Game Theory in Cricket*

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Abstract

The paper uses the natural setting of cricket to test theoretical predictions in game theory. In this setting, the agents play a one-shot-two-person constant sum game. The paper assesses whether trained professionals in cricket follow the 'mix' of strategies predicted by Nash equilibria. The test uses a unique dataset derived from commentary data comprising of bowler and batsman strategies and outcomes. The paper creates a model for bowler-bastman interactions in cricket and uses this in conjunction with the data to generate predicted Nash equilibrium frequencies. These predicted frequencies are then compared with the actual frequencies from the data. My study finds that players follow equilibrium play when we consider a model with simplified strategy sets, that is, their predicted Nash frequencies of strategies are within two standard deviations of the actual frequencies. However, the paper finds that equilibrium play is not followed when the strategy sets in the model are made more elaborate. The findings of the study are important because it provides evidence of equilibrium play even if it is in the simplified setting. Furthermore, this paper can be used to provide strategy implications for cricket players.

1 Introduction

Economists are often interested in behavior in situations when the decision makers have conflicting desires, especially when interdependencies exist. Such situations often require unpredictability, randomization and mutual outguessing between the agents. Game theory is extremely useful in analyzing such situations and makes predictions about how players will behave typically under the assumptions of rationality. Firms, consumers and other agents might not be completely rational but studying how ideally rational players behave allows economists to better understand how firms and consumers would behave under similar conditions. Nash (1950) defines equilibrium strategy in such situations as strategy choices for players from which they have no incentive to deviate. Many games have no pure strategy Nash equilibrium, that is, players do not play one specific strategy. In such games, the players play according to mixed strategy Nash equilibria wither they randomize over some or all of their pure strategies. Mixed strategy Nash equilibrium is at the heart of understanding the interactions between non co-operating agents in order to explain individual behavior in such settings. Since, the ability of game theory to model individual behavior has important theoretical and practical implications, it is important to be able to test the theory in real life situations.

However, this has proven to be extremely difficult because such testing requires utility functions and payoffs which are hard to model and understand in such settings. There is also the difficulty of determining strategy sets in natural settings. As a result, economists have had to rely on experimental data to test the theory. Unfortunately, most experiments regarding the theory of mixed strategy Nash equilibrium have not been able to show that the agents behave according to theory (see Brown and Rosenthal (1990), Rapport and Boebel (1992), Camerer (2003) for a survey) . It is important to note that experimental data may not be reliable due to the fact that people may behave differently in experimental settings and also because experiments may not allow players enough time to become proficient in the games. This raises the question of whether people behave according to theoretical predictions in any strategic situation.

This paper attempts to test economic theory using field data from professional international cricket matches. The specific features of the sport allow us to overcome the difficulties economists have faced before. Athletic competitions are reasonable settings to consider for this kind of testing because professional players are often highly motivated, skilled and experienced agents who understand the rules of the games they play. Many sports require unpredictability and requires players to play from a "correct" mix. This "correct" mix in game theoretic terms can be thought of as the mixed strategy Nash equilibrium. Rock – paper – scissors is a good example to consider. It is a game that is extremely easy to play and every player understands that they have to form some sort of mixture in their choices. They cannot choose to play, for example, rock in every turn because then their opponent would know to play paper in each turn. Game theory predicts that the players should randomize by playing each strategy 33.33 % of the time. Any deviation from this mix can have negative consequences for the players. For example, Walker and Wooders (2001) suggest that in tennis a server should choose right for half the serves and left for the other half. However, if a server chooses to serve only to the right the opponent will know what to expect and can position themselves to take advantage of this knowledge. Even though professional cricket players may not have undergone training in game theory, it is likely that their training and experience allows them to choose this mix rather subconsciously. The professionals are proficient in cricket and they know that a deviation from this mix might have negative consequences as motivated by the tennis example.

Cricket is a game that has become increasingly popular in recent times. The ICC Cricket World Cup in 2015 was estimated to have 2.2 billion viewers while the ICC Champions trophy in 2017 garnered 400 million viewers. However, people have yet to look at it through a game theoretic lens. The game is played out between two teams of eleven players and has parallels to baseball. The teams take turns batting (hitting) to score runs (points) while the opposition bowls (pitches) in an attempt to get the batting team out or restrict the number of runs scored. Unlike baseball, each team has only one inning, that is, they only get to bat once to score points. The total runs scored by a team is the sum of the runs scored each ball (pitch). So, a match can be thought of as a collection of games where each game is a ball bowled. The bowler's pitch and the batsman's shot almost completely determine the outcome of the game and so cricket provides a workable empirical example to test the theory. Additionally, cricket has the advantage of involving the same situation in each ball. For example, cricket always has two batsman and one bowler involved in each ball whereas baseball can have a different number of runners on the bases before each pitch. This makes cricket a more suitable application to consider. Much like in tennis and penalty kicks, the bowler tries to bowl in a way to outsmart the batsman and make sure that they score as few runs as possible. Hence, we use the interaction between the bowler and the batsman as a theoretical model of a cricket ball and use data on these interactions to test the theory.

The dataset used in the paper is constructed from archived commentary data and contains detailed information about bowler-batsman interactions in the ICC Champion's Trophy in 2017. For each ball included in the dataset, I have information on the bowler and the batsman, their strategy choices and the outcome of the ball. This information is then used to compute the actual frequencies of each strategy played by the bowler and the batsman. The data is also used to calculate 'win rates' for the batsman for each set of strategy choices made by the bowler and the batsman and definitions of success for the batsman. These 'win rates' are then fed into the model as probabilities of success for the batsman. This idea will be made clearer when we discuss the model. The probabilities of success in the model are used to calculate the Nash predicted frequencies. In the simplified model of 2 x 2 one-shot-constant-sum game, the Nash predicted frequencies of strategies are within two standard deviations of the actual frequencies. This finding is important because it suggests that players play according to equilibrium play and provides evidence to back theoretical predictions which has been generally difficult to obtain in literature. However, this finding disappears when we consider a 4 x 4 model of the game. This is possibly due to the subjective nature of data classification and the failure to account for player fixed effects. I discuss this further in Section 5.

The space of literature on game theoretic analysis of sports is yet to be saturated. Ignacio Palacios – Huerta (2002) and Chiappori, Levitt, Groseclose (2002) have tested mixed strategy Nash equilibrium predictions using soccer penalty kicks while Walker and Wooders (2001) have tested predictions using tennis serves. The papers find that players behave according to predicted equilibrium play. This paper uses similar models and predictions but in a completely new setting. This paper also uses more complex and heterogeneous strategy sets. Past papers look at choice of direction as the strategy choice for both agents involved. This results in strategy sets being identical for both the players. The manner in which the two players interact in cricket allows us to keep the strategy sets of the batsman and the bowler distinct. This is important because in real life situations the type of decisions that two agents have to make might be different. Unlike, Walker and Wooders (2001) this paper can observe the choices made by both the players and therefore provide empirical values for the payoffs of both the players. Therefore, I am able to analyze both players' behavior in terms of strategy choices. Previous literature have overlooked standard deviations in their discussions but I consider them in my analysis. Standard deviation sheds light on the variance of the predicted Nash frequencies of strategies and helps and allows to draw conclusions on whether players follow equilibrium play. The paper hopes to add onto the already existing literature by making a strong case for game theoretic predictions or by making players understand the mixture of strategies they should use better.

The remainder of the paper is organized as follows. The following section describes the structure and rules of cricket. Section 3 presents the theoretical model that is used to make predictions. Section 4 describes the data and contains summary statistics. Section 5 contains the analysis and the results and Section 6 discusses the robustness of the results. Finally, Section 7 concludes.

2 Cricket and rules

Cricket is a game between two teams of eleven players. Each team bats once to score as many runs as possible while the other team bowls to restrict the number of runs scored. There are three variations of matches, and we will focus on the one consisting of 300 balls per inning[1]. This type of a cricket match is called an One-Day- International (ODI) because it is completed in one day.

Cricket is usually played on a circular or an oval field with a pitch placed in the middle of the field. The pitch has three sticks at each end known as the wickets. The pitch is 22 yards (20.12 meters) in length measured from the wicket on one end to the wicket on the other end and 10ft (3.05 meters) in width. There is a rope running along the circumference of the field which is known as the boundary. Figure 1 illustrates a typical cricket field.

The bowler bowls from one end of the pitch while the batsman(striker) will try to hit the ball from the other end. There is another batsman (non-striker) waiting at the bowler's end who is not attempting to hit the ball. The batsman scores runs by hitting the ball. A run is successfully completed when the batsman on strike hits the ball with their bat and the two batsmen manage to run and change their ends. The batsmen can run as many times as they want as long as they do not get out. The ways in which a batsman can get out will be described below. If the batsman manages to strike the ball over the boundary, six runs are scored, or four runs if the ball bounces first. The batting team can also score runs if the bowler bowls 'poorly'. One run is awarded to the batting side if the bowler bowls too far wide from the batsman. The batting team keeps batting and scoring runs until all of their batsmen get out or until they have played the available 300 balls. So, the batting team wants to maximize the number of runs scored under the constraint of 300 balls or 10 outs.

The bowling side has to bowl 300 balls if they do not get 10 outs. The number of balls is

[1] Tests and T20s are the other two variations of matches. A T20 is different from an ODI in that each inning consists of 120 balls instead of 300. A Test match is a five-day match where each team gets to bat twice. A team usually keeps batting till they have gotten all out and there is no constraint on the number of balls they can face.

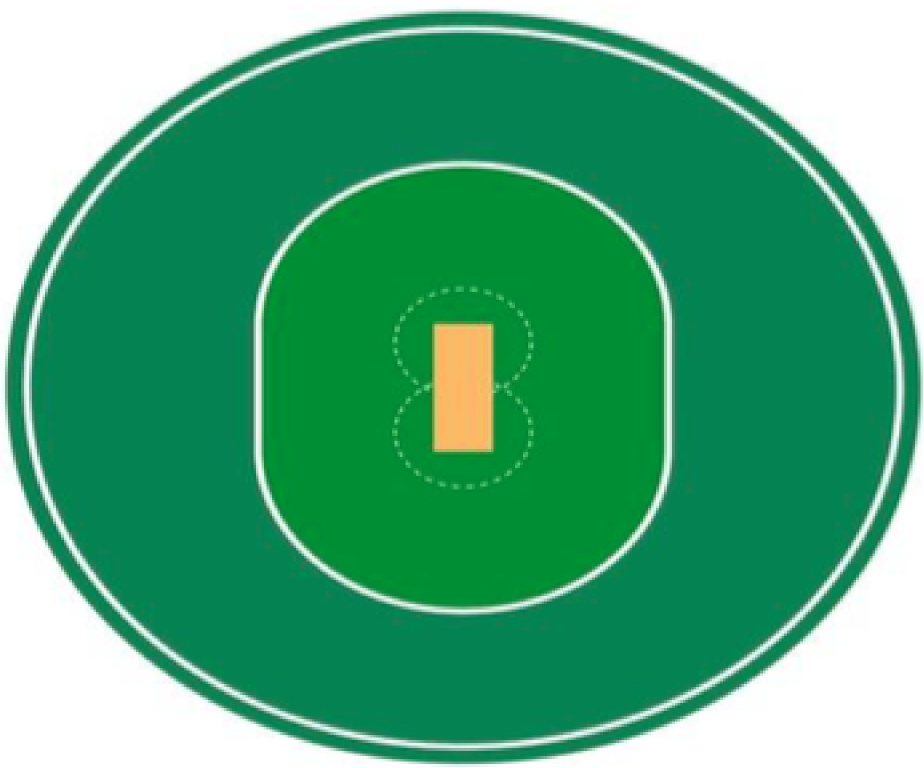

Figure 1: A typical cricket field

divided by 6 to make up 50 'overs'. An over is essentially a collection of 6 balls. Each bowler can only bowl one over at a time. The bowling side has to switch bowlers after each over. The bowler's job is to restrict the number of runs scored on each ball. They can do so by making sure a low number of runs are scored or by getting the batting team out. *Lord's The Home of Cricket* describes the ways in which a bowler can get a batsman out:

- Out Bowled – The batsman on strike is "Out Bowled" if his/her wicket is put down by a ball delivered by the bowler, even if it first touches the bat or the striker themselves. However, the ball cannot come into contact with anything else[2].

- Out Caught – The batsman on strike is "Out Caught" if a ball bowled by the bowler touches the batsman's bat and then is caught by someone on the bowling team without the ball touching the ground. The ball will be considered caught if the fielder obtains complete control over the ball.

- Out Hit Wicket – The batsman on strike is "Out Hit Wicket" if, after the bowler has started running to deliver the ball and the while the ball is in play, their wicket is put down by either their bat or themselves.

- Out Leg Before Wicket – The batsman on strike is "Out Leg Before Wicket" if the ball is intercepted by anything other than their bat and would likely hit the wicket otherwise. For example, the ball could hit the batsman's legs without hitting their bat first as they missed their intended shot. If the ball is projected to go onto hit the wicket, the batsman is out[3].

There are a few more modes of dismissals in cricket but I do not include them in our discussion because they cannot necessarily be credited to the bowler. For example, a batsman is 'Out Run Out' if they fail to successfully cross ends because the bowling team managed to

[2]For example, the ball can hit someone from the bowling team and then hit the wicket. In that case, the batsman would not be out.

[3]This is a subjective call and the final decision is made by the umpire.

get the ball to a wicket and remove it before the batsman reached that end. This type of dismissal requires effort from the fielders and does not have much to do with the ball being bowled. This has more to do with the decision of the batsmen to run and is independent of the shot played. This is more likely to happen due to poor running from the batsman or brilliant effort by the fielders. Since, I do not model running decisions or fielder actions in this paper I discard such dismissals.

3 Model

As mentioned above, we can consider each ball to be a strategic encounter between a bowler and a batsman. These interactions collectively make up a cricket match. The scoring rule is linear in the number of runs scored per ball which allows for separability, meaning we can look at each interaction in isolation. A batsman wants to maximize the number of runs scored in the 300 balls available and so they try to maximize the number of runs scored each ball. Similarly, the bowler wants to minimize the number of runs scored each ball. Hence, both sets of players are trying to win in each ball and so they are playing each ball like the last one making cricket a good example to consider.

The bowler can choose where to bowl (how far to throw) on the pitch and the batsman can choose which shot to play. The faster bowlers can bowl at speeds ranging between 75 miles per hour to 95 miles per hour. Given there is only about 20 meters between them, the batsmen do not have much time to react to the ball and often the shots they play are premeditated. As such, the game played by a batsman and bowler on a given ball can be modeled as a simultaneous move game. There are slower bowlers called spinners who rely more on the spin of the ball than its pace. Given that the ball does not come as fast, the batsmen have time to react and adjust. I do not consider the balls bowled by spinners in my model because of this reason.

The cricket pitch can be divided into segments as suggested by Figure 2. These segments are often referred to as lengths. The bowler can choose to bowl each ball in one of these lengths and, hence, their strategy choice is the length they choose to bowl. This is a coarse breakdown but generally coincides with bowler strategy. Players use this breakdown when analyzing matches. The batsman can choose to play either an attacking shot or a defensive shot. The clarity of rules in cricket allows us to easily determine the following outcomes: Out/0 runs, one run, two runs, three runs, four runs, five runs and six runs. It is important to notice that a batsman cannot score any runs if they get out because I do not account for modes of dismissals like run outs. So, after the bowler has made their choice of length and the batsman has made their choice of shots, the outcome is determined. The paper does not attempt to model the play after this stage, that is, the paper does not account for the actions of the fielders. However, the positioning of fielders can serve as a signaling mechanism for the bowler's strategy and could be a basis for a richer model in future research.

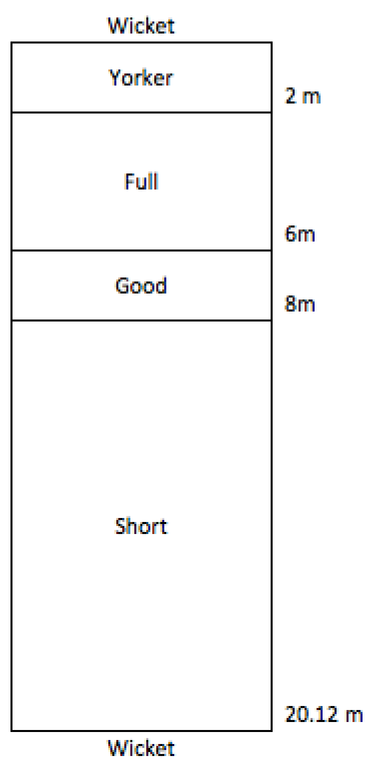

Figure 2: Division of the cricket pitch[4]

In order to consider the normal-form of this simultaneous move game, we attempt to define how the batsman or the bowler can win this one shot game, that is, how they can win each ball. Given that a team wants to score as many runs as possible, judging who "wins" a given ball is somewhat subjective. I define that a bowler wins a game if the outcome is "Out/0 runs"[5].The batsman wins otherwise. The structure of this simultaneous one-shot game between the two players leads us to the following 2 x 4 normal-form constant sum game:

Strategy sets for each player:

$S_{bat} = \{Attack, Defend\}$

$S_{bowl} = \{Yorker, Full, Good, Short\}$

With payoffs determined as follows:

		Bowler			
		Yorker	**Full**	**Good**	**Short**
Batsman	**Attack**	π_{AY}	π_{AF}	π_{AG}	π_{AS}
	Defend	π_{DY}	π_{DF}	π_{DG}	π_{AY}

Table 1: 2 x 4 normal form game

The payoffs in the cells represent the probabilities of successes for the batsman, which is sufficient to infer the probability of success for the bowler by the law of total probability. This is reasonable because we assume that each player during a given ball only cares about winning that game. They treat each ball like it is last the ball. It is also important to note that we will get different payoffs in the cells based on the definition of success we choose to use.

We can expand this model by considering a more complex strategy set for the batsman.

[4]Yorker is the fullest ball a bowler can bowl and is almost at the batsman's feet. It is considered the hardest to ball to hit. A full ball arrives at a half volley length to the batsman and is considered an easier ball to hit. A good ball is neither short nor full and is pitched slightly above the halfway mark of the pitch. A short ball is a ball that is pitched anywhere below the halfway line.

[5]We can consider alternative definitions of success. The data observes outcomes and so we can easily observe the number of runs scored each ball. We would just need to change the criteria for the dummy variable of bowler's success. The model can also easily accommodate alternative definitions, only the payoff numbers would be different. I do this later as robustness checks.

We can consider different types of attacking shots and defensive shots in the model. To that end, we consider the following attacking shots – elevated and along the ground (AT) – and the following defensive shots – deadbat and along the ground (DT). The elevated attacking shots come with more risk as there is a higher chance of getting out for the batsman (Out Caught scenario comes into play) whereas an along the ground attacking shot is relatively safer. The deadbat is the safest option in terms of not getting out, however, it means that there is less chance of scoring more runs. This is a constant sum game and such games are strictly competitive. There is a disadvantage in being predictable which induces players to anticipate rival's actions and so players would want to randomize in equilibrium. This insight tells us that we should not expect a pure strategy Nash equilibrium and since Nash (1950) guarantees an equilibrium we come to expect a mixed strategy Nash equilibrium. Hence, we get the following 4 x 4 one-shot normal-form two player constant sum game:

$S_{bat} = \{Elevated, AT, Deadbat, DT\}$

$S_{bowl} = \{Yorker, Full, Good, Short\}$

		Bowler			
		Yorker	**Full**	**Good**	**Short**
Batsman	**Elevated**	π_{EY}	π_{EF}	π_{EG}	π_{ES}
	AT	π_{ATY}	π_{ATF}	π_{ATG}	π_{ATS}
	Deadbat	π_{DY}	π_{DF}	π_{DG}	π_{DS}
	DT	π_{DTY}	π_{DTF}	π_{DTG}	π_{DTS}

Table 2: 4 x 4 normal-form game

Again, the payoffs in the cells represent the probabilities of success for the batsman. Even though these values are presently undetermined, the ideas about the strategies of the players and the nature of the game of cricket suggest that there can be no dominant strategies, or even pure strategy Nash equilibrium. This means that players cannot employ just any specific strategy as we saw in the tennis and the rock-paper-scissor examples because they run the risk of being predictable and the opponents can take advantage of this predictability. Players are more likely randomize over their pure strategies and so we need to solve for the mixed strategy Nash equilibrium. We will demonstrate this idea in the following example:

		Bowler			
		Yorker	**Full**	**Good**	**Short**
Batsman	**Elevated**	0.5	0	0.1	0
	AT	0	0.6	0.4	0.8
	Deadbat	0.2	0.8	0.4	0.9
	DT	0.3	0.3	0.5	0.4

Figure 3: Example of a game

We solved this game using the approaches mentioned in Avis, Rosenberg, Savani and Stengel (2010). We used the Nash equilibrium solver developed in this paper. We can notice that there are no dominant strategies for either player. The predicted frequencies from the mixed strategy Nash equilibrium is depicted below:

Bowler

	Yorker (%)	**Full (%)**	**Good (%)**	**Short (%)**
Nash predicted frequency	**63.89**	**16.67**	**19.94**	**0**

Batsman

	Elevated (%)	**AT (%)**	**Deadbat(%)**	**DT (%)**
Nash predicted frequency	**33.33**	**0**	**27.78**	**38.89**

The example's payoff numbers are hypothetical but they can be justified to a huge extent by the nature of the game and the strategy choices of the players. For example, a Yorker is a difficult ball to hit because it does not provide the batsman much room to play with it and is really hard to get elevation. An attacking shot for this type of ball is risky and will most often result in fewer runs. However, if we can observe both the bowler's and the batsman's choices we will be able to provide estimates for the values and use that to test the theory. The data will provide us with 'win rates' for the batsman which will represent probabilities of success and will be input into the model as payoffs. We can compute the Nash predicted frequencies by solving for the Nash equilibrium using the payoff values. The data will also hand us the actual frequencies for the strategies of both players and we can compare these frequencies with the Nash predicted frequencies.

4 Data

I obtain the dataset from *Cricinfo*[6], a cricket website that contains details and statistics of cricket matches, and the official website of *International Cricket Council*[7] (ICC). I collected the data from archived commentary of cricket matches. I look at cricket matches from the ICC Champion's Trophy in 2017. This tournament brings together the top eight teams in the world. This is appropriate to look at because the tournament attracts a lot of interest from viewers and is regarded as one of the most important tournaments in the sport. This means that the players are extremely motivated to play well to win. The Champion's Trophy features the top eight teams in the world divided into two groups. The teams in each group face off in a round robin format and then the top two teams from each group qualify for the knockout phase. The knockout stage involves two semi-finals and the tournament ends with the championship game.

The dataset contains the following information: over number, the bowler and the batsman involved, batsman's and bowler's strategies and the outcome of the ball (number of runs scored). The website allows me to determine the match number of the cricket game. I was careful in considering the outcomes of each ball because the outcome takes into account runs which are not scored off the batsman's bat. The ball can hit the batsman's body, for example, and they can still get runs on that ball if they successfully cross ends. However, I have only considered runs scored off the bat. I looked for specific keywords in the commentary to determine the strategies of the players. For example, "short" in the commentary of a

[6]http://www.espncricinfo.com/

[7]https://www.icc-cricket.com/champions-trophy

particular ball indicates that a bowler balled a short ball. The strategies of the batsmen are not often mentioned explicitly in the commentary. Again, I use certain keywords to determine the strategy used by the batsman. For example, I consider “hammered” to mean an aggressive along the ground stroke, “bunted” to mean a deadbat shot and “driven” and “flicked’ to mean a defensive along the ground stroke. An example of such a commentary of a particular ball is provided below:

46.5, Mashrafe Mortaza to Milne, 2 runs, slower ball, good length at middle stump, flicked to deep square leg’s right[8]

In this case, Mashrafe Mortaza bowled ball number 46.5 to Milne. The bowler chose to employ the short strategy and the batsman played a defensive along the ground shot resulting in two runs, success for the batsman according to my baseline definition.

I make sure that the matches included in the dataset met certain inclusion criteria. First, I only collect data from the first inning of the matches. The team batting first sets a target which the opposing team has to exceed in order to win the game. However, if I included the second innings I fear that knowledge of the target may lead to variations in strategy. For example, if a team is chasing a smaller target then they might play it safe in order to make sure they do not make mistakes. On the other hand, if they are facing a big target they might set out to be aggressive from the beginning. Considering the first inning only allows for a more uniform strategy perspective because batsman/bowlers want to maximize/minimize the number of runs scored. Players do not know what number of runs they have to obtain but they want to get the largest number possible. This works well with the definitions of success I use in this paper.

Secondly, I look at balls from the 41st to the 50th over[9]. So, the paper only considers

[8]http://www.espncricinfo.com/series/8037/commentary/1022363/bangladesh-vs-new-zealand-9th-match-group-a- icc-champions-trophy-2017?innings=1

[9] It is important to note that I do not consider leaving the ball as part of the strategy set of the batsmen.

the strategies of the last 60 balls of the first inning. This is, in part, motivated by a data constraint. The dataset was constructed by hand and it would be too cumbersome to include 600 balls per match. I also think that this is the point in the game when the batting side is the most urgent to score runs. This is easily seen when the runs scored per over (run rate) between 0-40 overs are compared with the runs scored per over between 40-50 overs. The average run rate for 0-40 overs for the matches we include our dataset is 5.15 runs per over compared to 7.05 runs per over for overs 40-50. A simple test of two means (t-test) reveals that that they are significantly different. This shows that our assumption of urgency from the batsmen is reasonable and also works well with our definition of success for the players. Importantly, the strategies across teams are more consistent in this stage of the game justifying the pooling of data across games. Some teams might start their innings aggressively while others might decide to start slower. Similarly, some teams might decide to slow down their run rate in the middle stages while others might decide to pick it up. However, all teams are likely to attempt to be aggressive in this stage of the game. This form of uniformity makes this stage more desirable from an empirical perspective as it is likely that the same equilibrium is being employed.

Thirdly, I only considered matches in which the first inning lasted more than 45 overs. This is to ensure that teams included in the sample had enough opportunity to score runs after the 40th over. An inning does not last more than 45 overs if the batting team gets all out. This might mean that they reached the 40th over already having conceded a number of outs. This would not provide them ample opportunity to be aggressive in the later stages and hence we do not want to consider these games. Lastly, I only look at interactions between batsmen and faster bowlers. As mentioned above, cricket usually employs two different types of bowlers: fast bowlers and spinners. I disregard spinners because considering them would possibly violate the assumption of simultaneous games in the model as batsmen would have time to react. Moreover, it would inflate my strategy space and generate a curse of dimensionality requiring too much data.

This is because it is extremely rare for a batsman to play that shot this late in the game.

Eleven games in the Champion's Trophy met the inclusion criteria for the dataset. I have 556 observations in the current data set. I expected to get 660 (60 X 11) observations but some of these were omitted because the bowlers were spinners. In another instance, Match 6 ended at 49.3. Table 3 provides a snapshot of the initial dataset. It contains information on the matches, number of balls that were bowled by spinners, the number of runs scored in the overs 40-50 in the matches included and the number of unique batsman and bowlers. We observe that spinners, who are omitted from the final dataset constitute about 14.7% of the data. Given the limited timeframe of the matches I consider, the number of unique batsman and bowlers are high. This makes following player-to-player interactions hard and I comment on this later.

Match	**#Balls**	**#Balls by spinners**	**#Runs**	**Run rate**	**#Unique Batsmen**	**#Unique Bowlers**
1	60	6	82	8.2	6	3
3	60	0	78	7.8	5	4
6	57	12	89	9.57	6	4
7	60	0	63	6.3	3	3
8	60	0	103	10.3	4	4
9	60	18	62	6.2	5	3
10	60	18	57	5.7	6	3
12	56	12	51	5.54	4	4
13	59	6	42	4.42	5	3
14	60	6	57	5.7	4	2
15	60	18	91	9.1	3	2
Total	652	96	775		51	35

Table 3: Snapshot of the initial dataset

The summary of the final data is presented in Table 4. The table shows the relative proportions of the different choices made by the bowlers and the batsmen with the total number of observations in the second column. The last letter represents the strategic choice made by the bowler and the first part of the string represents the choice made by the batsman. The last column contains the win rates for the batsman in each match. We have defined the win rate as the proportion of wins by a batsman, consistent with how payoffs were presented in the model above. The last row contains the win rates of the batsman per bowler-batsman strategy pair and this is the most crucial part of the summary of the data.

The 'win rate' for the batsman on all balls is 61.5%. This means that the batsman wins 61.5 % of the games (balls). This makes sense because it is easier for a batsman to succeed than for a bowler by our definitions of success. The 'win rate' is also consistently over 60% in all the matches. ATS is the most often observed outcome resulting about 18.9 % of the time. This occurs when the bowler bowls short and the batsman plays an attacking shot along the ground. The least observed outcome is EY standing at 0.5 %, that is, a bowler bowls a yorker and a batsman plays an elevated shot on only 0.5 % of the balls. Generally, the extreme forms of attacking (elevated) and defensive (deadbat) shots seem to be played less than the other two shots. The DTF outcome yields the highest win rate for the batsman at 84.3 %. The EG outcome is the most successful for the bowler, that is, the least successful for the batsman as the batsman wins only 22.2% of such encounters. We turn next to testing whether the players play according to Nash equilibria predictions.

Match	#Obs	EY	EF	EG	ES	ATY	ATF	ATG	ATS	DY	DF	DG	DS	DTY	DTF	DTG	DTS	Win rate
1	54	0.0	14.8	0.0	11.1	1.9	18.5	0.0	14.8	5.6	0.0	0.0	1.9	3.7	16.7	1.9	9.3	72.2
3	60	0.0	6.7	3.3	3.3	1.7	13.3	5.0	6.7	3.3	3.3	5.0	5.0	5.0	18.3	8.3	11.7	63.3
6	45	0.0	4.4	0.0	15.6	0.0	13.3	0.0	28.9	2.2	4.4	0.0	0.0	4.4	8.9	2.2	15.6	64.4
7	60	0.0	3.3	0.0	1.7	1.7	11.7	1.7	21.7	11.7	10.0	1.7	0.0	8.3	16.7	6.7	3.3	66.7
8	60	1.7	13.3	1.7	1.7	1.7	13.3	5.0	18.3	1.7	0.0	0.0	1.7	1.7	13.3	5.0	20.0	73.3
9	42	2.4	0.0	0.0	2.4	9.5	9.5	9.5	14.3	2.4	4.8	7.1	2.4	4.8	7.1	11.9	11.9	69.0
10	42	2.4	7.1	4.8	7.1	0.0	7.1	4.8	21.4	0.0	7.1	2.4	7.1	2.4	11.9	4.8	9.5	42.9
12	44	0.0	2.3	4.5	2.3	0.0	4.5	4.5	22.7	9.1	13.6	6.8	11.4	0.0	9.1	4.5	4.5	59.1
13	53	0.0	0.0	0.0	1.9	3.8	9.4	3.8	22.6	0.0	3.8	5.7	5.7	9.4	11.3	15.1	7.5	45.3
14	54	0.0	0.0	1.9	0.0	3.7	11.1	3.7	25.9	1.9	0.0	0.0	3.7	11.1	7.4	5.6	24.1	46.3
15	42	0.0	0.0	2.4	2.4	2.4	21.4	11.9	11.9	7.1	7.1	0.0	4.8	4.8	14.3	4.8	4.8	71.4
All Balls	556	0.5	5.0	1.6	4.3	2.3	12.2	4.3	18.9	4.1	4.7	2.5	3.8	5.2	12.6	6.5	11.3	61.5
Win rates	61.5	33.3	57.1	22.2	62.5	15.4	67.6	70.8	64.8	47.8	65.4	42.9	42.9	37.9	84.3	44.4	73.0	

Table 4: Distribution of strategies and win rates

5 Analysis and Results

Table 4 provides us with all the information I need to proceed with my analysis. In particular, the bottom row provides the 'win rates' for the batsman for each bowler-batsman strategy pair. These 'win rates' are the probabilities of success and I will use them as payoff values in my 4 x 4 normal-form game. For example, the 'win rate' for the batsman for the outcome EY is 33.3% which translates to a payoff of 0.33 for the batsman given the bowler bowls an yorker and the batsman plays an elevated shot. Since, the bowler's probability of success = (1 - probability of success for the batsman), we have 0.67 as the payoff for the bowler for the outcome EY. Table 5 provides an illustration of this normal form game:

		Bowler			
		Yorker	**Full**	**Good**	**Short**
Batsman	**Elevated**	0.33	0.57	0.22	0.63
	AT	0.15	0.68	0.71	0.65
	Deadbat	0.48	0.65	0.43	0.43
	DT	0.38	0.84	0.44	0.73

Table 5: Payoffs in the 4 x 4 game

The payoff values are then used to solve for Nash equilibrium following the approach in Avis, Rosenberg, Savani and Stengel (2010). The solver makes polyhedrons from best response functions and uses 'lexicographic reverse search' to enumerate the vertices of the best response function which correspond to the Nash equilibria of the game. I chose this approach because it provides all the Nash equilibria of a two-player game in strategic form. It is also easy to use and time efficient. The Nash equilibrium for my game comprises of the frequencies for each strategy for both bowler and batsman. The first row of Table 6 contains the Nash predicted frequencies for the batsman's strategies and the first row of Table 7 contains the Nash predicted frequencies for the bowler's strategies.

The strategy of bowling yorkers has the highest frequency of 44.6% followed by bowling good length balls which has a frequency of 41.9%. For the batsman, Nash equilibrium predicts that a deadbat shot would be played the most at about 90.5% of the time. The theory also predicts that the elevated shot is a dominated strategy and would never be played. These predictions intuitively make sense to me given the definition of success I am using in my model. I have defined an outcome of one run or greater as success for the batsman and so the batsman would be successful even if they manage to get just one run in a particular ball.

The batsman is essentially indifferent between scoring four runs, six runs or one run because he wins that particular ball regardless of any of the three outcomes[10]. Therefore, it makes sense that the batsman would play a safer shot with less risk of getting out (deadbat) rather than take excessive risk of playing an elevated shot with higher risk of getting out just to score one run. Similarly, yorker is considered to be the hardest ball to hit and reduces the number of runs possible to score from that ball. Hence, bowlers would like to employ this strategy the most in Nash equilibrium in order to increase their chances of winning.

The question of whether players follow these equilibrium predictions still remains. In order to answer that, we have to compute the actual frequencies of the strategies for each player. The data allows me to obtain these with a simple calculation. To calculate the actual frequency, I simply divide the number of observations with that particular strategy being played over the the total number of observations. So,

$$P_i = \tfrac{n_i}{n}$$

where $i \in$ {Elevated, AT, Deadbat, DT, Yorker, Full, Good, Short}, P_i is the actual frequency of strategy i being played, n_i is the number of observations where the batsman/bowler plays strategy i and n is the total number of observations. For example,

$$P_E = \tfrac{n_E}{n}$$

reports the the actual frequency of elevated shots where $P_{elevated}$ is the actual frequency of elevated shots, $n_{elevated}$ is the number of observations where the batsman plays an elevated shot and n is the total number of observations.The second row of Table 6 reports the actual frequencies of the batsman's strategies and the second row of Table 7 contains the actual frequencies of the the bowler's strategies.

[10]This suggests an alternative definition of success for robustness checks. For example, I define 'success' as four runs or greater for the batsman in one of the robustness checks in Section 6.

	Elevated (%)	AT (%)	Deadbat (%)	DT (%)
Nash predicted frequency	**0**	**7.9**	**90.5**	**1.6**
Actual frequency	**11.5**	**37.8**	**15.1**	**35.6**

Table 6: Frequencies of the batsman's strategies

	Yorker (%)	Full (%)	Good (%)	Short (%)
Nash predicted frequency	**44.6**	**0**	**41.9**	**13.5**
Actual frequency	**12.2**	**34.5**	**14.9**	**38.3**

Table 7: Frequencies of the bowler's strategies

It is easy to observe by glancing at the two tables that the Nash predicted frequencies are off by a decent margin from the actual frequencies. However, we do not know the amount of variation in the Nash predicted frequencies which would help us conclude that the players do not follow equilibrium play. We are unaware of the underlying distribution and the true error in the frequencies. We need to find the standard deviations for the Nash predicted frequencies so that we can say whether they are statistically different from the actual frequencies. Given that the sample size is fairly small, I used bootstrapping described in Efron(1982) to obtain standard deviation values for the Nash frequencies. This involved resampling with replacement from my sample in order to create a new sample. I treat this new sample as my new dataset to create a new version of Table 4. The 'win rates' from this new table are then used to solve for new Nash predicted frequencies. I repeat this process twenty-five times to obtain multiple Nash predicted frequencies and then calculate the standard deviation of these Nash predicted frequencies for each strategy for both players. It is important to note that actual frequencies also change when we resample but we expect that the standard deviation to be near zero if we do sufficient resampling[11]. I cap the resampling process at twenty five because the process is cumbersome as it involves a lot of manual adjustments[12]. The bootstrapped

[11]All variance in the actual frequencies are due to sampling variability.

[12]I used Stata to create the bootstrapped sample. I used this sample to create a new version of Table 4 in

standard deviations for the strategies for each player is reported in Table 8.

	Standard Deviation
Elevated	25.9
AT	22.3
Deadbat	38.5
DT	30.3
Yorker	23.8
Full	0.0
Good	22.2
Short	16.1

Table 8: Bootstrapped standard deviations for the strategies

We can use these standard deviations to determine whether players follow equilibrium play. We can see that the Nash predicted frequency for at least one of the strategies is not within two standard deviations of actual frequency. In particular, the Nash predicted frequency for a bowler employing a full strategy fails to be within two standard deviations of the actual frequency. The Nash predicted frequency and the standard deviation for the Nash predicted frequency for full is 0 and so the actual frequency of 34.5% is not in the closed interval [0]. Hence, we can reject the null hypothesis that the Nash predicted frequencies are statistically similar to the actual frequencies.

This result might be driven by the definition of success used in the model. I do the same test of the model using different definitions of success. I consider the case when the success for the batsman is defined to be two runs or more. In this scenario, I find two dominated strategies for both the bowler and the batsman. This is not ideal and so I move onto the case when the success for the batsman is defined to be four runs or more. The results are similar with two dominated strategies for the bowler and this definition also fails to conclude that players follow equilibrium play. Appendix A contains the tables with the Nash predicted and actual frequencies from these definitions of success. I do not consider the case when the success for the batsman is greater than or equal to six runs because the batsman can

Microsoft Excel. I use the 'win rates' from this table in conjunction with the approach mentioned in Avis, Rosenberg, Savani and Stengel (2010) to obtain new Nash predicted frequencies.

only achieve that when they hit an elevated shot. As a result, the elevated strategy would dominate the other strategies. Similarly, I do not account for success for the batsman as not getting out in a given ball. The data contains no observations of the batsman getting out employing the deadbat strategy and, thus, deadbat would dominate the other strategies. Additionally, the outcome of three runs only occurs two times and the outcome of five runs never occurs in the data. Therefore, I do not consider success for the batsman being greater than or equal to three runs as the predictions would be similar to the case when success is greater than or equal to four runs. Similarly, predictions when success for the batsman is five runs or more is the same as the predictions when success is defined to be six runs or more.

In this 4 x 4 game, the model fails to conclude that the players play according to equilibrium play. This result is consistent with possible alternative definitions of success. This may be due to the fact that the model fails to consider many factors. For example, the pitch the players play on may change from match to match. The strategies of players may be contingent on the pitch they are playing on. Similarly, different players have different abilities and this may play a role in their strategies. Unfortunately, the data does not allow me to test for these possibilities because it is not possible to follow specific player-to-player interactions due to a lack of sufficient number of observations.

In coding the data, there was a lot of subjective classification as discussed in the Data section. Since, the data is derived from commentary data it is possible that there were mistakes in the classification. It was not possible to check the accuracy of the commentary data by watching the games due to time constraints. Despite the fact that the players are professionals with high levels of training, it is possible that what the players intended to do and what ended up happening were different. Additionally, the breakdown of the pitch in the model that determines the strategy of the bowlers was coarse. The lines are not visible on screen and is easy for the commentator to get the strategy wrong.

For all the reasons mentioned above, I decide to simplify the model and consider a 2 x 2 version of it. I do this by grouping strategies together. The bowler's strategy choices of yorker and full are grouped together to form a new strategy called 'Up' and good and short are grouped together to form 'Down'. Similarly, for the batsman I grouped the two attacking shots to form 'Attacking' strategy and the two defensive shots to form 'Defensive' strategy. This grouping is an attempt to reduce the subjective nature of the classification. It might be hard to distinguish between the two kinds of attacking shots; however, it is less unlikely that an attacking shot would be classified as a defensive shot. Similarly, it might be hard to distinguish between a full and a yorker ball but it is easier to distinguish whether a ball has been pitched up or down. Thus, our new model is as follows:

Strategy sets for each player:

$S_{bat} = \{Attacking, Defensive\}$

$S_{bowl} = \{Up, Down\}$

		Bowler	
		Up	**Down**
Batsman	**Attacking**	π_{AU}	π_{AD}
	Defensive	π_{DU}	π_{DD}

Table 9: 2 x 2 normal form game

The payoff values in the cell are still probabilities of success for the batsman. Returning to the initial definition of success, I carry out the same process as the 4 x 4 game to obtain the following Nash predicted and actual frequencies:

	Attacking (%)	**Defensive (%)**
Nash predicted frequency	**67**	**33**
Actual frequency	**50**	**50**

Table 10: Frequencies of the batsman's strategies

	Up (%)	Down (%)
Nash predicted frequency	**50**	**50**
Actual frequency	**47**	**53**

Table 11: Frequencies of the bowler's strategies

I use bootstrapping to obtain the value of the standard deviation for the Nash predicted frequencies. I have to limit the resampling to twenty five due to time constraints. Again, we are not concerned with the standard deviation of the actual frequencies. The standard deviations of the Nash predicted frequencies are reported below:

	Standard Deviation
Up	39.90
Down	39.90
Attack	38.24
Defend	38.24

Table 12: Bootstrapped standard deviations for the strategies

Notice that the Nash frequencies for all the strategies are are within two standard deviations of the actual frequencies. In fact, they are all within one standard deviation of the actual frequencies. Thus, this 2 x 2 model suggests that players behave according to theoretical predictions.

6 Robustness

The paper finds that in the simplified 2 x 2 model both players behave according to predicted equilibrium play. However, this is entirely contingent on our definition of success. We had defined success for the batsman as scoring at least one run on a given ball. The data allow us to tweak the definition of success and test robustness of the model. I carry out the same procedure as above but with different definitions of successes like I previously did in the 4 x

4 model.

All possible alternative definitions reject the notion that players' behavior is consistent with equilibrium play. The players' Nash equilibrium contains a dominant strategy and given that there are only two strategies in this model; the players are predictable. I only look at two alternative definitions of success for the same reasons as in the 4 x 4 model. Appendix B contains the tables for these robustness checks. This result makes sense because certain definitions of success mean that players can only employ a certain strategy to achieve that success. However, this is not realistic as players need to be unpredictable in order to succeed in cricket. Hence, the model is not robust to alternative definitions of success.

It might be interesting to perform analysis on restricted subsets of data in the future. For example, we can only look at specific pairs of bowler-batsmen interactions. This has not been possible due to a data constraint in this project. There are way too many unique bowler and batsman interactions that do not allow us to follow interactions between separate interactions. An expansion of the dataset to include more matches might make this possible. We can also separate data based on number of outs remaining, that is, we can look at data with $> x$ outs remaining vs data with $\leq x$ outs remaining. We have not looked at spinning in this paper but it would be a good addition to the model. We can incorporate fielding positions for a richer model in the future. I have mentioned how this acts as a signaling mechanism and it would be interesting to see how the strategies evolve over different field settings.

7 Conclusion

Non-cooperative game theory is an important feature of economics because it helps us understand how agents behave under certain circumstances. This means that it is important for us to be able to test the predictions arising from this branch of game theory. The analysis in this paper uses a unique data set for one-shot-two-person constant sum game with trained professional players in natural conditions. We are able to conclude that players' behavior is consistent with the theoretical predictions given our initial definition of success with the 2 x 2 simplified model. However, these results are not robust to an extension of the model and neither is it robust to alternative definitions of success.

This should not, however, be considered conclusive. There are several limitations to the model and the analysis some of which is mentioned in Section 5. We are unable to follow two players and consider just their interactions. We are not able to account for different abilities of different players. We are not able to take into account the ground in which the match is played or the pitch in the ground. The ground is not standardized in ODIs and the dimensions of the ground can change from stadium to stadium. I do not account for this in the project. My model is also entirely contingent on our definition of success and strategies. It would be interesting to alter the definition of success and the strategy sets and see the results, something that could be an area for future research. For example, we can consider a batsman's strategy in terms of the direction they play the ball instead of considering the intensity with which they hit the ball. Similarly, we could look at bowling speeds or direction instead of the length. It would also be interesting to use the expected number of runs as a measure of success. The position in which the fielders are placed on the field can act as signaling mechanisms and could potentially alter the strategies of the player. We have not looked into this in this paper but it would be worthwhile to include this in the analysis of future research. Despite the limitations and possibilities of advancement, this paper provides some backing to the fact that there exists situations in which it is possible to test theoretical predictions and get positive results.

8 Appendix

8.1 A: 4 x 4 model

Success for batsman defined to be greater than or equal to two runs

	Elevated (%)	AT (%)	Deadbat (%)	DT (%)
Nash predicted frequency	**0**	**0**	**43.7**	**56.3**
Actual Frequency	**11.5**	**37.8**	**15.1**	**35.6**

Table 13: Frequencies of the batsman's strategies

	Yorker (%)	Full (%)	Good (%)	Short (%)
Nash predicted frequency	**87.5**	**0**	**0**	**12.5**
Actual Frequency	**12.2**	**34.5**	**14.9**	**38.3**

Table 14: Frequencies of the bowler's strategies

Success for batsman defined to be greater than or equal to four runs

	Elevated (%)	AT (%)	Deadbat (%)	DT (%)
Nash predicted frequency	15.4	0	84.6	0
Actual Frequency	11.5	37.8	15.1	35.6

Table 15: Frequencies of the batsman's strategies

	Yorker (%)	Full (%)	Good (%)	Short (%)
Nash predicted frequency	84.6	0	15.4	0
Actual Frequency	12.2	34.5	14.9	38.3

Table 16: Frequencies of the bowler's strategies

8.2 B: 2 x 2 model

Success for batsman defined to be greater than or equal to two runs

	Attacking	Defensive
Nash predicted frequency	100	0
Actual frequency	50	50

Table 17: Frequencies of the batsman's strategies

	Up	Down
Nash predicted frequency	100	0
Actual frequency	47	53

Table 18: Frequencies of the bowler's strategies

Success for batsman defined to be greater than or equal to four runs

	Attacking	**Defensive**
Nash predicted frequency	**100**	**0**
Actual frequency	**50**	**50**

Table 19: Frequencies of the batsman's strategies

	Up	**Down**
Nash predicted frequency	**100**	**0**
Actual frequency	**47**	**53**

Table 20: Frequencies of the bowler's strategies

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