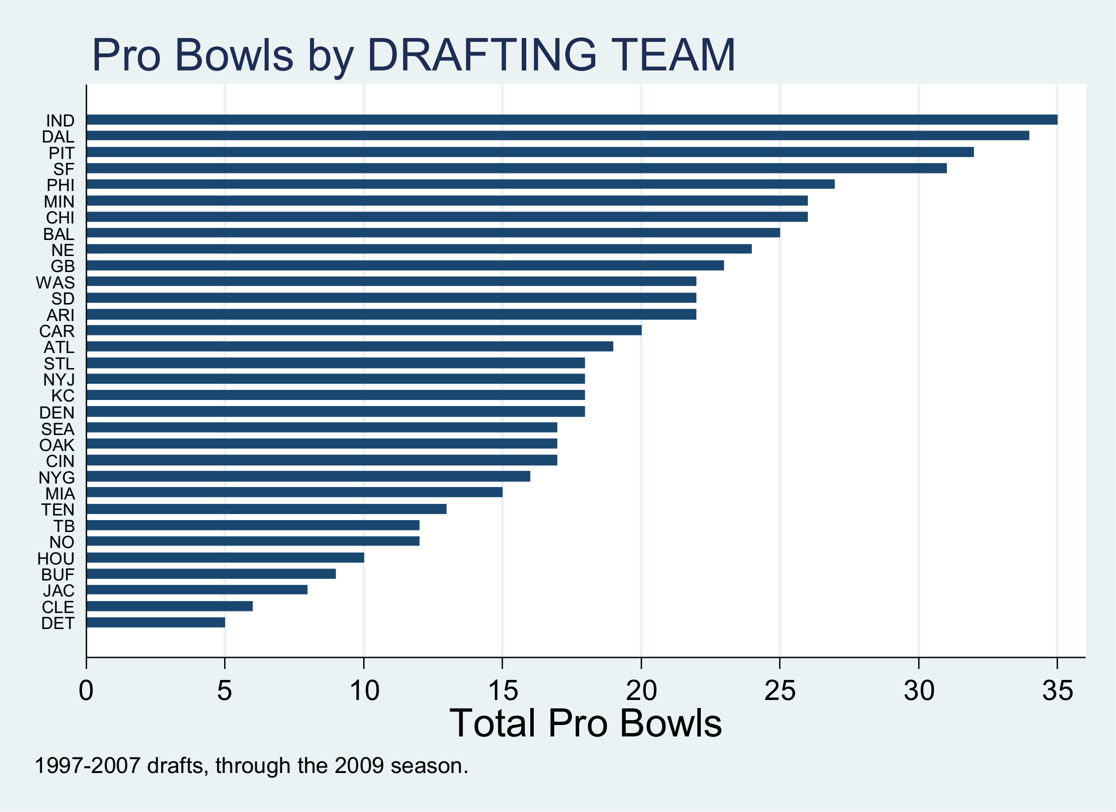
1991-2002 drafts, 1991-2008 seasons. Avg sal cap in years 6-8 vs expected.

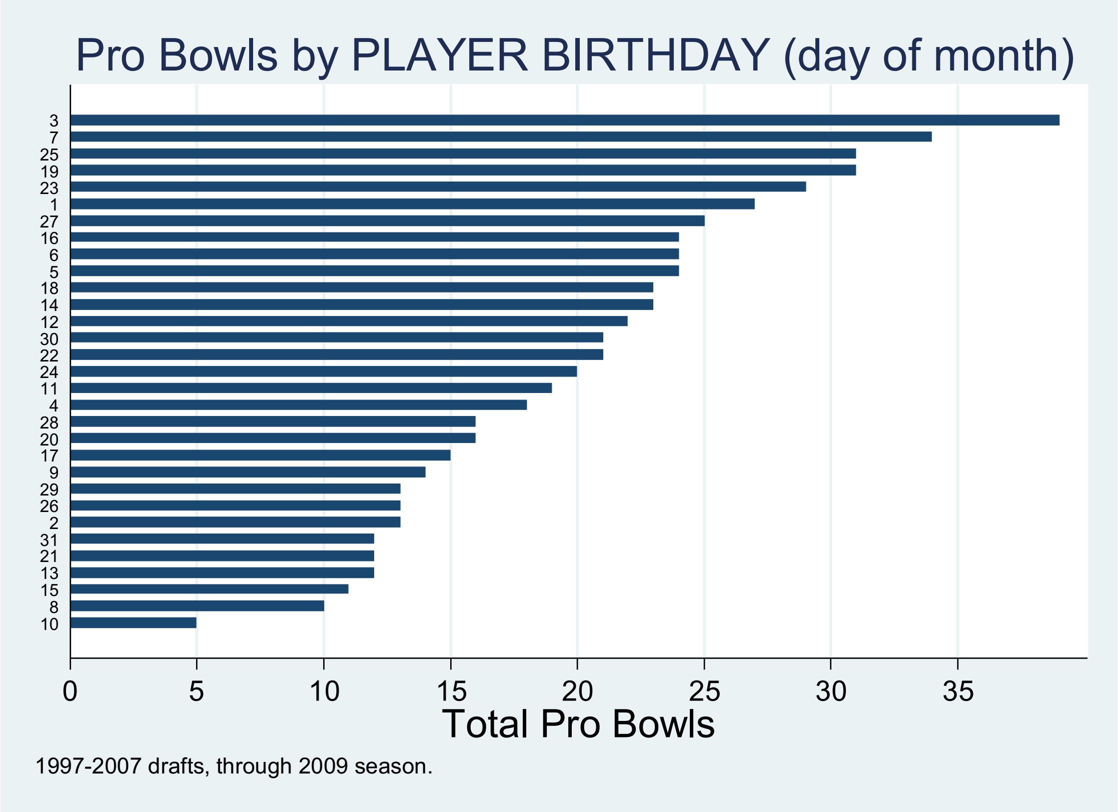
This is a Very Robust Pattern

- Performance Statistic
  - Games started vs. pro bowls vs. compensation
- Player's career stage
  - 1^{st} 5 years vs. free-agent years (>5^{th})
- Additional norming
  - Player position
- Decision-making unit
  - Actual individual in charge of a team's draft
- Draft stage
  - 1^{st} 3 rounds vs. Last 4 rounds


Pro Bowls by DRAFTING TEAM
IND
DAL
PIT
SF
PHI
MIN
CHI
BAL
NE
GB
WAS
SD
ARI
CAR
ATL
STL
NYJ
KC
DEN
SEA
OAK
CIN
NYG
MIA
TEN
TB
NO
HOU
BUF
JAC
CLE
DET
0
5
10
15
20
25
30
35
Total Pro Bowls
1997-2007 drafts, through the 2009 season.

Fictitious Variation





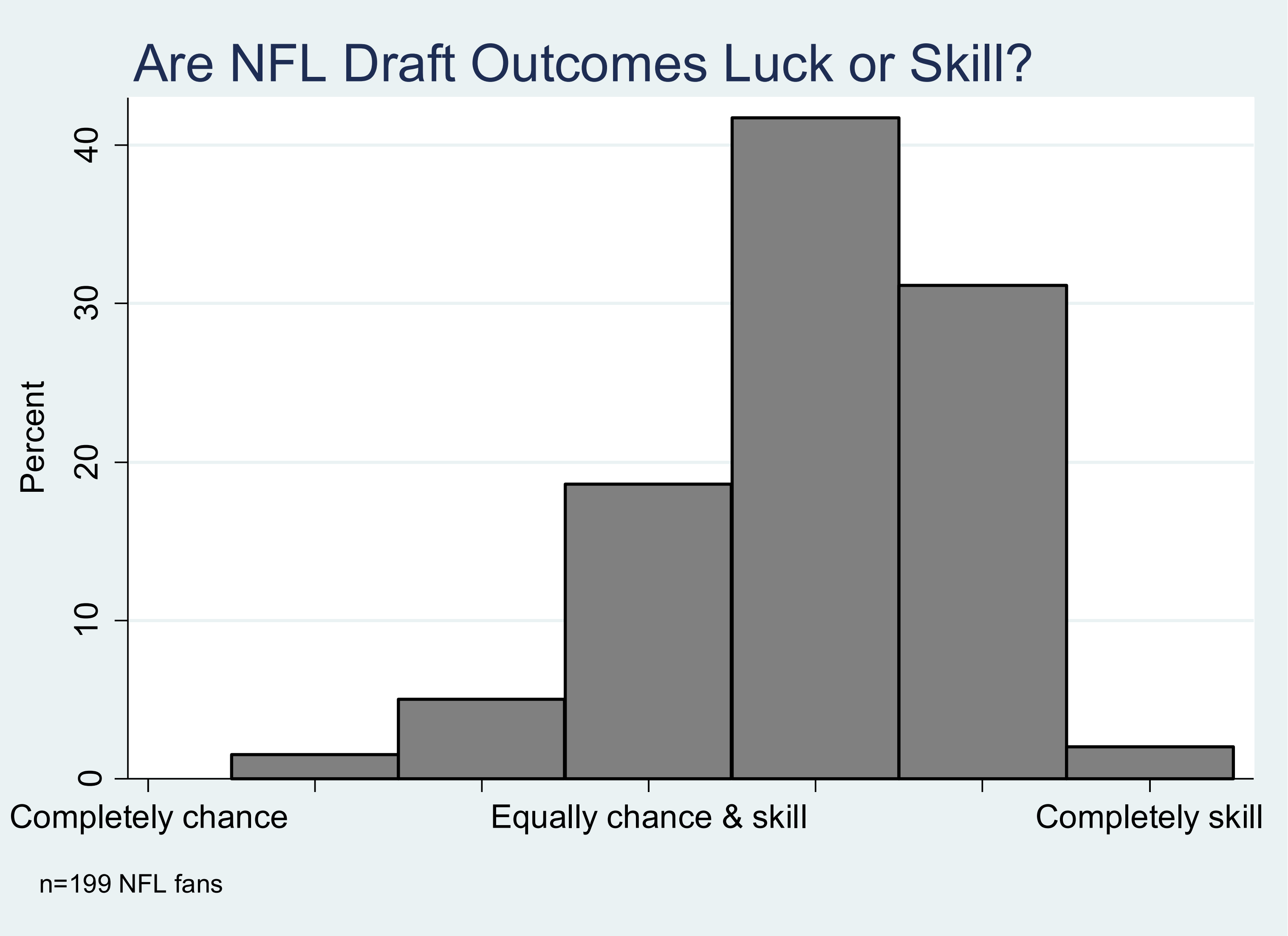
Even dramatically disparate outcomes
can be purely the product of chance.

Perceptions of Chance (with Berkeley Dietvorst

Please indicate to what degree you believe the success of NFL teams in making selections during the NFL draft is due to the drafting skill of each team versus random chance. Indicate to what degree differences between teams in terms of draft outcomes -- e.g., how well players perform long-term -- are due to attributes of the teams' management versus luck.

Draft outcomes are completely due to random chance			Draft outcomes are equally due to chance and drafting skill			Draft outcomes are completely due to drafting skill
○	○	○	○	○	○	○

Perceptions of Chance (with Berkeley Dietvorst



"If professional baseball players, whose achievements are endlessly watched, discussed and analyzed by tens of millions of people, can be radically mis-valued, who can't be? If such a putatively meritocratic culture as professional baseball can be sloppy and inefficient, what can't be?"

— MICHAEL LEWIS

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Finding Persistence: Regression to the Mean

Professor Cade Massey

Module Plan

- Extended example
- **Four key issues:**
  - **Regression to the mean**
  - **Sample size**
  - **Signal independence**
  - **Process vs. Outcome**
- Summary

A Simple Model

- There are two components to performance:
  - In informal terms: Real Tendency + Luck
  - In more formal terms: $y = x + e$,
    - x = true ability, and
    - e = error, randomly distributed around 0.
- What happens when we sample on extreme performance? What underlies extreme success and failure?
  - Extreme success = f(superior ability, positive error)
  - Extreme failure = f(inferior ability, negative error)
- Consequences?

A Regression to the Mean

- A study was recently conducted examining the performance of the 283 stock mutual funds that existed during the 1990s. The study divided the 1990s into an early period (1990-1994) and a late period (1995-1999). Below are the 10 funds that had the highest rate of return in the early period (with their names disguised), ranked from 1 to 10. Predict their rank for the late 1990s.

Ignoring Regression-to-the-Mean (2.Var Neglect)

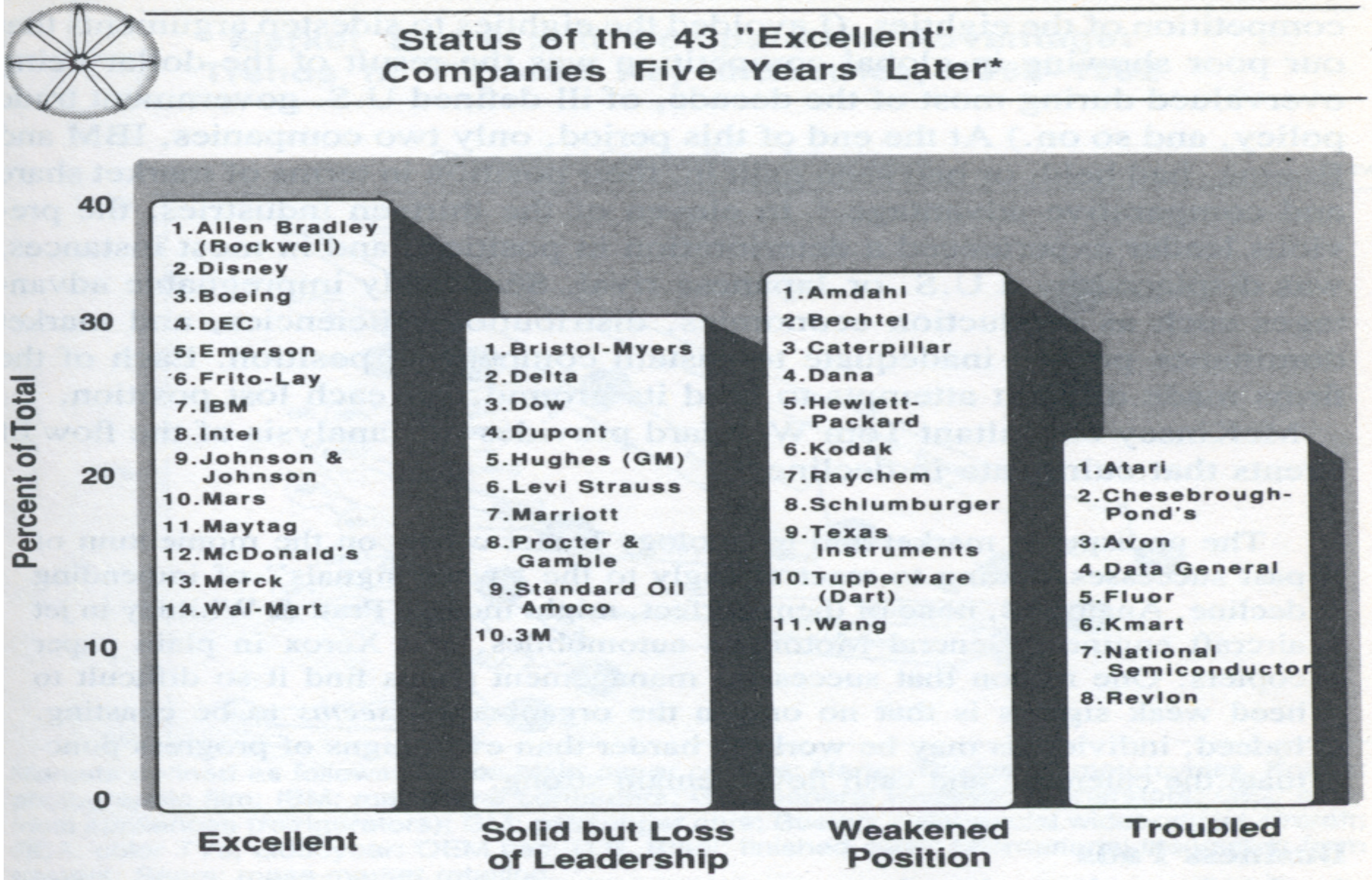
Early 1990s Fund & Rank	Late 1990s Estimated Rank (median)	Late 1990s Actual Rank
A 1	10	129
B 2	20	134
C 3	20	261
D 4	28	21
E 5	44	210
F 6	37	53
G 7	42	183
H 8	31	105
I 9	31	275
J 10	25	54
Total # funds = 283	**Avg. = 25, r=.51**	**Avg. = 142.5, r = -.03**

Examples

- Officer in the Israeli Air Force— “Punishment is more effective than praise. Whenever I punish a pilot after a really poor flight, I see better performance the next time. Whenever I praise a pilot after an excellent flight, I see worse performance the next time.”
- Peters and Waterman’s book, In Search of Excellence. They selected 43 high performing companies in the early 1980s, and looked to see what practices they used (some that they discovered were the organizational equivalent of “brushing teeth”)

Excellent Companies, 5 Years Later

FIG.1–1



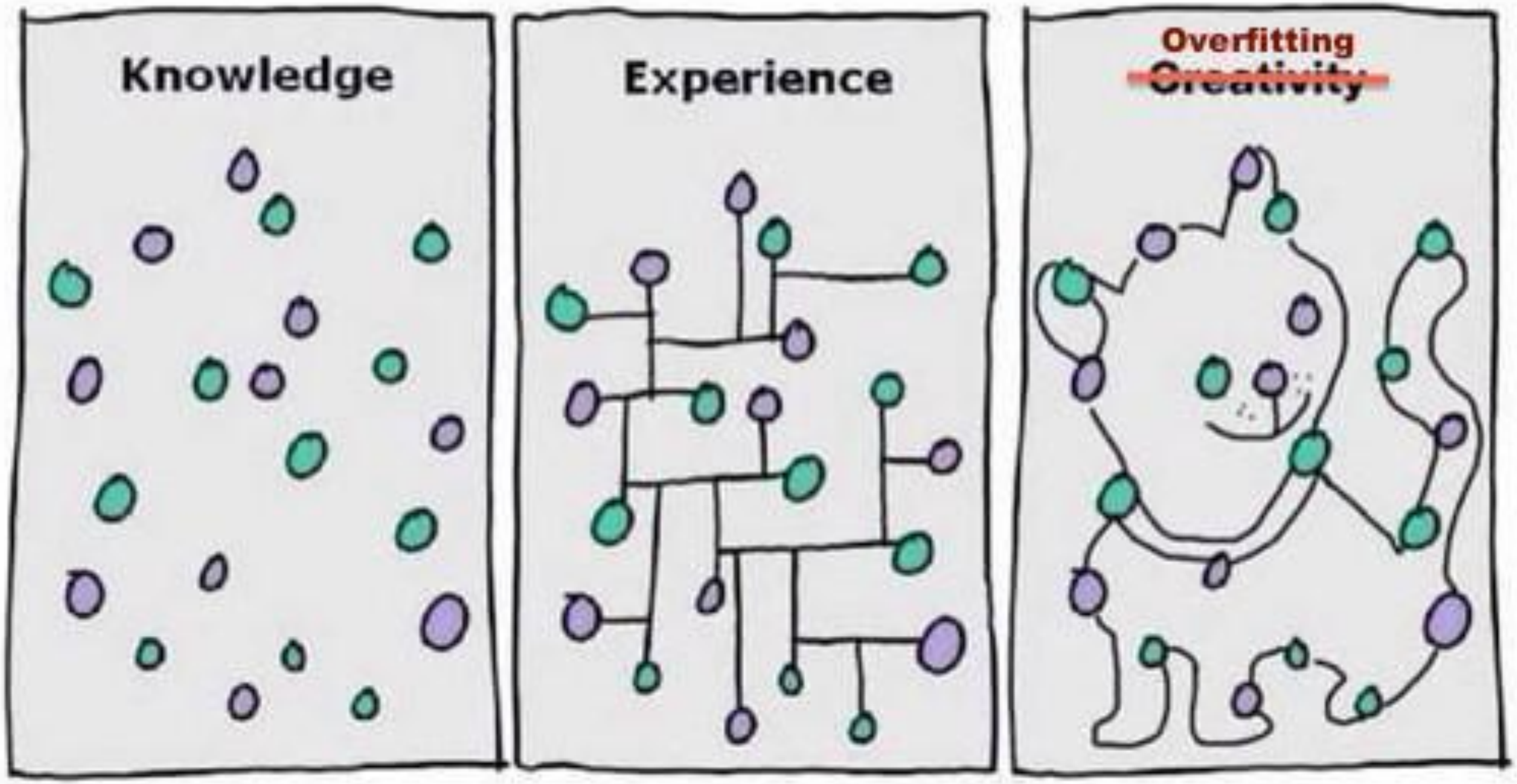
* The 43 "excellent companies" were identified in *In Search of Excellence*, by Thomas J. Peters and Robert H. Waterman, published 1982.

Regression to the Mean

- Anytime you sample based on extreme values of one attribute, any other attribute that is not perfectly related will tend to be closer to the mean value
  - "Attributes" can be:
    - Performance at different points in time
      - E.g., last year's stock returns and this year's
    - Different qualities within the same entity
      - E.g., a person's running speed and language ability

What Gets in the Way of Seeing This?

- Among other things:
  - Outcome bias
  - Hindsight bias
  - Narrative seeking
- In short, we make sense of the past
  - We find a story that connects <u>all the dots</u>
  - Chance plays too small a role in these stories


Knowledge
Experience
Overfitting
~~Creativity~~

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Extrapolating From Small Samples

Professor Cade Massey

Extrapolating From Small Samples

Your firm has two plants, one large and one small, which mass produce a standard computer chip. Other than the amount they produce, the two plants are identical in all essential regards. Both use the same technology to produce the same product. When properly functioning, this particular technology produces one percent (1%) defective items. Whenever the number of defective items from one day's production exceeds two percent (2%), a special note is made in the quality control log to "flag" the problem. At the end of the quarter, which plant would you expect to have more "flagged" days in its quality control log? Please mark one.

22% A) The small plant

30% B) The large plant

48% C) The same number on average

Extrapolating From Small Samples

- Principle: Sample means converge to the population mean as the sample size increases. (This is known as the Central Limit Theorem.) Thus, you will see more extreme values in small samples.
  - When are you more likely to see a .400 season batting average in baseball – May 1 or Sept. 1?
  - In which hospital are you more likely to see a dramatically higher % of boys than girls (or vice versa) born on any given day – a small community hospital (e.g., 5 births/day) or a large city hospital (e.g., 100 births/day)?

“Law of Small Numbers”

- People believe small samples <u>closely</u> share the properties of the underlying population
- This means they too readily infer the population’s properties (e.g., average) from the sample’s
- That is: They neglect the role variability (aka chance) inevitably plays in small samples

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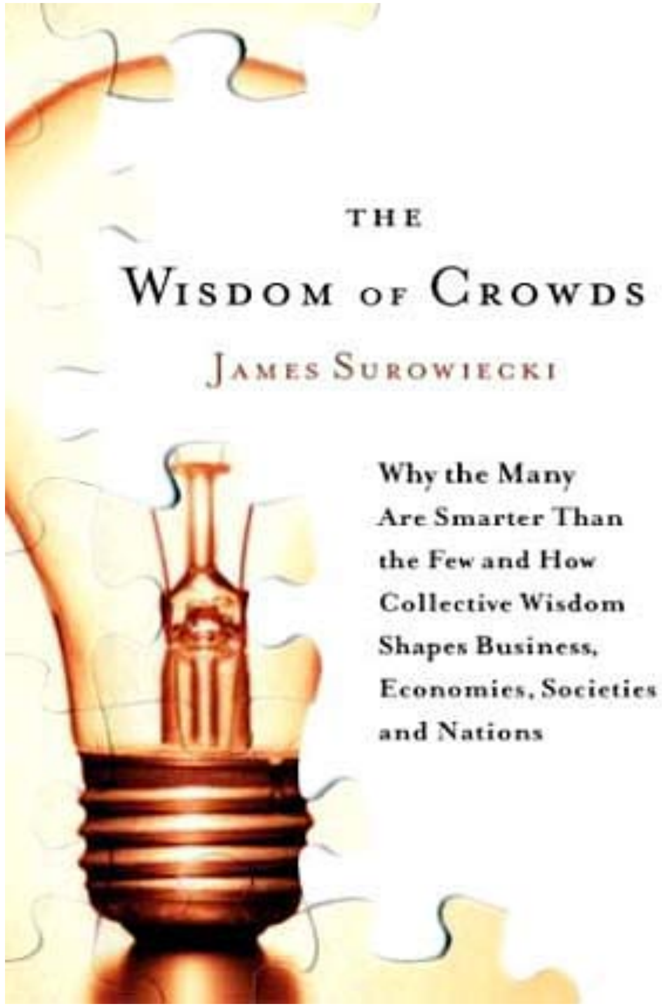
The Wisdom of Crowds: Signal Independence

Professor Cade Massey

The Wisdom of Crowds

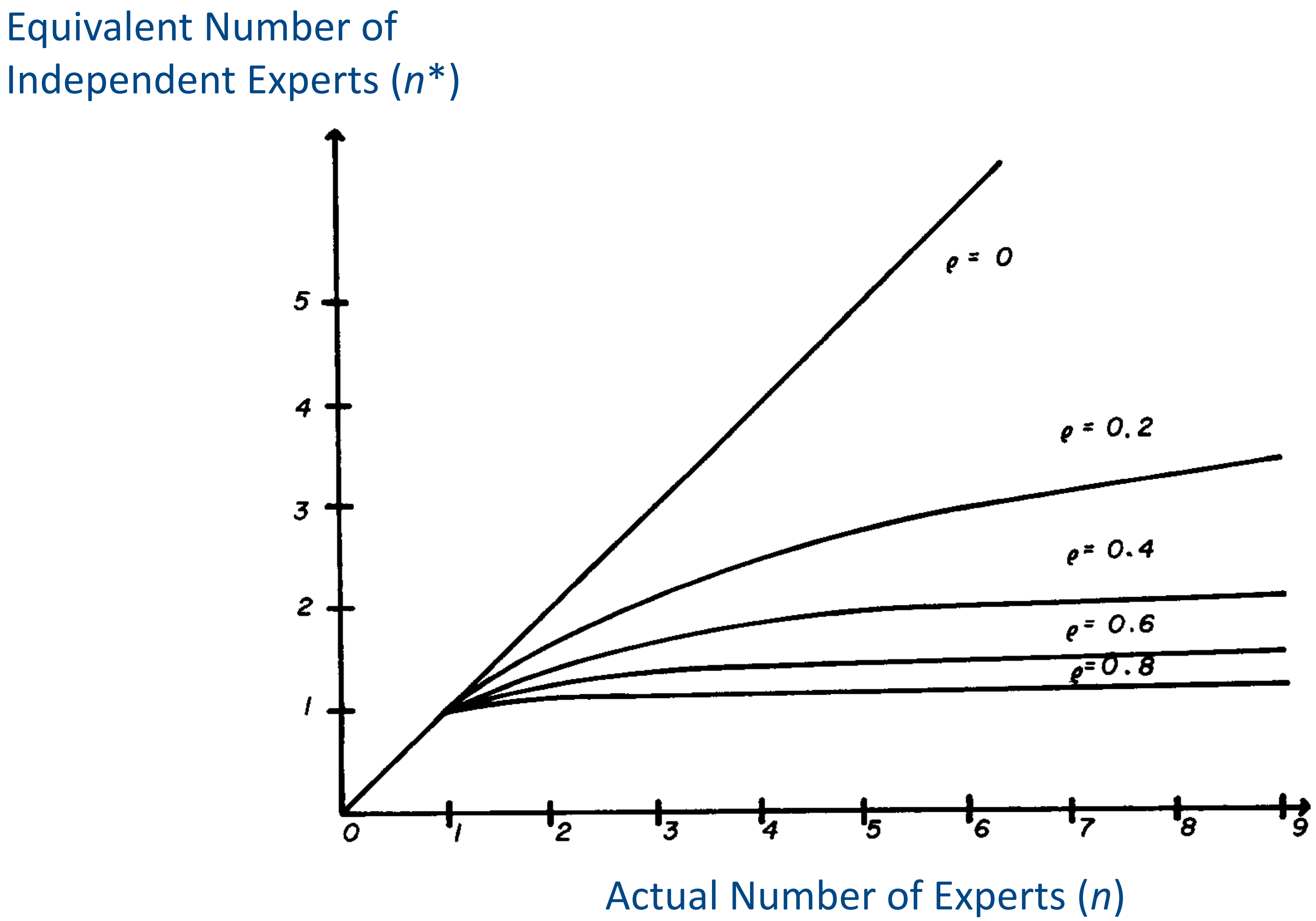


- The average of a large number of forecasts reliably outperforms the average individual forecast
  - Idiosyncratic errors offset each other
  - E.g., Galton's (1906) county fair contest
  - Many other examples

The Wisdom of Crowds

- But the value of the crowd critically depends on the independence of their opinions
- Independent means uncorrelated
- If correlated, the value of additional opinions quickly diminishes

Impact of Correlation



$$n^* = \frac{n}{1+(n-1)\rho}$$

$$n^* \to 1/\rho$$

as $n \to \infty$

Clemen and Winkler (1985)

Signal Independence

- People are bad at accounting for this effect
  - Even when you tell them exactly what the correlation is, people do not properly adjust (Enke & Zimmerman, 2015)

Signal Independence

- Sources of correlation between two opinions?
  - They've discussed it already!
  - They talk to the same people
  - They have the same background – from the same place, trained the same way, same historical experiences, etc.
- Need to find ways to keep opinions independent, and add independent perspectives to experienced groups

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Process vs. Outcome

Professor Cade Massey

Consider Broader Set of Objectives

- Organizations generally care about <u>how</u> a person goes about his/her job
  - Most important: impact on others
- People consider too few objectives (Bond, Carlson & Keeney, 2008)
  - Systematically omit nearly ½ of the objectives they later identify as personally relevant
- Leads many firms to rely on too narrow a set of performance measures

Process vs. Outcome

- Famously hard-charging Dell Computers changed their performance evaluations in the early 2000s
  - Before change: 100% results
  - After change:
    - 50% <u>what</u> an employee accomplished
    - 50% <u>how</u> he/she accomplished it, as judged those affected

Process vs. Outcome

- The more uncertainty in the environment, i.e., the less control an employee has over exact outcomes, the more a firm should emphasize process in their evaluations.

Process vs. Outcome

- Use analytics to better understand, and focus on, the processes that <u>tend to</u> produce desired outcomes
- Key issue: Identify the fundamental drivers of value


t: Goals


t-1: Shots


t-2: Possession

The No-Stats All-Star

By MICHAEL LEWIS
Published: February 13, 2009

"Knowing the odds, Battier can pursue an inherently uncertain strategy with total certainty. He can devote himself to a process and disregard the outcome of any given encounter. This is critical because in basketball, as in everything else, luck plays a role, and Battier cannot afford to let it distract him."

— MICHAEL LEWIS

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Summary of Performance Evaluation

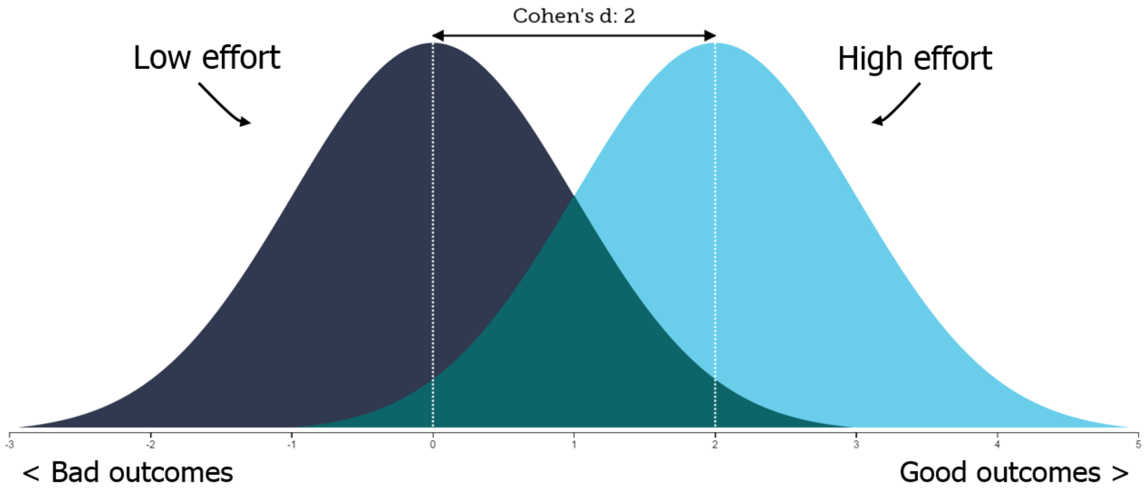
Professor Cade Massey

Performance Evaluation Summary

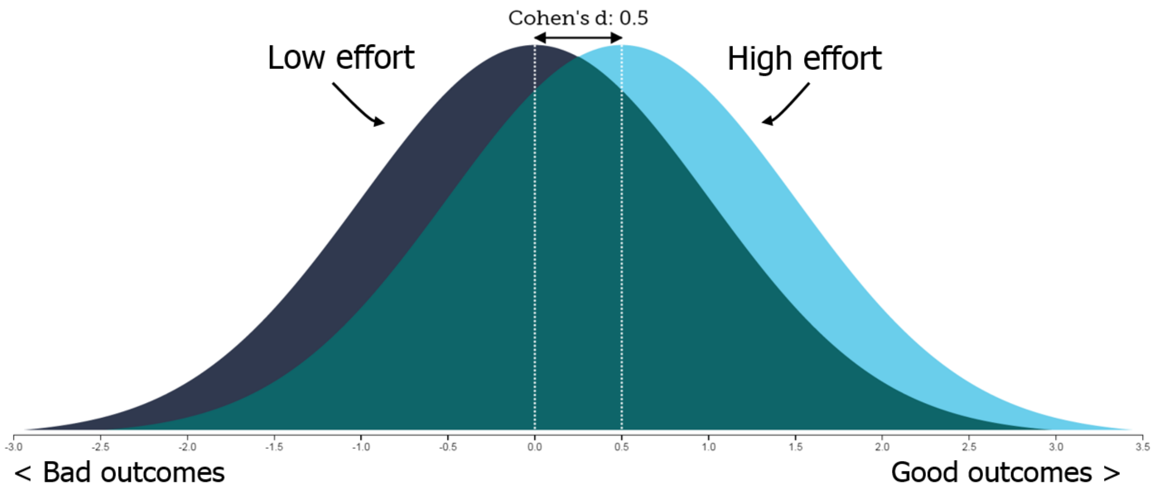
1. Understand your environment
   - Know you’re biased
   - Account for chance
2. Ask the critical questions

Understand Your Environment

- How much lottery and how much math problem?



vs.



Know You're Biased

1) Non-regressive predictions
2) Outcome bias
3) Hindsight bias
4) Narrative bias

Account for Chance

- The key issue: Persistence
- The more fundamental (skill-related) a performance measure is, the more it will persist over time
- The more chance-related a performance measure is, the more it will regress to the mean over time

Critical Questions

- Are the differences persistent or random? I.e., how do we know this isn't just good/bad luck?
- Is the sample large enough to draw strong conclusions? How can we make it larger?
- How many different signals are really tapping into here? How can we make them as independent as possible?
- What else do we care about? Are we measuring enough? What can we measure that's more fundamental?

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