Economic Theory Applied to Sports

ECONOMICS OF SPORTS (ECON 325)

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Introduction

This is a lecture about miscellaneous econom(etr)ics applications that don't neatly fit in the product or labor market categories.

They apply economic theory to decision-making on the field/diamond/pitch/court. Examples:

- Is there a "hot hand" in sports?
- In a baseball lineup, is there such a thing as "protection?"
- How do soccer players choose their strategies during penalty kicks?
- Why do football teams punt away their 4th Downs so often?
- Do they even "optimize their portfolios" of running and passing plays? Or is there a passing premium?

All of these questions have had very legitimate economics research performed on them.

- Some of it challenges the sports industry and fans' orthodox beliefs, too, so it's up to the reader to judge whether the academics have missed something or that misconceptions simply "die hard."

The myth of the “hot hand”

Statisticians, not just in the field of economics, had been accumulating evidence to debunk this commonly believed idea before the video game, “NBA Jam.”

If you grew up in the 90s, though, the game’s design, whereby making consecutive shots (“he’s heating up . . .”) built up momentum leading the ball to start on fire (“he’s on fire!”) and all your shots to go in, seemed plausible.

- *metaphorically*.

Yes you could play as Bill Clinton in NBA Jam for Super Nintendo.

“The Law of *small* numbers”

A term Gilovich, Vallone & Tversky (1985) applied to the human tendency to insist that small samples of a random process exhibit the same characteristics as large samples.

- If you toss a fair coin 10 times it should come up 5 heads and 5 tails.
- We get suspicious if heads comes up 6 or 7 times in a row, even though probabilistically runs like that are fairly likely in repeated sampling.

Streaks of made shots in basketball do not appear random to the observer, leading him to concoct the narrative of the “hot hand” to explain such a long streak.

- Aside: these guys are Psychologists, not Economists, but there is a branch of Economics (“Behavioral”) that synthesizes insights like theirs into our field, e.g., the use of heuristics and mental “shortcuts” to make decisions when calculating expectations is too mentally burdensome.
- Consider taking ECON 471 if this appeals to you.

Fooled by randomness

A corollary of the hot hand narrative is the idea that streaks and slumps are “due” to end: after several made (missed) shots the hot hand has to “wear off” and the shooter goes back to normal.

But maybe he was never otherwise to begin with!

- What if the hot hand is just randomness manifesting itself in a way that we are bad at detecting.

GVT test this by asking whether NBA players’ streaks of made (missed) shots are longer or more frequent than would be generated by random chance.

- E.g., tossing a coin with probabilities equal to the player’s lifetime FG%.

As an indication of the stakes, they did a survey of fans: in which 84% agreed that “it is important to pass the ball to someone who has just made several shots in a row.”

- Is it?

GVT's methods

Based on their survey, fans expect a player's FG% on his next shot to rise 11 points above his career average if he has made the previous shot.

Using data on the Philadelphia 76ers (series of consecutive shots by each player) in 1980-81, the authors test whether:

- Pr(next shot make|last shot make)=Pr(next shot(s) make), i.e., independence,
- The number of streaks of ≥ 2 consecutive makes (misses) is higher than the binomial distribution would predict,
- Whether hot handed-ness manifests itself across games, instead of within them: $E(FG\%\ next\ game | FG\%\ this\ game) = E(FG\%\ next\ game)$?

GVT’s results

The 76ers shot 52% from the field that year.

- On shots that followed 3, 2, and 1 misses by the shooter they shot 56%, 53%, and 54% respectively.
- On shots that followed 3, 2, and 1 makes by the shooter they shot 46%, 50%, and 51% respectively.
- There was only one player (Daryl Dawkins) for whom shot making was statistically significantly based on past shooting, and it was *negatively* predictive.
- Most of them were just insignificantly different from zero, i.e., failing to reject independence.

If anything this indicates that you get “worse” after making consecutive shots. “Cold hand?”

GVT's results, continued

If you make after a make or vice versa, it counts as a "run." If you have fewer of these runs than the binomial distribution would predict, you are "streaky" at shooting.

- I.e., your makes and missed are all "bunched together."

Daryl Dawkins is, again, the only player on the team that exhibits significantly different runs than is expected based on the binomial distribution—and he has *more* of them.

- An "anti-streak" shooter?
- As a team the 76ers had slightly more (not statistically significantly) runs than predicted by randomness.

GVT's results, continued

Finally they calculated the ratio,

$$\frac{SE(observed)}{SE(predicted|season\ FG\%)}$$

Where $SE(observed) = \left[\frac{1}{81}\sum_{i=1}^{82}\left(FG_{game\ i} - FG_{season}\right)^2\right]^{\frac{1}{2}}$,

And having a ratio greater than 1 means you had more variability and streakiness across games than would be predicted based on your season FG%.

No player on the 76ers exhibited this behavior that year. Dawkins had a ratio significantly smaller than 1, though, to the surprise of no one at this point.

GVT’s results, caveats

Maybe it’s just the 76ers?

- Authors analyzed the Knicks and Nets, too, found only 1 player with positive “hot hand” dependence.

Shot selection: streaks make you “greedy” and slumps make you “cautious.”

Defense: same idea, they “clamp down” on a streaker and “slack” on guarding a slump-er.

GVT analyzed *Free Throw* shooting by the 1980-81 and 1981-82 Boston Celtics and, again, found no dependence.

- And there’s no defense or choosing of where to shoot involved in free throws!

They also had Cornell’s men’s and women’s players shoot 100 shots per player in a gym and observed no statistical dependence in their shooting %s: overall they shot 47% in the gym.

- Probability of making after 3, 2, 1 misses was 45%, 47%, and 47%, respectively.
- Probability of making after 3, 2, 1 makes was 49%, 49%, and 48%, respectively.

Hot hand, subsequent literature

Albright (1993) finds very little evidence of streakiness in MLB batting performance during 1987-1990.

- Some individual players *did* exhibit (and anti-) streakiness, but for the league as a whole there was no evidence of persistence in batting performance.

Franc, et al. (2001) finds some momentum in Wimbledon tennis at the point level of observation.

- Winning the last point positively predicts winning the next.

Bar-Eli, et al. (2006) reviewed the literature during the intervening 20 years and conclude that there is still almost no evidence of a "hot hand" in sports.

- Bocskocsky, Ezekowitz & Stein (2014) control for shot selection and do find evidence of 1.2 to 2.4 "hot hand" effect on shooting %. Also Green & Zwiebel (2017) Arthur & Matthews in MLB (2017).

Sacred cows=yummy burgers?

Bradbury & Drinen (2008) analyze the effect of the on-deck hitter in baseball on the performance of the current hitter.

- In the business this is usually called “protection” in the lineup because the pitcher wants to face a high performing on-deck hitter with a minimum of runners on base. Conversely the pitcher might “pitch around” a strong hitter if the player on deck (“protecting him”) is weak.
- Caveat: pitchers may also dial the effort up (down) to the level of the current (or on-deck) hitter’s skill strategically to get deeper into games.

The question: does “protection” exist?

The stakes: since expected MRP is the basis of player salaries, do the parties take account of a player’s (non) protection externalities (“making others better/worse”), i.e., assuming they exist?

B&D methods

Use play-by-play data from MLB 1989-1992 to control for situational factors and observe whether the characteristics of the on-deck hitter affect the outcome of the current hitter's at bat.

- Specifically the OPS=SLG+OBP of the on-deck hitter.
- Protection says "positively" about hits but "negatively" about bases on balls.
- Strategic effort says "negatively" about hits and bases on balls.

B&D results

The effect of the next hitter's OPS on the outcome of the current at bat is:

- To decrease the likelihood of a base on balls (consistent with protection and strategic pitching effort),
- *And* to decrease the likelihood of all kinds of hits (consistent with strategic pitching effort),
- i.e., they try extra hard to get the players ahead of Bryce Harper out instead of pitching around them.
- The next guy after the on-deck ("in the hole") has no effect on the outcome of the current at bat.

Does this justify *penalizing* strong players in contract negotiations? Not really.

- The effect is small. A full standard deviation increase in OPS decreases the batting average of the hitter ahead of me by only 0.003 points.

Positive "protection" externalities *may* exist but their effect is smaller than the strategic effort effect.

- Bradbury in a 2007 paper finds that pitchers are also compensated in a way that is independent of the contributions of the defense behind them.

Extension: Joey Votto says protection comes from the hitter in front of you—not behind.

Game theory in it’s most literal application

Penalty kicks are the ultimate example of a simultaneous move game between two non-cooperative players (Kicker and Goalie).

Chiappori, et al. (2002) model this as a theoretical game in which both players choose an action from the set {L, C, R} and the combination of those actions determines the payoff.

- I.e., the kick scores a goal with a certain probability.
- The kicker’s gain is the goalie’s loss. A zero sum game.

Games (as you would learn more about in ECON 451) are usually presented in their normal form, i.e., a table of payoffs corresponding to intersections of the row player’s (K) actions and the column player’s (G) actions.

Chiappori, et al., model

	G		
K	L	C	R
L	P_L	π_L	π_L
C	μ	0	μ
R	π_R	π_R	P_R

Cells denote probability the goal is scored as a function of Kicker’s and Goalie’s actions.
The Kicker’s payoffs. The Goalie’s are just (-1) times the Kicker’s.

0, P_L and P_R are the lowest probabilities: when the Kicker goes the same way the Goalie dives, it is unlikely the shot goes in.

If the Goalie doesn’t guess correctly, the probability goes up ($\pi_L > P_L$) but not to Pr=1 because the Kicker could always hit it off the bar or miss completely.

Chiappori, et al., model, continued

	G		
K	L	C	R
L	P_L	π_L	π_L
C	μ	0	μ
R	π_R	π_R	P_R

A couple more assumptions round out the set-up.
Given that the Goalie dives one way, kicking to the opposite corner is better than the Center.
And this advantage gets bigger when the Kicker can go to his "Natural" side. Right-footed kickers tend to prefer going Left. I.e., $\pi_L > \pi_R > \mu$.
This advantage extends to "shanks" and cases where the Goalie *does* guess correctly: $P_L > P_R$ and $\pi_R - P_R > \pi_L - P_L$.

Equilibrium in game theoretic models

The solution is based on the idea that, in equilibrium, neither player could improve his strategy through his own actions alone.

- A "simultaneous best response by all players."

Called Nash Equilibrium, after Nobel Laureate, John Nash (1928-2015) who proved the existence of the equilibrium in a very general definition of games, as well as many other contributions.

Nash equilibrium

In simple games like the one to the right, the Nash Eq. can be found by identifying (underlying/circling) the individual best responses to the pure strategies of the other player.

- As if you knew what they were going to do ahead of time.

Then find the cell(s) with both players' responses underlined.

- Unless there isn't one. Which is OK.

There is still a solution in mixed strategies.

- This (and the penalty kicks game) is an example of a class of games called "matching pennies," after the most boring gambling game I've ever heard of.

	Pitcher (throws)	
Hitter (looks for)	Fastball	Change Up
Fastball	2,-2	-3, 2
Change Up	-2, 3	3,-3

Back to the (soccer) pitch

This is why you don't kick (dive) the same way every time. It makes you predictable and your chance of scoring (preventing) goals goes down.

The Nash in this game consists of playing the 3 strategies each with a specific ("mixing") *probability*.

- The Kicker maximizes his expected return by choosing probabilities of going Left ("g"), Center ("j"), and Right (1-g-j).
- The Goalie maximizes his expected return by choosing probabilities of going Left ("h"), Center ("k"), and Right (1-h-k).

This means solving 4 first order conditions (which is left as an exercise), but the solution is to equate the *scoring* probability of all 3 strategies.

- E.g., for the Kicker's L vs. R choice:

$$h^* * P_L + k^* * \pi_L + (1 - h^* - k^*)\pi_L = h^* * \pi_R + k^* * \pi_R + (1 - h^* - k^*)P_R.$$

Properties of the PK equilibrium

The Kicker chooses his natural side more often, but not as often as the Goalie dives to the Kicker's natural side.

For a right-footed Kicker, the outcome {L, L} is more likely than either {L, R} or {R, L}, which are both more likely than {R,R}.

Some of these basic insights are confirmed by looking at data from French and Italian soccer leagues.

But the rest of the paper tries to grapple with the issue of small sample size inference, due to the fact that penalty kicks are fairly rare.

- You see very few repetitions of Kicker-Goalie interactions in any data set.

From Chiappori, et al. (2002), The American Economic Review, pp. 1146-48.

TABLE 3—OBSERVED MATRIX OF SHOTS TAKEN

Goalie	Kicker: Left	Middle	Right	Total
Left	117	48	95	260
Middle	4	3	4	11
Right	85	28	75	188
Total	206	79	174	459

Notes: The sample includes all French first-league penalty kicks from 1997–1999 and all Italian first-league kicks (1997–2000). For shots involving left-footed kickers, the directions have been reversed so that shooting left corresponds to the "natural" side for all kickers.

TABLE 4—OBSERVED MATRIX OF OUTCOMES: PERCENTAGE OF SHOTS IN WHICH A GOAL IS SCORED

Goalie	Kicker: Left	Middle	Right	Total
Left	63.2	81.2	89.5	76.2
Middle	100	0	100	72.7
Right	94.1	89.3	44.0	73.4
Total	76.7	81.0	70.1	74.9

Notes: The sample includes all French first-league penalty kicks from 1997–1999 and all Italian first-league kicks (1997–2000). For shots involving left-footed kickers, the directions have been reversed so that shooting left corresponds to the "natural" side for all kickers.

Zero sum games

"Matching pennies" has numerous applications in sports.

Among them is passing and running play selection in football.

- McGarrity & Linnen (2010) represents a clever confirmatory test that NFL teams play a mixed strategy when it comes to play calling.

In football, however, there is some evidence that the Nash Equilibrium condition is violated.

I.e., that the expected gain of the marginal running play is less than the expected gain of the marginal passing play.

The "Equity Premium Puzzle"

The phenomenon in question is named after a more consequential one observed in Financial Economics.

Brought to our attention by Mehra & Prescott, in one of the great all-time Economics papers (1985), it inheres in the facts that:

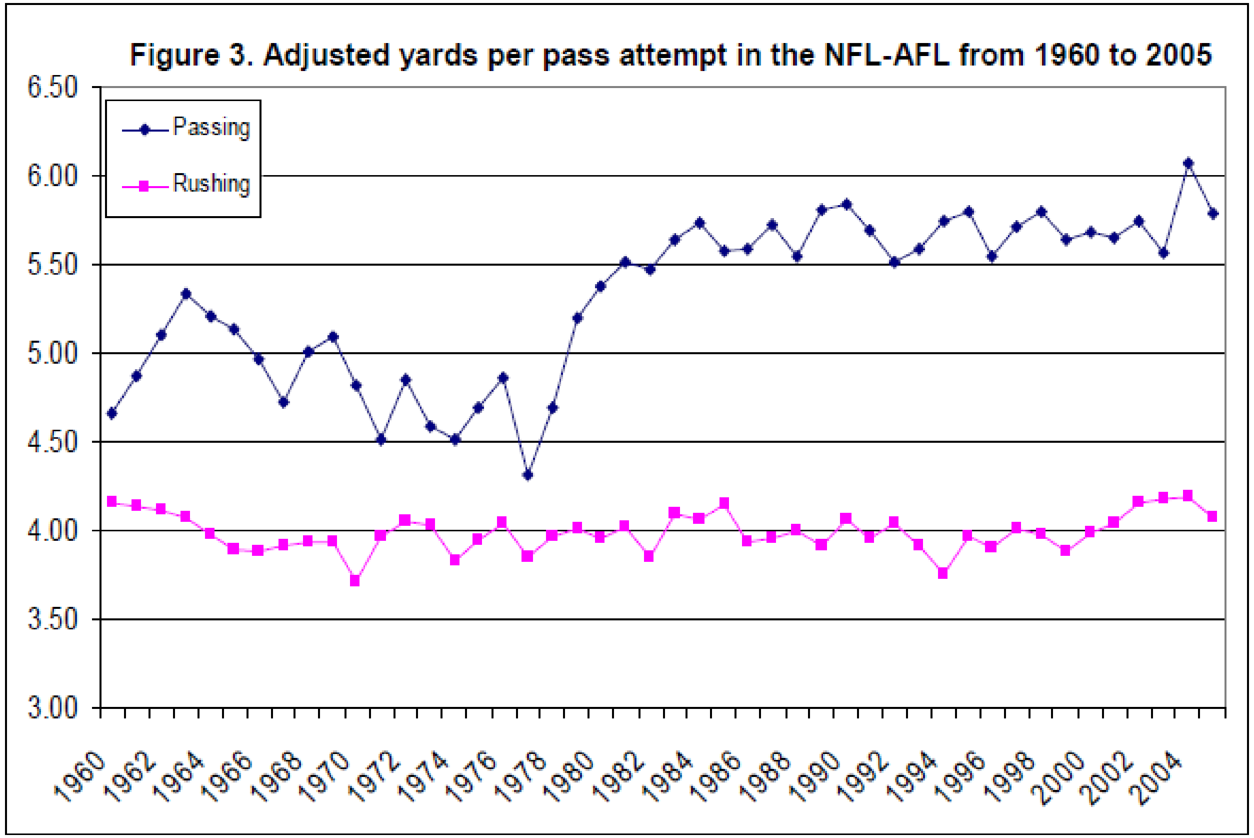
- Stocks are riskier than bonds,
- Stocks should command a "risk premium" (higher returns than bonds) to convince risk averse agents to hold them,
- And stocks' observed returns are much larger than bonds'—so much so that the people requiring this risk premium would be so risk averse that they'd never leave their houses out of fear.

The "passing premium puzzle"

In this metaphor:

- Pass plays are stocks, and
- Run plays are bonds.

Alamar (2006) is football's Mehra & Prescott, documenting a steady increase in passing efficiency over time that is un-matched by an increase in the frequency of passing.



Play-by-play data

Alamar tests the observations in (league) aggregated data by looking at 4,738 individual plays taking place in 2005

- Run from roughly in the middle of the field, to allow room for plenty of yards to be gained or lost.

Since the choice comes down to <u>risk</u>, Alamar wisely compares the entire distributions of play outcomes, e.g.,

- 58.11% of running plays (called on 1st and 10) gain 3 yards or less, but
- Only 46.52% of passing plays went for 3 yards or less.

Passing-rushing comparison

So passing has a higher *average* return and a smaller probability of a bad outcome (small gain, loss).

Within the lower tail, the median “bad” run still gains 1 yard, whereas the median “bad” pass is an incompletion (0 yards),

- But this isn’t much consolation when you’re giving up an average of more than 5 yards on the “good” ones!

It’s not that they shouldn’t run *at all*, just less than they do now.

Defense “dives left?”

McGarrity & Linnen might argue that teams don’t alter their run-pass balance precisely because defenses *do* alter theirs.

- Running has an “externality” by setting up the pass.
- The only reason passing returns are still so high is because coaches run often enough to “keep the defense honest.”

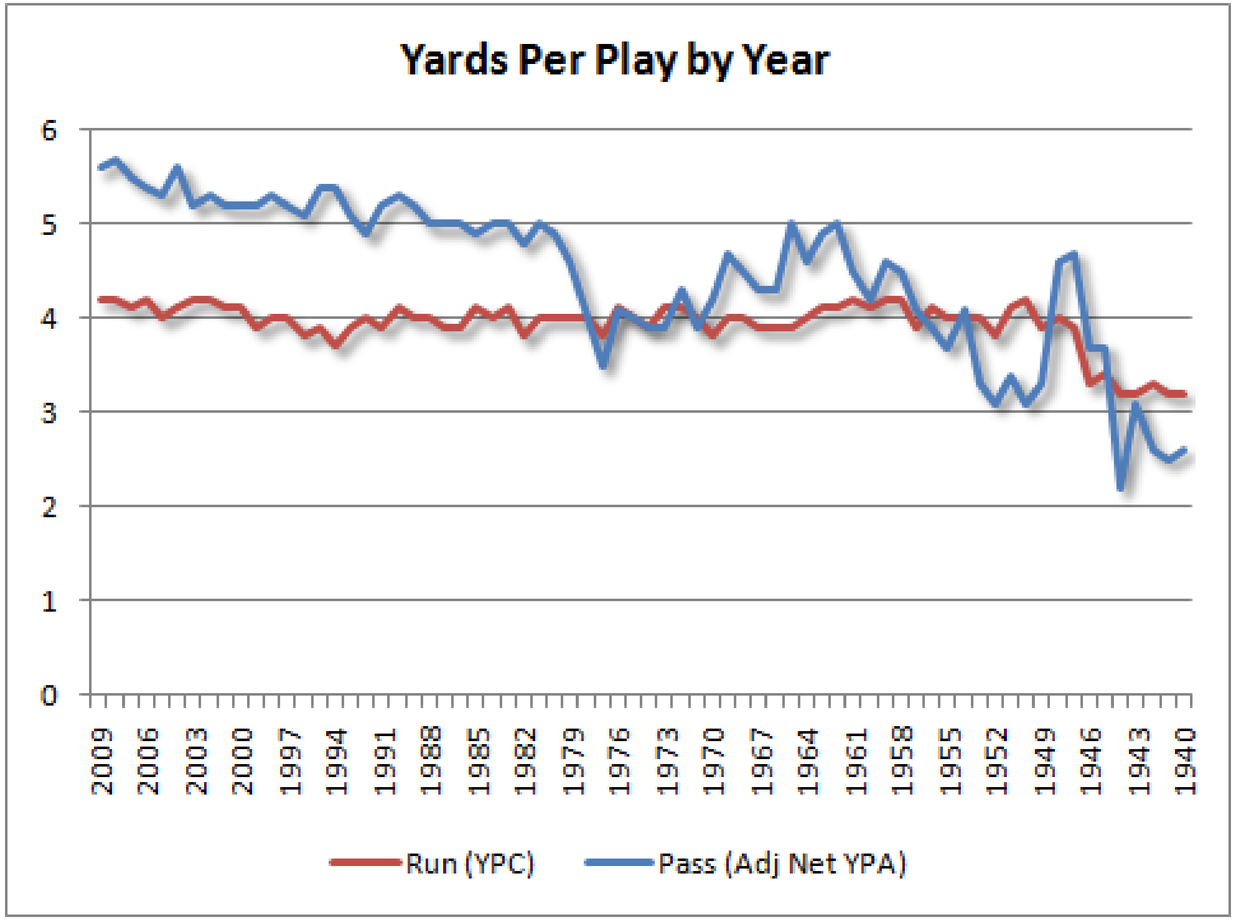
Alamar’s results contest that, though. The mean and variance of yards per passing play on 1^{st} and 10 is statistically no different from the mean and variance of passes on 3^{rd} and long (≥ 7 yards to go).

- The latter case is a predictable passing down, when teams pass 88% of the time.
- If the high return came from defenses not playing the pass, wouldn’t the return go down on 3^{rd} and long?

Passing premium, criticism

Brian Burke partly debunks Alamar's analysis, on the grounds that Alamar did not account for QB sacks in his paper.

- This would shrink the return to passing (and the premium).
- The figure at right is from Burke's article, showing a smaller but still positive passing premium.
- We also don't know how/if Alamar dealt with fumbles.



Passing premium, conclusion

The passing premium, if real, is perhaps not the puzzle that equity premiums are.

I'd say it's worth some additional scrutiny, and Burke's articles would be an excellent place to start.

- Here, here, and here.

I predict the correct analysis proceeding from a play-by-play analysis of the effects of the proportions of pass and run plays on the probability of scoring a touchdown* on each drive.

* Or on expected net points (see next slide).

The state of the game

The next methods we will discuss originated in baseball, but here we apply them to football.

The idea is to calculate an expectation of how many runs (points) a team will score, conditional on the current state of the game.

- In baseball there are only 24 men-on-base, out combinations in an inning, so it's a relatively controlled environment.
- Football has 4 downs and 100 yard lines and, even though 10 is quite common, many possibilities for the yards-to-go for a 1st down. I.e., many more permutations.
- F.C. Lane devised the earliest run expectancy matrix in 1916 by randomly sampling a large number of pro at bats and observing the state and how many runs scored, on average, following that state.

Run expectancy matrix example

A modern version, from FanGraphs.com, appears below.

The usefulness lies in the comparison of states. After a batter's at bat is over, the state will have changed and his contribution to the inning can be quantified in terms of runs.

- E.g., a strikeout with the bases loaded and no one out decreases the run expectancy by $1.52 - 2.282 = -0.762$ runs.

Runners	0 Outs	1 Out	2 Outs
Empty	0.461	0.243	0.095
1 _ _	0.831	0.489	0.214
_ 2 _	1.068	0.644	0.305
1 2 _	1.373	0.908	0.343
_ _ 3	1.426	0.865	0.413
1 _ 3	1.798	1.140	0.471
_ 2 3	1.920	1.352	0.570
1 2 3	2.282	1.520	0.736

". . . And the way we always knew what football coaches should've done"

If you could only apply this to football, you could evaluate the change in *points* expectancy after each play to quantify how much better or worse off the team is in the game.

- This change cannot plausibly be attributed to a single person's (batter's) contribution like in baseball.
- Although you could make a case for assigning it to the person who chose which play to run and trained the players to run it, i.e., the coach.

Certainly decisions like how to play a 4^{th} down are owned by the head coach and these comprise the focus of the (2006) Economics paper by David Romer.

- How would the risky decision to "go for it" on 4^{th} down compare to the conservative decision to punt?

What football coaches should've done

Given a points expectancy table (function?), the game state would most likely change in fairly predictable ways:

- You don't have the ball anymore but it's probably about 40 yards further from your end zone, or
- You've probabilistically turned the ball over on downs or still have it with a 1st and 10.

The assumption is that coaches try to maximize expected points, which is probably a good one for the majority of the 60 minutes.

- Let's find out what would happen if they did.

Expected points in football

This is what a conditional expected points function would look like for football.

- Based on Romer's estimates using about 11,000 plays from the 1998-2000 seasons.
- All of the authors that do this use only the 1st and 3rd quarters to exclude "garbage time" or "killing the clock" plays.

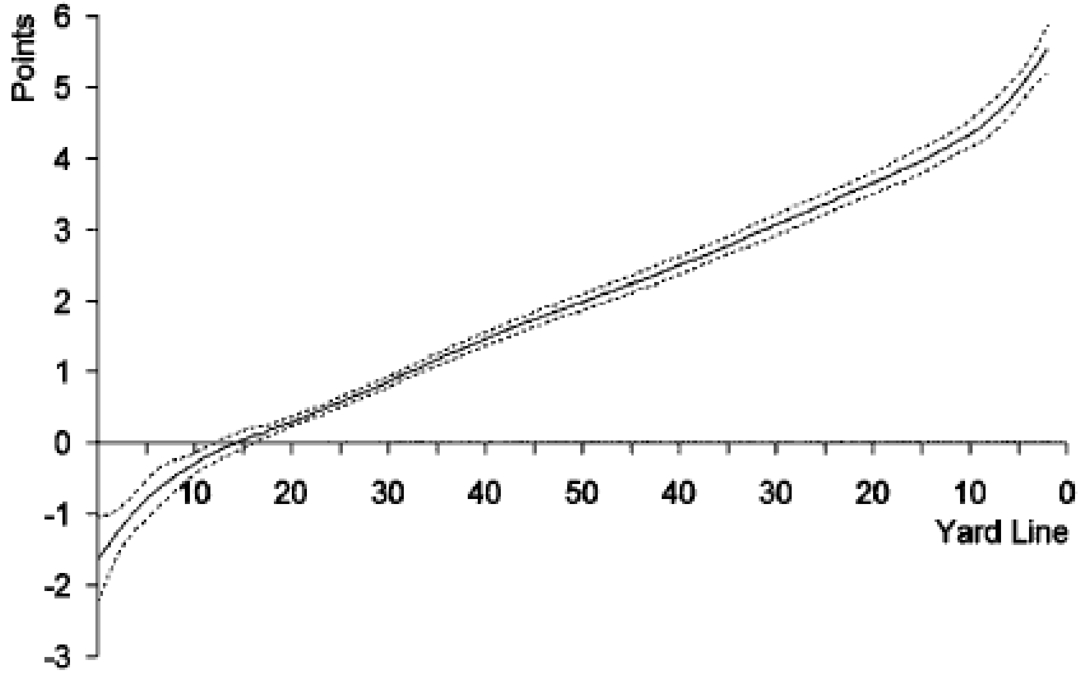


Fig. 1.—The estimated value of situations (solid line) and two-standard-error bands (dotted lines). The estimated value of a kickoff is −0.62 (standard error 0.04); the estimated value of a free kick is −1.21 (standard error 0.51).

Romer 2006. "Do Firms Maximize? Evidence from Professional Football." Journal of Political Economy, p. 346.

Expected points, continued

Subsequently sports analysts, most notably Brian Burke, augmentedRomer's initial estimates by conditioning the game states on down and distance.

- And throwing more data at the estimates.
- And more fancy econometric methods.

A couple prominent examples include:

- Burke's expected points functions for 1st, 2nd and 3rd downs, and
- Keith Goldner's estimates, including a (long) table listing the expectancies for all observed down-distance-yard-line combinations.

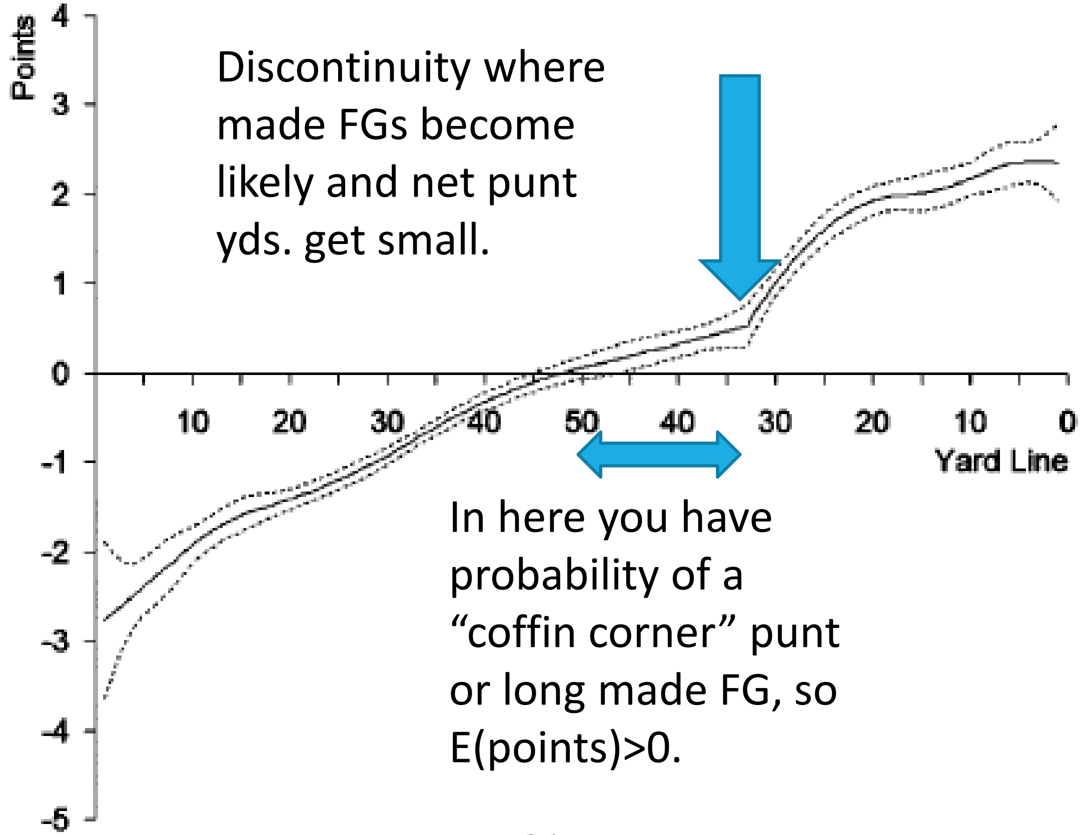
Romer’s findings (figures from page 349)

He first analyzes the value of kicking on 4th down. I.e., conditional on distance, if teams choose the better option between:

- Attempting a field goal using observed probabilities of success, and
- Punting, i.e., if you are out of field goal range.

The latter is obviously not a desirable option, and it decreases your expected points.

- It *could* still be the right choice, though, if the value of “going for it” is *more* negative.

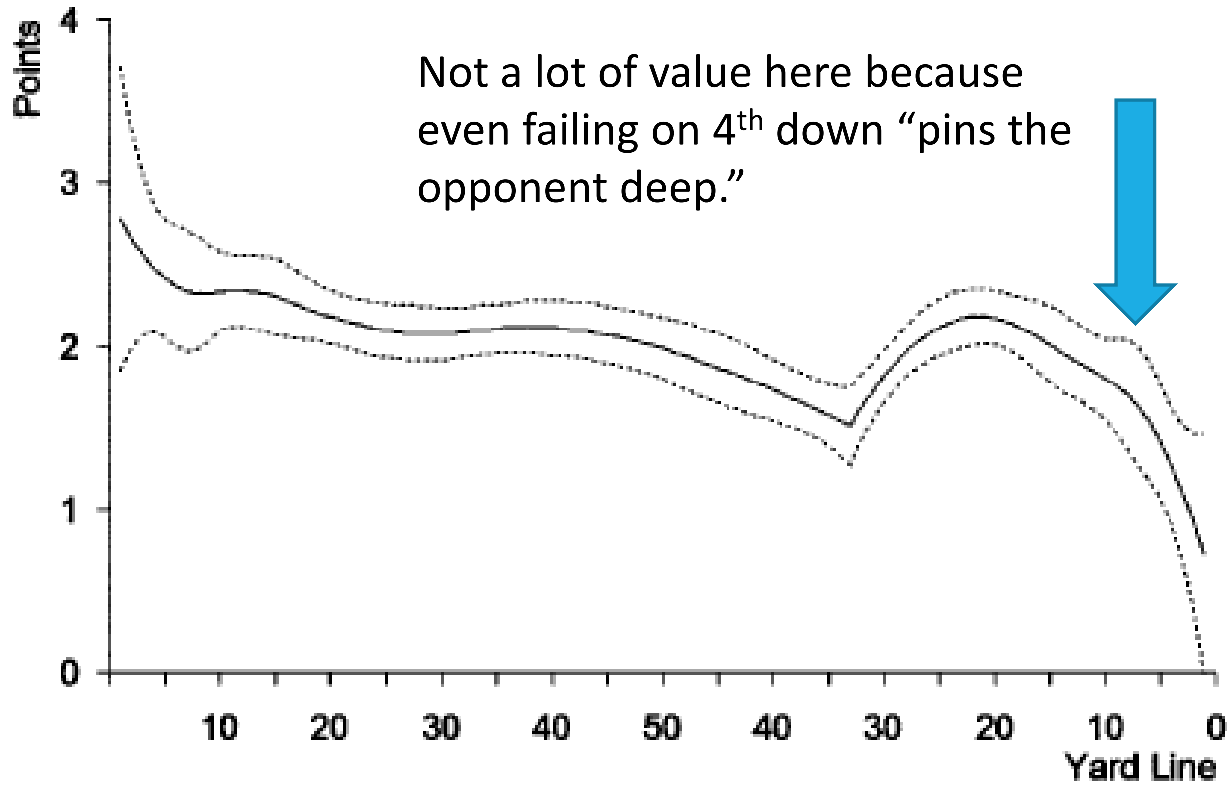


(a)

Romer’s findings, continued

This is what the value of kicking looks like <u>net of the value of a *failed* 4th down conversion attempt</u>, and conditional on field position.

- If you *know* you’re not going to make it, you should punt!



(b)

Romer’s findings, continued

But not all 4th down conversions fail!

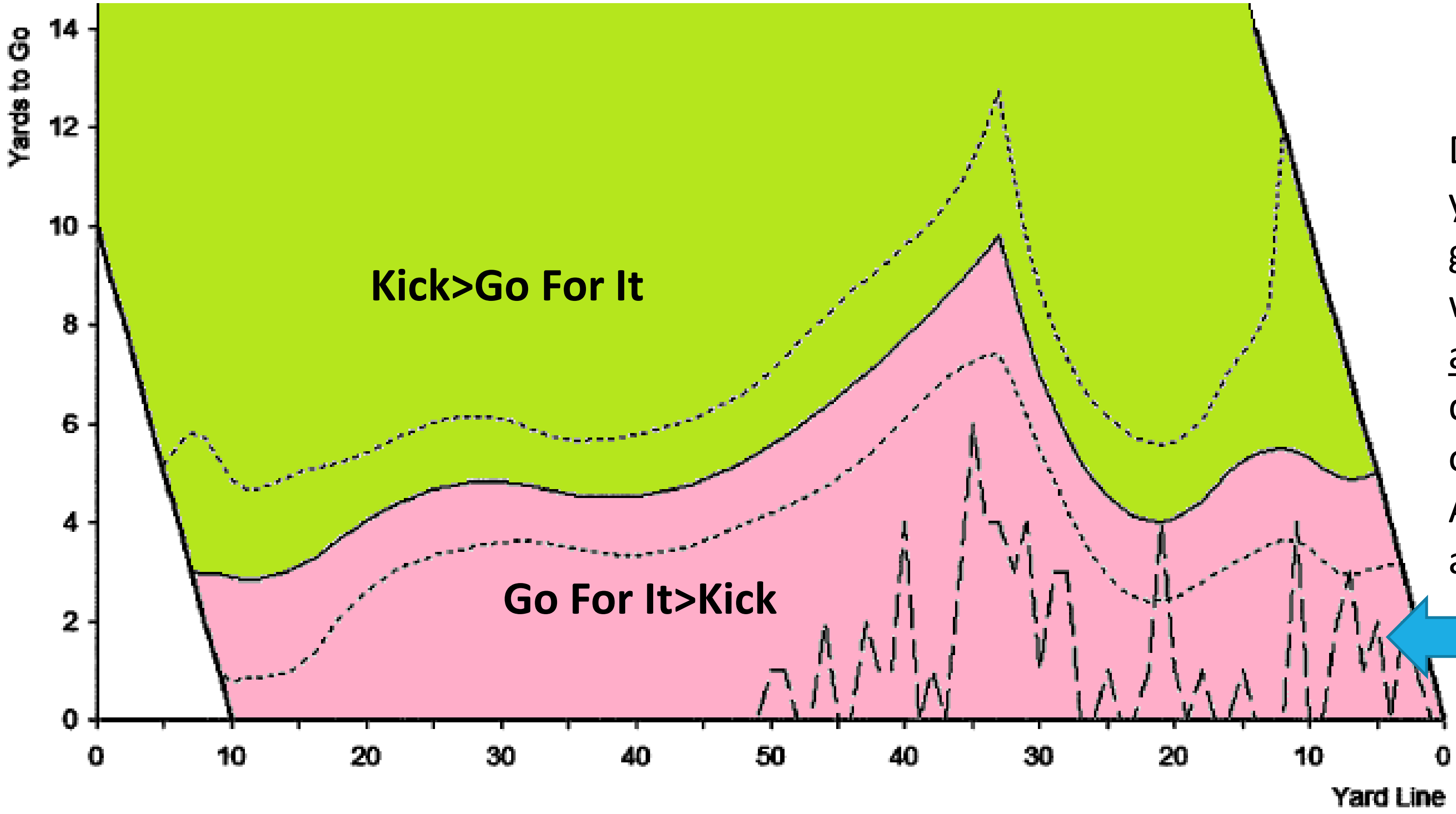
If you can make a similar comparison of the value of attempting a 4th down conversion, net of the value of assured failure to do so . . .

You can compare this difference to the value of a kick (optimally chosen punt/FGA) and predict whether kicking or going for it has higher expected points.

Get ready to be:

- A) Excited or
- B) Offended.

From Romer, page 353 (my shading)



Dashed line connects yard line and yards-to-go combinations where NFL coaches <u>actually</u> attempt 4th down conversions as often as they kick. A.k.a., "NFL coaches are wimps" line.

Jocks v. nerds (2006)

This is the finding that caused such a stir among the NFL orthodoxy.

Romer estimated that head coaches are <u>way</u> too conservative on 4th down.

- From many spots on the field, they should be attempting 4th down conversions twice or more times as long as the ones they *do* attempt,
- And the estimates say you should go for 4th down relatively often <u>in your own half of the field</u>, as long as the distance to the yellow line is short enough. You almost never see coaches try this!*

But macho head football coaches *love* being given this advice by a UC Berkeley Economist.

Burke estimated his own version, which confirms Romer's key conclusions, too.

*Google "high school football coach that never punts," though, if you haven't already read about Kevin Kelley in <u>Stumbling on Wins</u> or <u>Scorecasting</u>.

Summary

As explanation for the variance between prediction and observation,Romer entertains, e.g., risk aversion and momentum (that would be reversed by a failed 4th down).

- Coaches have either different preferences or additional knowledge that the model does not assume.

Burke adds to the list the Moneyball assessment that "conventional wisdom," i.e., from the early low-scoring days of the NFL, is simply very persistent.

- And he adds nuance to the risk aversion idea, suggesting that coaches are "loss averse," i.e., only risk averse about *gains*.
- This leads them, in an environment in which loss is likely, to prefer a small loss with near certainty to a gamble with diminishing marginal utility of gains and increasing marginal *dis*utility of losses.

If you want to apply points expectations to other choices on the gridiron, Burke's site published a lot of interesting content, prior to getting gobbled up by ESPN.

I know I said this wasn't a fantasy football class . . . But . . .

If you just want to have some fun with it, http://www.pro-football-reference.com/ has play-by-play data for individual games, so you can see how each play affected the probable outcome of the game.

Their data can be used to add up the effects of plays involving individual players on the expected points (winning %) in games he plays in.

Without getting too specific, this information might be an improvement over the "counting stats"* usually used in Fantasy leagues when it comes to isolating the contributions of individual players.

* Here I'm talking primarily about yards accumulated and being the one holding the ball when it crosses the goal line.

Go Pack!

Their data for individual games can also be used to see how each play affected the probable outcome of the game.

Here's a screenshot of one of my all-time favorite drives (right).

www.pro-football-reference.com/boxscores/201101230chi.htm#pbp_data::none

uto IPUMS CPS Email Krannert School of M AEAweb: JEL GUIDE Purdue Baseball Low Hanging Fruit Cities Bikes Food Anecdotal Value P

Bears @ Packers | Scoring | Team Stats | Player Stats | Starters | Pass/Rush Direction | Drives | Play-by-Play

						21	14	0	0	0.0
4				CHI 30	Robbie Gould kicks off 59 yards, returned by Charles Woodson for 14 yards (tackle by Garrett Wolfe)	21	14	0	0.61	0.0
4	4:38	1	10	GNB 25	James Starks right end for no gain (tackle by Charles Tillman)	21	14	0.61	0.06	2.6
4	3:55	2	10	GNB 25	James Starks right end for -2 yards (tackle by Danieal Manning)	21	14	0.06	-0.89	3.4
4	3:50	3	12	GNB 23	Aaron Rodgers right end for 1 yard (tackle by Lance Briggs)	21	14	-0.89	-1.77	5.6
4	3:07	4	11	GNB 24	Tim Masthay punts 58 yards, returned by Devin Hester for 11 yards (tackle by Brandon Underwood)	21	14	-1.77	-0.87	2.1
4	2:53	1	10	CHI 29	Caleb Hanie pass incomplete short middle intended for Matt Forte	21	14	0.87	0.33	1.1
4	2:49	2	10	CHI 29	Caleb Hanie pass complete short left to Matt Forte for 1 yard (tackle by Nick Collins)	21	14	0.33	-0.23	0.6
4	2:44	3	9	CHI 30	Caleb Hanie pass complete short left to Greg Olsen for 10 yards (tackle by A.J. Hawk)	21	14	-0.23	1.6	2.8
4	2:38	1	10	CHI 40	Caleb Hanie pass incomplete short right intended for Devin Hester. Penalty on Caleb Hanie: Intentional Grounding, 10 yards	21	14	1.6	-0.3	0.5
4	2:33	2	20	CHI 30	Caleb Hanie pass complete short middle to Matt Forte for 11 yards (tackle by Sam Shields)	21	14	-0.3	0.5	0.9
4	2:01	3	9	CHI 41	Caleb Hanie pass complete short middle to Matt Forte for 8 yards (tackle by Robert Francois)	21	14	0.5	-0.13	0.2
4	1:54	4	1	CHI 49	Chester Taylor right tackle for 4 yards (tackle by Desmond Bishop)	21	14	-0.13	2.46	2.9
4	1:34	1	10	GNB 47	Caleb Hanie pass complete short right to Matt Forte for 13 yards (tackle by Clay Matthews)	21	14	2.46	3.31	4.5
4	1:27	1	10	GNB 34	Caleb Hanie pass incomplete	21	14	3.31	2.77	2.2
4	1:21	2	10	GNB 34	Caleb Hanie pass complete short left to Greg Olsen for 7 yards (tackle by Sam Shields)	21	14	2.77	3.01	2.5
4	1:15				Timeout #2 by Chicago Bears	21	14	0	0	
4	1:15	3	3	GNB 27	Earl Bennett left end for -2 yards (tackle by Desmond Bishop)	21	14	3.01	1.54	0.3
4	0:47	4	5	GNB 29	Caleb Hanie pass incomplete deep left intended for Johnny Knox is intercepted by Sam Shields at GNB-12 and returned for 32 yards (tackle by J'Marcus Webb)	21	14	1.54	-1.86	0.0
4	0:37	1	10	GNB 44	Aaron Rodgers kneels for -1 yards	21	14	1.86	1.18	0.0
					End of Regulation	21	14	1.18	0	