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OPTIMAL MIXED STRATEGY PLAY: PROFESSIONALS CAN, STUDENTS CANNOT, BUT WHAT ABOUT THE IN BETWEEN CASE?

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Abstract:

Using penalty kicks in collegiate soccer matches, we test whether kickers choose where to place shots, and whether goalies choose where to dive in a way that is consistent with optimal mixed strategy play. The previous literature, studying professional soccer players, provides evidence of mixed strategy play in penalty kick scenarios. These results contrast with the evidence obtained in a lab, studying subjects who only play a game a few times and have insignificant monetary payoffs. These lab results find no evidence of mixed strategy play. The contrast between the results obtained from these very different environments makes it unclear which result generalizes to other settings. By studying college athletes, we analyze the middle ground, which is where most strategic decisions will be made. We find that college players employ optimal strategic play in some respects, but not in other respects.

Key words: *Mixed Strategy, Soccer, Amateurs*

1. Introduction

There are two testable predictions of mixed strategy play: (i) payoffs are identical among all strategies, and (ii) choices are serially independent. Previous laboratory research has found no evidence that players use mixed strategies. However, these studies observe subjects who have little game experience and who have insignificant monetary incentives. Furthermore, experimental settings may be unable to yield generalizable results because they do not replicate actual choices made outside of the laboratory. Researchers have dealt with the problems associated with laboratory research by testing mixed strategy play outside of the laboratory, using professional sports data instead. Research using data from profession sports often suggests that professional athletes employ mixed strategies.

In the previous literature, choices are made in two extremely different environments. While laboratory subjects have no training and small monetary incentives, professional athletes have extensive training and extremely large monetary incentives. However, most real-world decisions are made somewhere in the middle, and are made by people with moderate training and with modest monetary incentives. This paper observes college soccer for the purpose of discovering how sophisticated strategic play is in the middle ground between the extreme environments used in previous experiments.

We test both predictions of mixed strategy play in a penalty kick scenario. At odds with a prediction of mixed strategy play, this paper finds that the payoffs are not always equal across all strategies for both the kicker and the goalie. In support of a prediction of mixed strategy play, we find that both goalies and kickers effectively randomize in their own shot and dive direction decisions, meaning that choices are serially independent. These results indicate that college players play mixed strategy games with a level of sophistication that falls somewhere between the sophistication found in a laboratory and that found in the choices of professional athletes.

2. Literature Review

Laboratory research suggests that players do not use optimal mixed strategies. However, these subjects share several characteristics that may explain why. Furthermore, experiments conducted in a laboratory simplify choices and create an artificial environment such that choices made in the laboratory may not give insight into real world decisions.

One paper observes student behavior in a simple card game where each player had four cards and won each hand by laying down a card that would beat the opponent's card (O'Neill, 1987). In this game, high cards would beat low cards, but the lowest card could beat the highest card. Each player had three low cards and one high card. Therefore, there was risk associated with playing the high card. In this study, students could win a maximum of $5 after 30 minutes of gameplay. Subjects either played high cards too often, played low cards too often, or switched between high and low cards too often in response to previous plays.

Another paper observes players in a simplified poker game. Players were not required to have played poker before and were instructed to expect around $10 for participation in the experiment. This study allowed one player to have extra information. It found that informed players bluff too infrequently, while uninformed players call too often (Rapoport, Abraham, and Olson, D., 1997). This means that players did not vary their strategies and were likely not concerned with predictability.

Other research finds similar results in their laboratory tests of mixed strategy play (Mookherjee and Sopher, 1997). This experiment studied players in a variety of simple games, but in each game, players have no prior experience or training and only had the ability to win about $10-$60 throughout game play. This result suggests that players either underplayed or overplayed choices in each simple game played, meaning that payoffs were not equal across strategies.

These studies share several distinctive traits that may influence mixed strategy play among the subjects studied. In each experiment, subjects had little knowledge about the game that they were playing, little experience playing the game, and very little incentive to win (payoffs were monetary, but relatively insignificant). With such small payoffs, it is possible players had insignificant incentive to master the games they were playing, and thus likely had little motivation to randomize strategies or to play each choice the appropriate number of times.

Sports data provides another environment to test mixed strategies. In contrast to laboratory studies, professional athletes have years of practice and extensive training devoted to skill and strategy development. Furthermore, professional athletes have a large monetary stake in their performance. Better players are paid more, so there is a large incentive to play strategically. Additionally, because people bet heavily on sports, the data will be high quality,

The drawback to sports data is that there are far too many possible actions and possible outcomes in most sports interactions than are empirically quantifiable. For example, in the pitcher-batter interaction, the pitcher can throw a fastball, curveball, slider, change-up, inside, outside, strike, ball, etc. while the outcomes could be a strike, foul, home run, single, ground ball, fly ball, etc. These sport interactions can often be too complex to model well. The first paper to overcome this challenge used the serve-return play in professional tennis to find the first empirical evidence supporting mixed strategy play in sports (Walker and Wooders, 2001).

Penalty kicks in soccer have also been effectively used to test whether players employ optimal mixed strategies. The first such paper used professional soccer to test for mixed strategy play, using 459 penalty kick interactions from two different professional soccer leagues (Chiappori, Levitt, and Groseclose, 2002). Professional players can kick a ball at an average of 125mph, giving a goalie 0.2 seconds to save the ball before it is in the back of the net. Thus, the goalie has three choices; he can stay in the middle, dive to the left, or dive to the right. Professional goalies spend time studying their opponents and know which foot is the opponent's dominant foot. Therefore, a keeper will always know which side the kicker is most comfortable using because of natural proclivity (right-footed players naturally kick left and left-footed kickers naturally kick right). Likewise, kickers know that the goalie knows which direction they are more comfortable kicking, but can also choose right, middle, or left. Therefore, a kicker-goalie interaction is useful for testing mixed strategy play because the actions and outcomes are quantifiable.

This paper examined the same players over multiple kicks (Chiappori, Levitt, and Groseclose, 2002). It finds that kickers who more frequently take penalty kicks randomize actions. The authors are unable to reject their null-hypothesis that goalies and kickers have equal scoring probabilities across strategies. They conclude that kickers and goalies develop a mixed strategy in a penalty kick scenario.

Another paper examined 1,417 penalty kicks from professional games in Spain, Italy, England, and other countries (Palacios-Huerta, 2003). It differs from the first paper by significantly increasing the number of observations, and specifying a "natural side" and a "non-natural side" instead of the right, middle, and left approach used in the first paper. Both papers find that the probability of scoring was statistically the same over multiple strategies for players.

Our study builds on the work by using college soccer to test mixed strategy play. In this study we adopt the "natural, non-natural" methodology. However, our study controls for other unobservable forces by observing all kicks within a penalty kick shootout in an NCAA Division 1 College Cup tournament, rather than penalty kicks taken throughout a season.

Furthermore, using shootout data enables us to omit the variable of time, which was used to as a measure for nervousness (Palacios-Huerta, 2002). We account for "psychological pressure" in our model by measuring score differentials and kick importance (when the kick has the potential to end the match). However, the most significant methodological difference in this study comes from the sequence of decisions that we analyze. Instead of observing individual players over multiple kicks across several games like both previous aforementioned soccer papers did, we use time-lagged variables to observe the choices of both kickers and goalies within each penalty shootout.

This research adds to the literature by studying collegiate soccer players instead of professionals. As test subjects, college athletes fall between the two ends of the spectrum in skill, experience, and incentive to win. College athletes are not basing their entire livelihoods on their ability to play soccer; they are not paid to play like professional athletes are. However, in many cases college athletes are given scholarships or stipends in return for the work they do playing for their respective colleges, resulting in some small level of monetary incentive. College players also spend (as NCAA regulations allow) 10-15 hours per week practicing soccer and developing skills. However, most college soccer players are only beginning to master the game and have far less skill and experience than professional players do. Thus, college athletes fall in the middle of the spectrum, giving insight into whether results from the laboratory or from professional athletes generalize to wider groups.

3. Explanation of Choice

In our model, strong side and weak side are defined both for the kicker and the goalie. The kicker chooses his strong side if the direction of his shot is opposite to the foot he used to kick. For example, a right-footed kicker will naturally kick to his left making a left-side shot choice his strong side. On the other hand, if the right-footed kicker chooses the middle or right side (kickers choose the middle only 6.7% of the time in our data set), then the kicker is said to have chosen the weak side.

The same rule is applied to goalies. The goalie can observe and determine the kicker's dominant foot, giving him the knowledge of the kicker's strong side. Therefore, if the goalie dives to the kicker's strong side, the goalie has also chosen the strong side. However, if the goalie stays in the middle (goalies choose the middle only 5.4% of the time in our dataset) or dives to the kicker's weak side, the goalie is said to have also chosen the weak side.

4. Data

The data was collected from Division 1 Men's soccer games from the NCAA College Cup Tournament from 2013, 2014 and 2015. We observed footage of games that went into overtime and resulted in penalty kicks, meaning that the penalty kicks we observed only happened in a shoot-out scenario and were not taken throughout the course of the match. Each variable was derived either through watching game footage or though box score information available online.

Unfortunately, there is not an accessible archive of college soccer game footage, so game footage was found though the NCAA, conference websites, and school video archives. However, in many cases the footage was incomplete. Many coaches were personally contacted and much of the footage used for data collection was acquired this way. However, beyond these sources, the rest of the footage from which the data was derived was found on YouTube.

In this project we observe 148 penalty kicks from three college cup tournaments. We find that kickers who kick either to the middle or to their weak side score 72% of the time, while kickers who kick to their strong side score 68% of the time (*Table 1)*. We also find that goalies dive to the kickers' middle or weak side save the kick 28% of the time while goalies who dive to the kickers' strong side save the shot 31.5% of the time. Kickers and goalies each achieve success at roughly similar percentages across the set of choices that they each face.

Table 1: **Kicker Shot Percentages**

VARIABLES	Kicker Made Percentage	Goalie Saved Percentage
Strong	68%	31.5%
Not Strong	72%	28%

* We observe 148 penalty kicks in our study

Are the Payoffs Between Choices Equal:

Kickers

The following model tests whether kickers are equally likely to score regardless of the shot direction they choose.

$Made_{it} = \alpha + \beta_1 SWKICK_{it} + \beta_2 SDNDEATH_{it} + \beta_3 Score + \varepsilon$

The dependent variable in this model is $Made_{it}$, which has a value of one if the kicker scored and zero otherwise. The subscript i indicates separate shootouts and the subscript t indicates the specific shot number taken in shootout i. $SWKICK_{it}$ represents whether or not the kicker chooses to shoot to his strong side, while $SDNDEATH_{it}$

indicates that the shot was taken when the match has gone into sudden death. In a penalty kick scenario, each team takes five kicks. If after these five kicks, the teams are tied, the game goes into sudden death, meaning that the first team to outscore its opponent in a round is the victor. Score is a vector of variables that indicate the score right before the shot is taken. The model also includes goalie fixed effects. This model and subsequent models are all estimated using probit estimation.

In these regressions, we split our sample size into two categories. One regression includes kicks from teams that shoot first, while the second regression includes kicks from teams that shoot second in the shootout. We make this distinction because variables in the Score vector will have a different impact depending on if the kicker is in the first or second shooter category. The vector Score is comprised of three variables describing score differentials: Up1, Down1, and Down2. The first kicker regression does not include the variable Down2 because there are no kicks in our dataset where a kicker from the first team takes a shot from a deficit of two points. Furthermore, second kickers rarely shoot with an advantage of one point, so Up1 is not included in the second shooter regression.

The results from *Table 2* show that, in the second round of kicks, the kicker's choice of where to kick does not appear to affect his probability of scoring. However, we do see that the team that kicks first is less likely to score when the kicker chooses his strong side. Specifically, these results suggest that kickers who kick in the first round score 10% less often when they choose to kick to their strong side than when they choose to kick to their weak side. We calculated this change in probability for the representative case when the match is in sudden death and the first kicker's team has an advantage of one point. The coefficient is significant at the 10% level in a one tailed test. We use a one tailed test because a kicker who kicks to one side too often is likely to choose his strong side because this is his most comfortable shot. A goalie who knows this tendency will have an advantage, which would explain the negative coefficient.

Table 2: **Kicker Regressions**

VARIABLES	First Kicker Made	Second Kicker Made
SWKick	-0.606*	-0.347
	(-1.46)	(-0.85)
SDNDEATH	0.867	0.336
	(1.49)	(0.51)
Up 1	-0.599	
	(-0.98)	
Down 1	0.733	0.792*
	(1.19)	(1.61)
Down 2		1.062
		(1.35)
Constant	1.364	-0.396
	(1.70)	(-0.51)
Goalie Fixed Effects	Yes	Yes

T-Statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 also shows that during the second round of kicks, a deficit of one point is positively related to whether a kicker scores when he is shooting second in the round. The coefficient is significant at the 10% level in a one tailed test. Kickers shooting second usually face a one-point deficit, so it is the typical case. Therefore, the positive coefficient suggests that these kickers perform better when facing a typical situation, that is, one they are comfortable in.

Goalies

Next we test to see whether goalies are equally likely to save a shot regardless of the direction in which they dive. We split the data into two categories: those that kick first in the round and those that kick second in the round, like we did in the kicker regressions. This model is almost identical to the one we used for kickers, although we modify it so that it captures the goalies' decisions. The dependent variable is $Saved_{it}$, which is a one if the goalie saved the shot and a zero otherwise. The independent variable of primary interest is now $SWDive_{it}$, which is a one if the goalie dived to the kicker's strong side, and a zero otherwise. If we had used Missed instead of Saved as the dependent variable, our results may have been misleading because Missed includes instances where the goalie may have chosen the incorrect side, but the kicker missed anyway. Again, subscript t represents shot number t in shootout i.

As *Table 3* shows, when kicks occur in the beginning of the round, dive direction is not related to whether or not the goalie saves the shot. However, when kicks are taken second in a round, we find that goalies are less likely to save the shot when diving to the kickers' strong side. These estimates suggest that, during the second shot of each round, goalies are 36% less likely to save the shot if they dive to the kickers' strong side. This change in outcome was calculated in the representative case when teams are in sudden death and the team of the goalie in the second kick of the round is in a deficit of one point. The coefficient is statistically significant at the 10% level, using a one tailed test. We use a one tailed test because, if goalies are going to pick a side too often, they are more likely to go to the kicker's strong side because they know that the kicker is more comfortable kicking to this side.

***Table 3:* Goalie Regressions**

VARIABLES	First Kick Saved	Second Kick Saved
SWDive	-0.280	-0.668*
	(-0.73)	(-1.45)
SDNDEATH	-1.025*	0.248
	(-1.77)	(0.36)
Up 1	0.520	
	(0.86)	
Down 1	-0.864	-1.132**
	(-1.44)	(-1.99)
Down 2		-1.079
		(-1.26)
Constant	-0.923	1.406
	(-1.28)	(1.41)
Goalie Fixed Effects	Yes	Yes

T-Statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We also find that Sudden Death and Score deficits both play a role in goalie dive success. Specifically, during the first shot of each round, the goalies save fewer shots when the game goes into sudden death. Additionally, we find that in the second part of each round, goalies save fewer shots when their team is down by one point. This result mirrors the results of kickers, which showed that kickers who took shots in the second part of a round made more shots when there was a deficit of one point.

Kicker and Goalie Discussion

It appears that kickers, who go first, do what they are comfortable doing—going to their strong side too often, resulting in predictable actions that the goalie is able to exploit. However, we find that for shots taken in the second in part of each round, kickers become more strategic, playing an optimal mixed strategy, while the goalies dive to the kicker's strong side too often. This suggests that neither goalies nor kickers play an optimal mixed strategy in every circumstance.

Are Decisions Serially Independent?

Kickers

In a mixed strategy game, neither kickers nor goalies want to be predictable because opponents can exploit a pattern. If a goalie usually dives to the kicker's strong side, then kickers will respond by kicking to the weak side instead. We measure potential predictability by testing for serial correlation in the choices of both kickers and goalies. There are two ways that a player's actions can be serially correlated. Positive correlation means that there are too many runs of the same choice, while negative correlation means that the player switches between their choices too often. Walker and Wooders (2001) found that professional tennis players switched their serve location between their opponents' left and right side too often, meaning that their serves had negative serial correlation and were predictable.

We also attempt to find patterns in kick and goalie choice that would suggest predicable play. The following model tests whether kickers' choices are serially independent, meaning the directional choice made on the previous kick has no influence on the current kick.

$SWKICK_{it} = \alpha + \beta_1 SWKICK_{i\,(t-1)} + \beta_2 SDNDEATH_{it} + \beta_3 Score + \varepsilon$

In this model, $SWKICK_{it}$ represents the direction that the kicker shoots. The variable is a one if the kicker chooses his strong side and a zero otherwise. Subscript t represents a shot taken in shootout i. Our independent variable of interest is the lagged dependent variable. Variable $SDNDEATH_{it}$ and the Score variables are the same as they appeared in previous models, representing shots taken in sudden death and score differentials. We also split our data into two categories like we did in previous regressions. The categories are first kick and second kick.

In order to lag the dependent variable, we must omit the first observation of each penalty kick shootout. In a probit estimate, a lagged dependent variable will cause bias in the estimates because unobserved heterogeneity found in the error term is likely to be correlated with the lagged dependent variable. We overcome this problem by estimating a dynamic probit (Heckman, 1981). Generally, this approach uses information associated with the first (skipped) kick to form initial conditions that overcome the bias in the subsequent maximum likelihood estimate.

We find no serial correlation in the kicker's decision of where to place his shot (*Table 5)*. This leads us to conclude that kickers do not make choices that are influenced by previous choices, which supports the second testable prediction of optimal mixed strategy play.

Table 5: **Kicker Dynamic Probit Regression**

VARIABLES	First Kick SWKick	Second Kick SWKick
Lagged SWKick	-0.048	.250
	(-0.148)	(0.794)
SDNDEATH	-0.228	0.166
	(-0.531)	(0.395)
Up 1	-0.517	-0.146
	(-1.127)	(-0.184)
Down 1	0.0456	-0.022
	(1.00)	(-0.060)
Down 2		0.793
		(1.281)
DIT	Yes	Yes
FIT	Yes	Yes

DIT and FIT estimates are random parameters in the dynamic probit model
T-Statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

<u>*Goalies*</u>

We repeat this process when testing for serial independence among goalie decisions. We split up the data into first kick and second kick categories, but our depended variable is now $SWDive_{it}$. This means that our main independent variable changes to $SWDIVE_{i(t-1)}$, which is the lag of our dependent variable. The dynamic probit estimates suggest goalies can randomize their choice of dive direction.

Table 4: **Goalie Dynamic Probit Regression**

VARIABLES	First Kick SWDive	Second Kick SWDive
Lagged SWDIVE	-0.229	-0.440
	(-.427)	(-0.819)
SDNDEATH	-0.124	0.391
	(-0.167	(0.482)
Up1	0.295	5.602
	(0.649)	(.000)
Down 1	0.0005	-1.168
	(0.001)	(-1.028)
Down 2		-1.054
		(-1.066)
DIT	Yes	Yes
FIT	Yes	Yes

T-Statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

4. Conclusion

This paper examines whether college level kickers and goalies make decisions during penalty kicks that are consistent with optimal mixed strategy play. Our results are mixed. We find that goalies and kickers can randomize their choices of where to kick or where to dive, as optimal play predicts. However, at times both kickers and goalies choose to kick or to dive to the kickers' strong side too often. Under these circumstances, each would be successful more often if he chose to kick or dive to the weak side more often.

We conclude that imperfect mixed strategy play is likely present in real-world scenarios where skills and incentives fall somewhere between those of professional athletes and those of subjects in a laboratory setting. Laboratory tests find no evidence of mixed strategy play and professional sports research often finds strong evidence of optimal mixed strategy play. The results in this paper suggest that strategic ability falls along a continuum that is related to experience and incentives.

This research provides an important first step in understanding how choices are made by actors under moderate amounts of monetary incentives and moderate amounts of training. Future research should study interactions in other college sports as well as in interactions outside of sports.

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Notes

[i]. Now part of Intercontinental Exchange Futures due to the expansion of the ICE in 2001, according to https://www.theice.com/about.jhtml

[ii]. It describes a strategy implemented after a period of substantial gains from an open long position on the stock market. To prevent a potential risk of depreciation to the extent of reaching the proposed level of liquidation of the contract, we must adopt a strategy of protection. The strategy provides the buying of a put option "out of the money" and simultaneously selling a call option "out of the money".

[iii.] On the goods market, the WTI oil type is known as slightly sweet oil, which refers to a type of oil which contains less than 0.5% sulphur, thereby rendering sweet to this type of oil rather than acid which is having higher sulphur content. This type of oil is used to produce gasoline, diesel and kerosene.

[iv]. The term "Seven Sisters" appeared in 1950 when the businessman Enrico Mattei, then head of the state-owned Italian oil company Eni, described the "Iran Consortium" cartel which consisted of seven oil companies that have dominated the global oil industry from mid-1940 to 1970 (Sampson, 1975). The group was formed of Anglo-Persian Oil Company (now British Petroleum); Gulf Oil; Standard Oil of California (SoCal); Texaco (now Chevron); Royal Dutch Shell; Standard Oil of New Jersey (Esso); Standard Oil Company of New York (now ExxonMobil). Before the 1973 oil crisis, members of the Seven Sisters controlled about 85% of world oil reserves, but in recent decades the dominance of these companies and their successors decreased as a result of the growing influence exercised by the OPEC cartel and by the state-owned oil companies from emerging market economies. Financial Times used in 2007, the label of "Seven New Sisters" to describe a group that includes most influential national oil and gas companies based in countries outside the Organisation for Economic Co-operation and Development (Hoyos, 2007). According to Financial Times, this group includes: China National Petroleum Corporation (China), Gazprom (Russia), National Iranian Oil Company (Iran), Petrobras (Brazil), PDVSA (Venezuela), Petronas (Malaysia) and Saudi Aramco (Saudi Arabia).

[v]. The U.S. system of price controls on oil was created to control the price of oil and to equalize the cost of crude oil to refineries. Companies that had easier access to cheaper oil and with a controlled price paid money to oil refineries that did not obtained oil so easy. They were dependent on more expensive internal and external oil. The government has acted as a bank for this program, collecting from some companies and providing subsidies to others. After a reclassification made in the last months of the program, the government lost more of its assets and shareholders were asked to pay the debts recorded by the bank. President Reagan lifted all regulations on oil prices, including the system of price controls, in a very short time after taking office (Hayward, 2001, pp. 267-268).

[vi]. According to statistics published by the CFTC on crude oil, available at http://www.cftc.gov/oce/web/crude_oil.htm.

[vii]. For example, pension funds that diverted cash into indexes connected to the expense of crude oil.

[viii]. Oil and gas revenues account for more than 50% of the federal budget revenues (U.S. Energy Information Administration, 2014)