Chance and Cricketing Outcomes

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Chapter 2

Chance and Cricketing Outcomes

2.1 Introduction

It is generally acknowledged that chance plays a part in determining cricketing outcomes, both for teams and for individual players. In the first instance, the two captains toss a coin before the start of a match and whoever wins the toss can choose whether their team will bat or bowl first. Conventional wisdom has it that in a Test Match, with two innings played by each side over a match lasting five days, the pitch (or wicket) is at its most benign on the first two days; thereafter it starts to deteriorate, cracks appear, the wicket becomes more bowler-friendly, batting becomes progressively more difficult, and is most difficult on the fifth and last day of the match. The team that wins the toss has, therefore, the advantage that it can bat first (using the first two days), when conditions are most favourable for batting, while the team that loses the toss must bat its second innings on days when conditions are least favourable to the batters.

In limited overs cricket — in which the team scoring the highest number of runs in a fixed number of overs wins the match — the quality of the pitch is relatively invariant over the course of the match.[1] When playing conditions are taken out of the equation, conventional wisdom has it that the side batting second has the advantage that it knows its target (the number of runs scored by the team batting first) and can pace itself accordingly.[2] The team that wins the toss can, therefore, chase, rather than having to set, a target.

Another aspect of chance is what transpires during play: the dropped catch or the missed stumping after which the reprieved batter goes on to make a big score; the lofted cover drive of the in-form batter that is snaffled on the boundary; rain (or bad light) stopping play just when a team is in the ascendant. All these unexpected events — the catch should have been taken, the stumping should not have been missed, the drive should not have gone to hand, it should not have rained — mean that,

[1] This being approximately eight hours when the number of overs is set at 50 ('one-day' cricket) and about four hours when they are fixed at 20 ('T20' cricket).
[2] These observations must be qualified for day-night matches, which span daylight and evening hours, in which evening dew on the field means that playing conditions are different during the day and night parts of the match.

in addition to its intrinsic abilities, a team's results also depend upon a slice (or several slices) of luck. These episodes of luck, punctuating the passage of play, are a key factor in making the outcomes of matches between teams of different abilities unpredictable.

Another aspect of luck, examined by Aiyar and Ramcharan (2010), which impacts on individual players rather than on the team, is whether players made their first or 'debut' appearances in international cricket on home or on foreign soil. Aiyar and Ramcharan found that international Test players who were lucky enough to play their first match at home performed significantly better on debut than those whose first match was overseas. The reason for this is that international cricketers, having been brought up on a diet of domestic pitches and conditions, have had their skills honed to playing in local conditions and would, therefore, be likely to debut more strongly at home than abroad (Woolmer *et al.*, 2008). For example, Indian batters are supposed to be more comfortable playing on the spinners' wickets of Mumbai and Chennai and less comfortable on the bouncy tracks of Perth or Johannesburg, and vice versa for Australian and South African batters. Furthermore, Aiyar and Ramcharan (ibid.) estimated that players' subsequent careers were strongly affected by their debut performance: a 10% higher debut score implied a 5% increase in overall productivity.

This chapter discusses in some detail the element of luck as it pertains to team performance, looking first at the importance of the toss and then at the extent to which match results are due to ability and/or to luck. The importance of the toss is analysed employing Bayes' Theorem which draws a distinction between the prior probability of an event happening before the data have been observed (say, winning a match prior to the toss) and the posterior probability which updates one's prior belief after observing the data (winning a match after the outcome of the toss is known).

2.2 Analysis of Toss Outcomes in Test Matches[3]

Between 19 March 1877 and 4 March 2021, England's men played a total of 1,034 Test Matches. Of these, England won the toss in 506 matches and lost the toss in the other 528 for a 'toss success rate'

[3] Unless otherwise stated, the data for this section are from Ric Finlay's *Tastats* database (www.tastats.com.au). This database includes records, tables, ratings, and player biographical information covering *inter alia* men's and women's international cricket and major T20 leagues around the world.

of 48.9%. Of these 506 ‘toss-winning’ matches, England won 191, lost 136, and drew 179 for a win/loss (W/L) ratio of 1.40; of the 528 ‘toss-losing’ matches, England won 186, lost 172, and drew 170 for a W/L of 1.08. So, judging by the W/L ratio, winning the toss was important to England’s men’s Test Match success: England won only 8% more times than it lost in matches which began with losing the toss, while it won 40% more times than it lost in matches which began with winning the toss.

The experience of England’s men with the pre-match coin toss can be compared with that of England’s women cricketers. England’s women played their first Test Match against Australia at the Gabba in Brisbane on 28 December 1934; since then they have played 95 matches, most recently on 18 June 2019 against Australia at Taunton.[4] Of these 95 games, England won the toss 54 times for a ‘toss success rate’ of 56.8%. Of these 54 ‘toss-winning’ matches, England won 11, lost 7, and drew 36 for a W/L ratio of 1.57. Of its 41 ‘toss-losing’ matches, England’s women won 9, lost 7, and drew 25 for a W/L ratio of 1.29. So, comparing the men’s and women’s Test teams for England, women had a higher W/L ratio than men for both ‘toss-winning’ (1.57 versus 1.4) and ‘toss-losing’ (1.29 versus 1.08) matches. Measured in terms of relative W/L ratios in ‘toss-winning’ and ‘toss-losing’ situations, winning the toss conferred a greater advantage to England’s men’s Test team than it did to its women’s team.[5]

<Table 2.1>

Table 2.1 shows the men’s Test Match W/L ratio for seven countries — Australia, England, India, New Zealand, Pakistan, South Africa, and the West Indies — and the women’s Test Match W/L ratio for Australia, England, India, and New Zealand, both in aggregate over all Test matches (from 1876-2021 for men and 1934-2019 for women) and then in the context of the toss-outcomes of the matches.[6] This Table clearly shows that, over the history of Test cricket, Australia’s men and

[4] England played India in a Test Match at Bristol starting on 16 June 2021, but that is outside the time frame of this analysis.

[5] 1.3 = 1.4/1.08 for men and 1.22 = 1.57/1.29 for women. Aggregating over all Test matches, the W/L ratio was 1.22 for men and 1.43 for women.

[6] In 1970, the International Cricket Council (ICC), as a signal of disapproval of South Africa’s apartheid regime, banned the country from participating in international cricket, lifting the ban in 1991 after a majority rule government showed signs of emerging.

women have been the most successful teams. Australian men won 1.74 matches, and Australian women won 2 matches, for every match that they lost. In matches in which they *won* the toss, Australian men won 1.99 matches, and Australian women won 5 matches, for every match lost, while in matches in which they *lost* the toss, Australian men won 1.52 matches, and Australian women won 1.25 matches, for every match lost. The most unsuccessful team was just across the Tasman Sea: New Zealand men won only 0.6 matches, and its women won only 0.2 matches, for every match lost. For New Zealand's men, winning the toss proved to be an advantage — as it was for men's Test teams for all the other countries — with W/L ratios of 0.65 and 0.55 for matches in which they, respectively, won and lost the toss. However, for New Zealand's women, winning the toss was a disadvantage — unlike for women's Test teams for the other three countries — with W/L ratios of 0.17 and 0.25 for matches in which they, respectively, won and lost the toss.

Win the Toss, Win the Match?

So how does winning the toss help in winning a Test Match? After winning the toss, England's men batted first on 409 occasions (80.8%) and put the opposition in in the remaining 97 matches (19.2%). In their 420 toss-winning matches, Australia's men batted first in 336 matches (80%). The results are not very different for women. England's women batted first in 43 of the 54 matches in which they won the toss (79.6%) while Australia's women did the same in 23 of their 28 toss-winning matches (82%).

<Table 2.2 and 2.3>

Tables 2.2 and 2.3, which show the equivalent numbers for a selection of Test playing countries, show that in most cases the team that won the toss chose to bat first giving credence to conventional wisdom: choose to bat if you win the toss. This was particularly true of men's Test Matches involving Australia, England, India, or South Africa: these countries chose to bat in 75–80% of the matches in which they won the toss. For England and India, deciding to put the opposition in after winning the toss usually rebounded against them: their W/L ratio was considerably lower when they decided to bowl first than when they chose to bat first (0.91 versus 1.56 for England; 0.45 versus

1.46 for India).[7] In terms of the W/L ratio, Australia's men, like the West Indies, were largely unperturbed by whether, after winning the toss, they elected to bat or to bowl (Australia W/L ratio: 1.98 versus 2.05; West Indies W/L ratio: 0.94 versus 1.03).[8]

New Zealand's cricket grounds, with their notoriously fresh first-day 'green-tops'[9] provide an incentive for the toss-winning team to ask the opposition to bat first: New Zealand decided to bowl first in 43% of Test Matches in which it won the toss, and it was asked to bat first in 39.2% of matches in which it lost the toss. Its W/L ratio when it chose to bat first was considerably lower than its W/L ratio when it chose to bowl (0.4 versus 1.23): for New Zealand, at least, asking the opposition to bat appeared to be a better strategy than asking them to bowl. The overall W/L ratio for New Zealand when it batted first, regardless of whether it chose to or was asked to, was 0.58; its W/L ratio when it bowled first, again regardless of whether it chose to or was asked to, was 0.62.

Another team for which choosing to bowl first (W/L ratio 1.3) was a better strategy than batting first (W/L ratio 1.11) was Pakistan. This was largely due to two grounds in Pakistan — Lahore and Karachi — which favoured bowling first. The W/L ratio at Lahore was 0.2 for teams batting first and 5.0 for teams bowling first, while in Karachi, it was 0.39 for teams batting first and 2.57 for teams bowling first. In the 83 Test Matches (of a total of 435 matches) that Pakistan played at Karachi or Lahore, it won the toss on 38 occasions and chose to bat first on 27 (71%) of these, flying in the face of statistics suggesting that it would be better off choosing to bowl rather than to bat. More generally, Pakistan followed conventional wisdom and chose to bat first in 142 of the 208 (68%) Test Matches in which it won the toss.

The policy of choosing to bat in Test Matches, after winning the toss, applied with equal force to women as it did to men. Australia, England, and India chose to bat first for, respectively, 82.1%, 79.6%, and 72.2% of the Tests in which they won the toss. Most surprisingly, New Zealand's women

[7] England's Nasser Hussain decided to bowl first against Australia at the Gabba on 7 November 2003: Australia were 364 for 2 at close of play and went on to score 492.
[8] Australia's Ricky Ponting, however, after winning the toss, put England in to bat at Edgbaston on 4 August 2005: England scored 407 in a day.
[9] So called because of the extra cover of grass on the pitch. This allowed fast bowlers to obtain exaggerated movement of the new ball off the wicket, which combined with the ball skidding through, made first day batting very difficult.

bucked the inclination of their men of putting the opposition in after winning the toss: New Zealand's women chose to bat first in 19 of the 20 matches in which they won the toss, in contrast to its men who batted first in only 127 of their 222 toss-winning matches. In many instances, however, because of small sample sizes, the W/L ratio could not be reported when women's Test teams went against conventional post-toss decision: for example, Australia's women chose to bowl first on five occasions, chalking up three wins without a loss; similarly, India's women won the only Test Match in which they chose to bowl first; and New Zealand's women drew the only Test Match in which they put the opposition in to bat.

2.3 A Bayesian Analysis of the Importance of Winning the Toss

The Reverend Thomas Bayes (1701–61), an 18th century Presbyterian minister with a parish in Tunbridge Wells, England, proved what is arguably the most important theorem in statistics.[10] This was a theory of 'conditional probability' to show how the calculation of probabilities could be extended from events that were independent to events that were inter-dependent. This theory was first presented as a paper read to the Royal Society, two years after Bayes' death, by another chaplain and mathematician, Richard Price. The paper by Bayes was titled 'An Essay Towards Solving a Problem in the Doctrine of Chance' and forms the basis of what, today, is celebrated as Bayes' Theorem.[11]

Bayes' Theorem relates the probability of a hypothesis being true (event A), *given that the data have been observed* (event T) to the probability of observing the data (event T), given that the hypothesis is true (event A). It essentially provides an updating rule by which one's prior belief that the hypothesis is true, *before any data have been observed*, is updated to a posterior belief about the theory's validity, *after the data have been observed*. The updating factor is the ratio of the probability of observing the data, *if the hypothesis is true*, to the probability of observing the data, regardless of the validity of the hypothesis. A mathematical statement of Bayes' Theorem is set out in the box below.

[10] See *The Economist*, 'In Praise of Bayes', 28 September 2000, https://www.economist.com/science-and-technology/2000/09/28/in-praise-of-bayes
[11] See Mlodinow (2008).

Box 2.1: Mathematical Statement of Bayes' Theorem

Bayes' theorem is encapsulated by the well-known equation (*P* in this equation represents probability and the symbol | denotes that the event following | has already occurred):

$$P(A|T) = \frac{P(T \mid A)}{P(T)} \times P(A) \qquad (2.1)$$

where: $P(A)$ represents the *prior* belief that the hypothesis is true *before the data have been observed*; *P(T)* is the probability of observing the data, *regardless of whether the hypothesis is true or not*; *P(T|A)* is the probability of observing the data, given that the hypothesis is true, and $P(T \mid A) / P(T)$ is the Bayesian 'updating factor'. The updating factor is the ratio of the probability of observing the data when the theory is true, to that of observing the data regardless of whether the theory is true or false:

$P(T) = P(T \mid A)P(A) + P(\tilde{T} \mid A)P(\tilde{A})$, $\tilde{A}$ being the event that the theory is false.

The updating factor translates a *prior* (that is, *before* observing the data) belief about the hypothesis's validity (*P(A)*) into a *posterior* (that is, *after* observing the data) belief, *P(A|T)*.

Bayes' theorem has been extensively applied in law and in medicine. For example, in the area of law it has shed light on the so-called 'prosecutor's fallacy' whereby a prosecutor argues that since the probability of observing a particular piece of evidence, T (say, blood type identical to that found at the scene of the crime), *under the assumed innocence of the defendant*, A, is very small (that is, $P(T \mid A)$ in equation (2.1) is low), the probability of the defendant being innocent, *given that his blood type matches that at the crime scene*, must also be very small (that is, $P(A \mid T)$ must also be low). This fallacious reasoning stems from the assumption that the ratio $P(A)/P(T)$ in equation (2.1) is equal to unity (Thompson and Schumann, 1987; Aitken, 1996). If, however, the prior belief that the defendant is innocent, $P(A)$, relative to the probability of finding a blood type identical to that found at the scene of the crime, $P(T)$, is high then $P(A \mid T)$ could be high even though $P(T \mid A)$ was low.

In medicine the theorem has been used to analyse, for example, the efficacy of breast screening. Proponents of screening would argue, on the basis of the 'screening fallacy', that because the probability of the screen returning a positive result, *given that the patient has cancer*, is large (that is, $P(T \mid A)$ is high), the probability of the patient having cancer, *given that the screen returns a positive result*, must also be large (that is, $P(A \mid T)$ must also be high). This fallacious reasoning again stems from the assumption that the ratio $P(A)/P(T)$ in equation (2.1) is equal to unity. If, however, the proportion of persons with cancer in the population, relative to the proportion of positive screen results, is small (i.e. $P(A)/P(T)$ in equation (2.1) is low) then $P(A \mid T)$ could be appreciably smaller than $P(T \mid A)$. The size of this difference represents cancer 'over diagnosis' and has been estimated at 10% (Zackrisson *et al.*, 2006). In effect, one in ten women diagnosed with breast cancer would not require treatment.

This section applies these ideas to examining the importance of winning the toss (the data or test) in winning a match (the theory or condition). At the pre-match coin-tossing there are two possible outcomes for a team (call it, X): it wins the toss (event T) or it loses the toss (event $\tilde{T}$); the data are observed or are not observed or, equivalently, the test is positive or it is negative. On the back of these data, the probabilities of two further events can be distinguished: (i) the probability of winning the match (the theory is true or the condition exists) if the toss was won (the data were observed); in other words, winning the toss (data were observed) would have been *succeeded* by winning the match (theory is true); (ii) the probability that if the match had been won (the theory was true or the condition existed) it would have been *preceded* by winning the toss (the data would have been observed).

The question of interest is not about the likelihood that, if the toss was won, it would have been *succeeded* by winning the match — that is, (i) above — but, rather, the likelihood that winning the match would have been *preceded* by winning the toss — that is, point (ii) above. It is important to emphasise that conceptually these are separate questions in much the same way that the probability that a test for a medical condition would report positive, *if one has that condition*, is conceptually different from the probability that one has that condition *if the test is positive.* A medical practitioner would be more interested in the second question than in the first.

Similarly, the question of interest is not about the likelihood that if *X* had won the toss (the test is positive) then it would go on to win the match (the condition exists) but, rather, it is the likelihood that if the match was won (the condition exists) then the toss would also have been won (the test is positive). Again, it is important to emphasise that these are two separate questions in much the same way (to use a current example) that the probability that a COVID test will be positive, *if one has COVID*, is conceptually different from the probability that, *if the test is positive,* one does have COVID. The strength of Bayes' Theorem is that it can provide an answer to the second set of questions by linking it, via equation (2.1) above, to the first set.

As discussed above, Bayes' Theorem states that the probability of a theory being true (event *A*: the team wins the match), *given that the data have been observed* (event *T*: it wins the toss) is given by equation (2.1), above. After the data have been observed, the Bayesian 'updating factor' in equation (2.1), $P(T \mid A) / P(T)$, translates one's *prior* belief about the theory's validity ($P(A)$) into a *posterior* belief ($P(A|T)$) which, in the context of cricket, translates one's *prior* belief that a team would win the match into a *posterior* belief that it would win *after the toss outcome had been observed*.

The first question of interest is that *if the match were won by X* (event *A* occurred or, in terms of the language above, the condition existed), what is the probability that the data would have been observed (that is, event *T*, winning the toss occurred or, equivalently, in terms of the language above, the test showed positive)? This probability is referred to as the *sensitivity* of the toss: the greater the sensitivity, the greater the likelihood that a match that was won would have been *preceded* by a ‘good’ toss.

Similarly, the *specificity* of the toss is defined as the likelihood that, *if a match were lost by X*, then the data would not have been observed (that is, event *T*, winning the toss would not have occurred or, equivalently, in terms of the language above, the test showed negative). Following from this, *1-specificity* is the probability of a *false positive*: the probability that a match that was *lost* (false: the condition did not exist) was preceded by winning the toss (the test showed positive). Similarly, *1-sensitivity* is the probability of a *true negative*: the probability that a match that was won (true: the condition did exist) would have been preceded by losing the toss (the test showed negative).

Box 2.2: Mathematical Derivation of the Probability of Winning the Toss

The probability of winning the toss, *P(T)*, is the weighted sum of the probabilities of a 'true positive' (*X* wins the match, event *A*, after winning the toss) and a 'false positive' (*X* does not win the match, event $\tilde{A}$, after winning the toss), the weights being the strength of one's prior belief,

$$P(A),\ \text{where}\ P(\tilde{A}) = 1 - P(A):$$

$$P(T) = P(A \cap T) + P(\tilde{A} \cap T) = P(A) \times \overbrace{P(T \mid A)}^{\text{prob of a true positive}} + P(\tilde{A}) \times \overbrace{P(T \mid \tilde{A})}^{\text{prob of a false positive}} \quad (2.2)$$

By analogous reasoning:

$$P(\tilde{T}) = P(A \cap \tilde{T}) + P(\tilde{A} \cap \tilde{T}) = P(A) \times \overbrace{P(\tilde{T} \mid A)}^{\text{prob of a false negative}} + P(\tilde{A}) \times \overbrace{P(\tilde{T} \mid \tilde{A})}^{\text{prob of a true negative}} \quad (2.3)$$

Equation (2.3) says that the probability of losing the toss is the weighted sum of the probabilities of a 'false negative' (*X* wins the match after losing the toss) and a 'true negative' (*X* loses the match after losing the toss), the weights being the strength of one's prior belief, *P(A)*.

Substituting the expression in (2.2) into equation (2.1) yields:

$$P(A \mid T) = \frac{P(A) \times P(T \mid A)}{P(A) \times P(T \mid A) + P(\tilde{A}) \times P(T \mid \tilde{A})} = P(A) \times \frac{P(T \mid A)}{P(T)} \quad (2.4)$$

2.4 Pre- and Post-Toss Probabilities of Winning in Test Matches and One-Day Internationals

Tables 2.4 to 2.6 put empirical flesh on Bayes' Theorem as applied to winning/losing the toss in cricket. Table 2.4 shows estimates for seven men's Test Match teams and four women's Test Match teams of the probability of their winning a Test Match after having won the toss ($P(A|T)$.

Using England as an illustration, England's men won 377 of the 1,034 Tests that they played up to March 2021, implying that, based on historical data, the *prior* probability of England's men winning a Test Match was $P(A)=0.36$. Of the 377 Tests *won* by England, it won the toss on 191 occasions. This means that the probability that a victorious Test would have been preceded by winning the toss, $P(T \mid A)$ = 191/377 = 0.51. Of the 1,034 Tests *played* by England, it won the toss on 506 occasions, meaning that the probability of winning the toss for England's men was $P(T)$ = 506/1034 = 0.49. From Bayes' Theorem, the prior probability ($P(A)=0.36$) should be updated by multiplying by the 'updating factor', $P(T \mid A)/P(T)$ = [0.51/0.49] to yield the posterior probability $P(A|T)$ = 0.37.[12]

<Table 2.4>

The crucial point in the above calculations was the value assigned to $P(T)$, the probability of winning the toss. If one tossed a coin an infinite (or large) number of times, one would expect to get heads 50% of the time. For a small number, however — say 10 tosses — it would be uncommon for the coin to come out five heads and five tails: indeed, this would happen only 24.6% of the time in 10 tosses of a fair coin.[13] This is very evident in the results of the toss for men's and women's matches. In the men's Test Matches, where the number of matches played by each team was several multiples of hundreds, the observed value of $P(T)$ hovered around 50%: Table 2.1 shows that the West Indies had the highest percentage of toss wins at 52% while South Africa with 47.6% had the lowest percentage.

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[12] This result could have also been obtained from first principles. England's men played a total of 1,034 Tests up to March 2021. Of these 1,034 Tests, England won the toss on 506 occasions and, of these 506 toss-winning Tests, England won 191, and did not win 315, matches. So, the probability of winning a Test, *having won the toss*, $P(A|T) = 191/506=0.37$. See Gigerenzer (2002, chapter 6) and Strogatz (2010), for the calculation of conditional probabilities from first principles.

[13] From the binomial formula: $\frac{10!}{5!5!}\times(0.5)^{10} = 0.246$ where ! represents the factorial of the number.

The number of women's Test Matches was, however, much smaller, and consequently showed greater variation: Australia's women, who played 74 Tests, were 'unlucky' with the toss, winning only 37.8% of their tosses while England's women, who played 95 Tests, were 'lucky' with the toss, winning 56.8% of their tosses. So, while, taken over many matches, the element of luck associated with the toss dissolves into a $P(T)$ at or near to 0.5, for a smaller number of matches there could be considerable inter-team variation in toss outcomes. In this chapter, $P(T)$ is the observed proportion of tosses won in matches played.

Similarly, since England's women won 20 of the 95 Test Matches that they played up to June 2019, the implication was that the *prior* probability of England's women winning a Test Match was $P(A)=0.21$. Now of these 20 victorious Tests, England's women won and lost the toss in, respectively, 11 and 9 Tests, meaning that $P(T \mid A)$ =11/20 = 0.55. Consequently, the posterior probability of England's women winning a Test, after having won the toss, was $P(A|T) = (0.21/0.5) \times 0.55=0.23$.

The results in Table 2.4 show that winning the toss did not have much effect on the probabilities of men's teams from England, India, New Zealand, and Pakistan winning a Test Match — the prior and posterior probabilities of winning were almost identical. Two countries were, however, considerably affected by winning the toss: the *prior* probabilities of the Australian and South African men's teams of winning a Test Match rose from 0.47 and 0.38, respectively, to *posterior* probabilities of 0.51and 0.44, respectively, when it was known that they had won the toss. Similarly, for women, there was little difference between the *prior* and *posterior* probabilities of winning a Test Match for England and New Zealand (the *prior* and *posterior* probabilities were almost identical). The toss, however, did make a difference for Australia and India: the *prior* probabilities of Australian and Indian women winning a Test Match rose from 0.27 and 0.14, respectively, to *posterior* probabilities of, respectively, 0.36 and 0.22 after they had won the toss.

In one-day internationals (ODI), however, the toss had only a limited effect on the likelihood of winning a match. In the men's game, as Table 2.5 shows, the prior probability of winning a match, for all the teams listed, was not very different from the posterior probability of winning calculated after the team had won the toss. This conclusion was broadly unaltered with respect to women's ODI but subject to two qualifications. England and India both suffered from winning the toss: for both countries, the posterior probabilities of winning the match (after winning the toss) were smaller than the prior probability of winning: for England, the probability fell from a prior of 0.59 to a posterior of 0.55 while, for India, it fell from a prior of 0.56 to a posterior of 0.53, and for New Zealand, it fell from a prior of 0.5 to 0.48. The second qualification is that Pakistani women benefited from winning the toss: their prior probability of winning (0.29) rose to a posterior of 0.36 after winning the toss.

<Table 2.5 and 2.6>

The ODI pattern of the toss not significantly affecting the probability of winning was also evident in T20 Internationals (T20I) for men. In these matches, too, the prior probability of winning the match was not greatly different from the posterior probability of winning the match on the back of winning the toss (Table 2.6). Similarly, in the women's T20 Intrrnational matches, winning the toss had only a small influence on the match outcome. For Australia, as Table 2.6 shows, the probability rose from a prior of 0.67 to a posterior of 0.7; for England, it rose from 0.72 to 0.76; for New Zealand, it rose from 0.58 to 0.63; for Pakistan, it rose from 0.4 to 0.45, and for South Africa it rose from 0.45 to 0.5.

2.5 Decision Making After the Toss

The key to understanding these results is that while winning the toss gave teams the power to decide whether to bat or to bowl first, it was not always clear that they arrived at the right decision. Sometimes winning the toss in cricket is the equivalent of a *zugzwang* in chess: a situation in which the obligation to make a move puts one at a disadvantage. A team in cricket may either bat first (set a target) or bowl first (chase a target) *by choice*, because it wins the toss, or *by imposition,* because it loses the toss. This results in four questions:

1. For teams that won the toss, was the probability of winning significantly different between choosing to bat or to bowl first?
2. For teams that lost the toss, was the probability of winning significantly different between being asked to bat or to bowl first?

3. For teams that set a target by batting first, was the probability of winning significantly different between doing so by choice or by imposition?
4. For teams that chased a target by batting second, was the probability of winning significantly different between doing so by choice or by imposition?

These questions are answered below for men's and women's Test and ODI matches by employing a multivariate framework. With respect to Test Matches, the analysis below is restricted to matches which resulted in a win/loss, meaning that drawn matches were excluded. With N matches played by a team, indexed $i=1\ldots N$, the variable of interest is the probability of winning a match, denoted $P(Y_i)$, where the variable $Y_i=1$ if the team won match i and $Y_i=0$ if it lost the match. This probability is examined in the context of two variables: (i) winning the toss (the variable $T_i=1$) or losing the toss ($T_i=0$) before the match; (ii) batting first (the variable $B_i=1$) or bowling first ($B_i=0$). The two variables — winning/losing the toss and batting/bowling first — are allowed to interact so that the probabilities of winning after setting or chasing a target depended upon whether these outcomes (setting or chasing) were the result of choice (winning the toss) or imposition (losing the toss). This provides answers to questions 1 and 2, above. Similarly, interaction between winning/losing the toss and batting/bowling first variables means that the probability of winning after batting/bowling first depended on whether these outcomes were the result of choice (toss was won) or imposition (toss was lost). This provides answers to questions 3 and 4, above.

Box 2.3: Mathematical Exposition of the Regression Model

Since the variable to be explained, Y_i, took binary (1,0) values the appropriate model was a logistic model which, in the context of the above discussion, can be written as:

$$\log\left[\frac{\Pr(Y_i=1)}{1-\Pr(Y_i=1)}\right] = \alpha + \underbrace{\beta T_i}_{\text{Toss effect}} + \underbrace{\delta B_i}_{\text{Batting/Bowling first effect}} + \gamma \underbrace{(T_i \times B_i)}_{\text{interaction effect}} + \underbrace{u_i}_{\text{error term}} = Z_i \qquad (2.5)$$

And from equation (2.5), the probability of winning the match can be computed as:

$$\Pr\left[Y_i = 1\right] = \frac{e^{Z_i}}{1+e^{Z^i}} \qquad (2.6)$$

Where the term *e* in equation (2.6) represents the exponential term.

The probability of winning, $Pr(Y_i=1)$, can be computed under a number of different scenarios: (i) $T_i=1$, and $B_i=1/0$ which answers question 1, above; (ii) $T_i=0$, and $B_i=1/0$ which answers question 2; (iii) $B_i=1$ and $T_i=1/0$, which answers question 3; (iv) $B_i=0$, and $T_i=1/0$, which answers question 4.

<Table 2.7>

Table 2.7 shows the probabilities of winning, for men's Test Matches for a selection of countries, under each of the scenarios in questions 1–4, above. Since the logit equations pass through the means, these probabilities are identical to the mean sample proportions of victories for these scenarios. The second and third columns of Table 2.7 show the probabilities of winning under four scenarios, each with two rival outcomes: (i) winning the toss and batting/bowling first; (iii) losing the toss and batting/bowling first; (iii) batting first, after winning/losing the toss; (iv) bowling first, after winning/losing the toss. The third column, headed 'Difference', shows the difference between the probabilities of winning recorded in the first and second columns.

The usual way of assessing the importance of the difference in probabilities between two rival outcomes is through statistical significance. This means asking what the probability is of obtaining the observed difference *if the null hypothesis was that there is no difference*. If this probability is sufficiently low (conventionally below 5%), then this casts doubt on the credibility of the null hypothesis and, therefore, the analyst would reject (or at least, not accept) the 'no difference' null hypothesis. Differences in probabilities which were (statistically) significant are marked with an asterisk in Table 2.7: the likelihood of observing these differences, under the null hypothesis that the differences were zero, was 5% or less. Unfortunately, the analysis for men's Test Matches, shown in Table 2.7, could not be replicated for women's Test Matches because of the small number of Test Matches played by women: women's teams from the four countries in Table 2.3 (Australia, England, India, and New Zealand) played a total of only 250 Test Matches compared to the 2,864 games played by their male counterparts.

Table 2.7 shows that for England's and India's men's Test Match teams, choosing to bat first was a better strategy than choosing to bowl: for England's men, the probability of winning fell from 0.609 when they chose to bat to 0.476 when they chose to bowl while, for India's men, the probability of winning fell from 0.594 when they chose to bat to 0.310 when they chose to bowl. As the last column of Table 2.7 shows, the difference in probabilities for both countries was significantly different from zero. For Australia, Pakistan, and the West Indies, the difference in probabilities between choosing to bat and to bowl was not significantly different from zero even though, in purely numerical terms, the probability of winning was, for all three countries, greater when they chose to bowl, rather than bat first.

On the other hand, for New Zealand and South Africa, choosing to bowl first offered a higher probability of winning than choosing to bat: for New Zealand's men, the probability of winning fell from 0.552 when they chose to bowl to 0.285 when they chose to bat while, for South Africa's men, the probability of winning fell from 0.725 when they chose to bowl to 0.538 when they chose to bat. As the last column of Table 2.7 shows, the difference in probabilities for both countries was significantly different from zero.

Taking the case of New Zealand: excluding draws, it played a total of 280 Test Matches of which it won 105 and lost 175. Of these 105 Test victories, 68 (nearly two-thirds) occurred in New Zealand where the W/L ratios for teams batting and bowling first were, respectively, 0.82:1 and 1.33:1.[14] In particular, New Zealand played 41 Test Matches at Wellington where the W/L ratios for teams batting and bowling first were, respectively, 0.46:1 and 2.15:1. Of these 41 matches in Wellington, New Zealand won the toss 21 times: of these 21 toss-winning matches, it elected to bat 9 times and lost all 9 matches; on the other hand, it elected to field on 12 of the 21 occasions that it won the toss, and won 10 of these matches.

The results for South Africa are almost certainly a statistical artefact. South African grounds favour batting first with W/L ratios of 1.2:1 and 0.83:1 for, respectively, batting and bowling first. So, there was nothing about the domestic environment in South Africa that favoured bowling first. South Africa won the toss in 159 Test Matches (of which 96 were played in South Africa) and elected to bat in 119 of these matches (75%), winning 64 (53.8%); on the 40 occasions that it chose to bowl first, it won 29 matches (72.5%) of which five were in New Zealand.

A curious case is that of Pakistan. Grounds in Pakistan strongly favoured bowling first with W/L ratios of 0.55:1 and 1.83:1 for, respectively, batting and bowling first, and yet Pakistan's likelihood of winning after choosing to bat first (52.5%) was not significantly lower than its

[14] The W/L ratios for other countries for, respectively, batting and bowling first were: Australia 1.32:1 and 0.76:1; England 1.29:1 and 0.78:1; India 1.13:1 and 0.89:1; Pakistan 0.55:1 and 1.83:1; South Africa 1.2:1 and 0.83:1; and the West Indies 0.94:1 and 1.07:1.

likelihood of winning after choosing to bowl first (56.5%). A reason for this is that after the terrorist attack in Lahore on the visiting Sri Lankan cricket team on 3 March 2009, Pakistan adopted the United Arab Emirates (UAE) as its 'home' country and played all its Test Matches there. Of the 126 Test Matches in which it won the toss, 38 were played in Pakistan and 16 in the UAE. Unlike grounds in Pakistan, the UAE's pitches favoured batting first with W/L ratios of, respectively, 1.9:1 and 0.53:1 for batting and bowling first.

For teams that lost the toss, Australia, New Zealand, and South Africa all had significantly higher probabilities of winning if they were put into bat rather than being asked to bowl (Australia: 0.693 versus 0.573; New Zealand: 0.491 versus 0.265; South Africa: 0.733 versus 0.4) while India had a significantly higher probability of winning if it was asked to bowl, rather than to bat, first (0.478 versus 0.316).

In terms of batting first, the probability of winning was significantly higher for India if it batted first by choice rather than by invitation (0.594 versus 0.316) but, for New Zealand and South Africa, the probability of winning was significantly lower if they batted first by choice rather than by invitation (New Zealand: 0.285 versus 0.491; South Africa: 0.539 versus 0.733). In terms of bowling first, the probability of winning was significantly higher for Australia, New Zealand, and South Africa if they bowled first by choice and not by invitation (Australia: 0.672 versus 0.573; New Zealand: 0.552 versus 0.265; South Africa: 0.725 versus 0.4) while, for India, the probability of winning was significantly lower if it chose, as opposed to being required, to bowl first (0.310 versus 0.478).

2.6 Luck versus Ability in Determining Match Outcomes

A staple in sport is speculation about how much of a particular set of outcomes associated with a sporting contest (say, the number of wins and losses by a team in the course of a league season) is the result of 'luck' — that is, represents the outcome of a random process — and how much is the result of 'ability' (or lack of it) so that, for a particular team, victory will, systematically, be observed more frequently than defeat or vice versa. This section and the next make use of probabilities derived from the binomial distribution to estimate the ability–luck ratio in the number of wins and losses recorded by teams in the Men's Big Bash League (MBBL) and the Women's Big Bash League (WBBL) in

Australia. In brief, 'luck-based' outcomes for each team are compared with those that would result with both luck and ability playing a role in determining outcomes. This allows one to identify the roles that luck, and ability play in determining the probability of a team winning a match.

Box 2.4 shows that in N trials, with a probability of p of success, and $1-p$ of failure, in a single trial, one can compute the probability of say K successes ($K \le N$) and the formula for this computation is represented by equation (2.7). Suppose that the result of each match was determined by pure 'luck' which is equivalent to the result being decided by the toss of a *fair* coin (that is, $p=0.5$) with say, heads representing a win and tails a loss. Under such conditions, with an infinitely large number of league matches, the percentage of wins and losses for each team would approach 50%. With each of the eight teams in the MBBL and the WBBL playing 14 matches, the probability of a 50% win rate (7 wins), would be 0.209.[15] In other words, the chances of a team winning exactly half its matches, *with each match being decided by the toss of a fair coin*, would be less than one in five. From the perspective of this chapter, the relevant question is: what would have been the probability of the *observed* number of wins by each team if the outcome of each match had been decided by pure luck, that is, by the toss of a fair coin? So, for example, if team X won 10 of the 14 matches that it played in a season, and if team Y won 5 out of its 14 matches, then the probabilities of obtaining 10 and 5 wins (out of 14 matches) based upon pure luck — or, equivalently, the toss of a fair coin — would be, from equation (2.7) in Box 2.4, 6.1% for X's 10 wins and 12.2% for Y's 5 wins.[16]

Now consider ability. Suppose that the win rates of two teams, X (0.71=10/14) and Y (0.36 = 5/14) were a *true* reflection of their abilities, meaning that their chances of beating one of the other eight teams in a match were, *on average*, 71% and 36%, respectively.[17] This means that the outcome of matches involving teams X and Y would still be determined by the toss of a coin but this time by *biased* coins such that the chances of obtaining a head (win) or a tail (loss) from a single toss of this

[15] From the binomial formula: $\frac{14!}{7!7!}\times(0.5)^{14} = 0.209$ where ! represents the factorial of the number.

[16] Respectively, $\frac{14!}{10!4!}\times(0.5)^{14} = 0.061$ and $\frac{14!}{5!9!}\times(0.5)^{14} = 0.122$.

[17] This does not mean that the chance of X beating *each* of the other teams was 71%, rather the chance of X winning was 71% on average.

coin were, respectively, 71% and 29% for *X* and 36% and 64% for *Y* . So, there would still be an element of uncertainty as to whether *X* or *Y* would win or lose a particular match but this time the uncertainty would be anchored in judgement about their respective abilities: the biased coins would be such that there was a 71% chance of a heads (win) for *X*, and a 36% chance of a heads (win) for *Y*.

Against this background, the relevant question is: what would have been the probability of the observed number of wins by *X* and *Y* if the outcome of each match had been decided by *ability-based* luck, that is by the toss of biased coins? Under the hypothesis that the winning and losing was determined by the toss of *biased* coins (the bias of the coins reflecting the team's observed proportion of wins: 10/14 for *X* and 5/14 for *Y*), the probabilities of *X* winning 10 matches out of 14, and *Y* winning 5 matches out of 14, were, respectively, 23% and 21.8%.[18] The difference between the probability of team *X* winning 10 matches out of 14 on the basis of ability-based luck (23%) and on the basis of pure luck (6.1%) expressed as a ratio of the ability-based luck probability — $\left[(23-6.1)/23\right]$ — is defined as the proportion of 10 wins out of 14 that is due to ability: for team X this is 73%. Similarly for team *Y*, the proportion of 5 wins out of 14 that is due to (a lack of) ability is $44\%=\left[(21.8-12.2)/21.8\right]$.

[18] From equation (2.7), respectively, $\frac{14!}{10!3!}\times(0.71)^{10}\times(0.29)^{4}=0.23$ and $\frac{14!}{5!9!}\times(0.36)^{5}\times(0.64)^{9}=0.218$

Box: 2.4: The Methodology of Bernoulli Trials

In a series of N Bernoulli trials — with probability p of success (match was won), and $1-p$ of failure (match was lost), in a single trial — the probability of K successes is:

$$Q(N,K,p)=\frac{N!}{K!(N-K)!}p^K(1-p)^{N-K} \tag{2.7}$$

where ! represents the factorial of a number.

More generally, If K represents the number of games won by a team from its N league games, we define, from equation (2.7): (i) the probability of K wins, *based on 'pure luck'*, as $Q(N,K,0.5)$ (and denote this probability as *R(K)*); (ii) the probability of K wins, *based on 'ability-based luck'*, as $Q(N,K,p),$ where $p=K/N$ is the *observed* proportion of wins (and denote this probability as *S(K)*). Now, given that a team has won K games out of N, *S(K)* embodies the effect of both ability and luck while *R(K)* embodies the effect of just luck. Consequently, the *change* in the probability of K wins (from N matches) from *R(K)* to *S(K)* represents the effect of ability upon the chance of victory. We may thus define:

$$\theta(K)=\frac{S(K)-R(K)}{S(K)} \tag{2.8}$$

as the *proportion* of the probability of K wins (out of N matches) that is due to ability, with $(1-\theta)$ representing the proportion that is due to luck.

2.7 Empirical Results for Luck versus Ability

Table 2.8 shows the results of the pre-qualifying Men's Big Bash League matches for 2020 and Table 2.9 does the same for the Women's Big Bash League for 2019, with both sets of matches played in various locations in Australia.[19] Table 2.8 shows that in the MBBL for 2020, Sydney Sixers won 9 of their 14 matches while, at the other end of the spectrum, Melbourne Renegades could only win 4 of their 14 matches. Table 2.9 shows that in the WBBL for 2019, Brisbane Heat and Adelaide Strikers won 10 of their 14 matches while Sydney Thunder, Hobart Hurricanes, and Melbourne Stars could only manage to win, respectively, 5, 4, and 2 of the matches that they played.

<Tables 2.8 and 2.9>

Under the hypothesis that winning and losing was purely a matter of chance, determined by the toss of a fair coin, the probabilities of Sydney Sixers winning 9 out of 14 matches in the MBBL, and Brisbane Heat winning 10 out of 14 matches in the WBBL were, respectively, 12.2% (Table 2.8, 5th row) and 6.1% (Table 2.9, 5th row). At the other end of the winning spectrum, the probability of Melbourne Renegades winning 4 out 14 matches in the MBBL, and Melbourne Stars wining 2 out of 14 matches in the WBBL, were, respectively, 6.1% (Table 2.8, 5th row) and 0.56% (Table 2.9, 5th row).

Turning now to ability, suppose that the win rates of Sydney Sixers (0.64=9/14) and Melbourne Renegades (0.29 = 4/14) in the MBBL, shown in Table 2.8, were a *true* reflection of their abilities meaning that the chances of Sydney Sixers and Melbourne Renegades winning an MBBL match were, *on average*, 64% and 29%, respectively. This means that the outcome of a match involving Sydney Sixers would still be determined by the toss of a coin but this time by *biased* coins such that the chance of Sydney Sixers calling heads correctly (winning) was 64%; conversely, another unfair coin would give Melbourne Renegades a chance of only 29% of calling heads correctly. So, there would still be an element of uncertainty as to whether Sydney Sixers or Melbourne Renegades would win or lose a particular match but this time the uncertainty would be anchored in judgement

[19] For the WBBL, 2019, rather than 2020, was analysed because in 2020, 16 of the possible 112 WBBL matches were abandoned, due to rain, compared to only two abandoned matches in 2019.]

about their respective abilities: the ‘biased’ coins would be such that there was a 64% chance that Sydney Sixers, and a 29% chance that Melbourne Renegades, would win a match.[20] Under ability-based luck, the probabilities of Sydney Sixers winning 9, and of Melbourne Renegades winning 4, out of 14 matches were, respectively, 21.8% and 23.1% (Table 2.8: 6th row).

Similarly, as shown in Table 2.9, if the win rates for Brisbane Heat (0.71=10/14) and Melbourne Stars (0.14=2/14) were a true reflection of their abilities, then ability-based luck would mean that the unfair coins would give Brisbane Heat a 71% chance, and Melbourne Stars a 14% chance, of winning the toss if they called heads. Under this scenario, the probabilities of Brisbane Heat winning 10, and of Melbourne Stars winning 2, out of 14 matches were, respectively, 23.1% and 29.2% (Table 2.9: 6th row).

The win rates for teams which won exactly 7 of their 14 matches (Brisbane Heat, Adelaide Strikers, and Hobart Hurricanes in the MBBL and Sydney Sixers in the WBBL) was 0.5 meaning that now there was no distinction between ‘fair’ and ‘biased’ coins. The probability of winning through pure luck was the same as that of winning through ability-based luck and the probability of 7 wins out of 14 was 20.9% under either scenario. These teams which won 7 out of 14 matches represent the mid-point in Tables 2.8 and 2.9: the results for these teams could not distinguish between luck and ability.

Teams to the *left* of this mid-point of 7 wins in 14 matches — Sydney Sixers, Perth Scorchers, and Sydney Thunder in the MBBL and Brisbane Heat, Adelaide Strikers, Perth Scorchers, and Melbourne Renegades in the WBBL — displayed *positive* ability. For example, the probabilities of Sydney Sixers winning 9 (MBBL), and of Brisbane Heat winning 10 (WBBL), out of 14 matches purely by chance (that is, on the toss of a fair coin) were, respectively, 12.2% and 6.1%. If, however, their observed win rates — 0.64 (9/14) for Sydney Sixers and 0.71 (10/14) for Brisbane Heat — were an accurate reflection of their abilities vis-à-vis the other teams, then the probabilities of Sydney Sixers winning 9, and of Brisbane Heat winning 10, out of 14 matches on ability-based luck were, respectively, 21.8% and 23.1%. So, the contributions of ability and of luck to their victories was 44%

[20] To give a practical flavour to the proceedings, it is assumed that in a match involving Rajasthan and Mumbai, Rajasthan flipped the coin and Mumbai called ‘heads’ with a 64% chance of the unfair coin landing heads.

and 56%, respectively, for Sydney Sixers in the MBBL (Table 2.8, penultimate and last rows) and 73.6% and 26.4%, respectively, for Brisbane Heat in the WBBL (Table 2.9, penultimate and last rows).[21] For lower win rates, the contribution of ability fell and that of luck rose. So, for Sydney Thunder in the MBBL and Melbourne Renegades in the WBBL, each with 8 wins in 14 matches, the contributions of ability and luck to their performance were, respectively, 13.7% and 86.3%.

Teams to the *right* of this mid-point of 7 wins in 14 matches — Melbourne Stars and Melbourne Renegades in the MBBL and Sydney Thunder, Hobart Hurricanes, and Melbourne Stars in the WBBL — displayed *negative* ability. For example, the probabilities of Melbourne Renegades (in the MBBL) winning 4, and of Melbourne Stars (in the WBBL) winning 2, of their 14 matches purely by chance (that is, on the toss of a fair coin) were, respectively, 6.1% and 0.56%. If, however, their observed win rates — 0.29 (4/14) for Melbourne Renegades in the MBBL and 0.14 (2/14) for Melbourne Stars in the WBBL — were an accurate reflection of their (lack of) ability vis-à-vis the other teams then the probabilities of Melbourne Renegades winning 4, and of Brisbane Heat winning 2, of their 14 matches on ability-based luck were, respectively, 23.1% and 29.2%. So, the contributions of inability and of luck to their victories were, from equation (2.8), 73.6% and 26.4%, respectively, for Melbourne Renegades in the MBBL (Table 2.8, penultimate and last rows) and 98% and 2%, respectively, for Melbourne Stars in the WBBL (Table 2.9, penultimate and last rows). For higher win rates, the contribution of inability fell and that of luck rose. So, for Melbourne Stars in the MBBL and Sydney Thunder in the WBBL, each with 5 wins in 14 matches, the contributions of inability and luck to their performance were, respectively, 29.6% and 70.4%.

The above analysis is along the lines of Burke (2010) who compared the variance of the distribution of observed results with the variance of the distribution of outcomes under a series of Bernoulli trials in which the probabilities of success and failure in a single trial were the same. The methodology proposed here is, however, different from his — and, arguably, represents an improvement — since it pays explicit attention to the binomial probabilities instead of simply relying on an aggregate measure of dispersion like the variance.

[21] $0.44 = (21.8 - 12.2)/21.8$ and $0.736 = (23.1 - 6.1)/23.1$

2.8 Conclusions

'The harder I practise, the luckier I get' was the South African golfer Gary Player's withering dismissal of the role of luck in determining sporting performance. And, indeed, there are many who would share this view, encapsulated in phrases such as 'you make your own luck' or 'leave nothing to chance'. The latter phrase speaks of an attitude in which sportspersons attempt to control as many as possible of the different factors that could influence the result of a match: careful preparation and paying attention to detail enables one to take advantage of the opportunities that present themselves during a game.

Carried to its extreme, the 'leave nothing to chance' philosophy can generate superstitions among competitors which border on the risible: arranging water bottles in a particular order (Rafael Nadal); tying one's shoelaces in a specific way (Serena Williams); a batter's long and unvarying routine before facing each ball (Jonathan Trott); an umpire's little hop whenever the score was the 'unlucky' 111 (David Shepard). All of these are predicated on the belief that performing a specific ritual before a competition provides a sense of control over one's environment. It is 'leave nothing to chance' carried to a neurotic extreme.

Those who decry the importance of luck in cricket fail to recognise that unremitting practice, of the Gary Player school, is not sufficient to lead on to excellence. It is not enough to just practise: one must practise the right things in the right way with the right advice.[22] For practice to be effective, it needs to be buttressed by 'facilities' — coaches, gym, diet, equipment — which then coalesce with a sportsperson's dedication to produce 'effective practice'. It is precisely in access to such facilities that luck enters the picture: some persons have access to excellent support facilities which, combined with their own commitment, allows them allows them to develop careers which flourish; the less fortunate, lacking in access to such facilities, are thwarted from progressing very far, no matter how fiercely their ambition burns; and for many a lack of support means that the flame of sporting ambition is never lit and they turn their focus to other activities.

[22] See Syed (2010, chapter 3) on the importance of the quality, as opposed to the quantity, of practice.

Perhaps no one has expressed the importance of a supporting environment so clearly as Ed Smith (2012) who writes how he and his sister — who, between the two of them, was generally regarded as better at sports and was equally competitive — went to different secondary schools after their primary education: she to a state school, he to an independent school. Although her school was academically excellent, and she went on to read English at Oxford, a lack of sporting facilities meant that she withdrew from competitive sport. Smith, on the other hand, went to a school with the most superlative facilities for sport. As he writes, 'What happened to my sister's sporting experience is that she ran out of opportunities [at her state school]. What happened to my sporting experience is that I received the best sporting education that money could buy. I played cricket for England; she didn't play for any team in any sports again' (Smith, 2012, p. 24).

And the role of luck in all this? Smith's father happened to be a teacher at Tonbridge School and, as a teacher's son, Ed could study there without paying fees. Since Tonbridge school was for boys only, and since the family could not afford to educate their daughter at an independent school, she went to the local state school. Had Tonbridge School been a mixed school — or had the family been wealthier — sporting parity between the siblings would have been preserved. With the family fortunes as they were, had the father been teaching at a girls' only school, Rebecca and not Edward Smith might have been playing for England. That is the role of luck: it presents opportunities to some while simultaneously denying them to others. This theme of luck in a broader sense — compared to the more prosaic terms in which it has been discussed here — with implications for diversity and social justice, is taken up in more detail in the next chapter.

Table 2.1: Test Match Outcomes After Winning/Losing the Toss

Country	Total Matches	Win-Loss Ratio X:1	% of Tosses Won	Win-Loss Ratio for "Toss-Winning" Matches	Win-Loss Ratio for "Toss-Losing" Matches
Men					
Australia	834	1.74	50.4	1.99	1.52
England	1,034	1.22	48.9	1.40	1.08
India	550	0.96	49.5	1.18	0.79
New Zealand	446	0.60	49.8	0.65	0.55
Pakistan	435	1.05	47.8	1.17	0.96
South Africa	443	1.10	47.6	1.41	0.86
West Indies	552	0.89	52.0	0.97	0.81
Women					
Australia	74	2.00	37.8	5.00	1.25
England	95	1.43	56.8	1.57	1.29
India	36	0.83	50.0	4.00	0.20
New Zealand	45	0.20	44.4	0.17	0.25

First match for men: Australia versus England, Melbourne, 15 March, 1877; last match for men: India versus England, Ahmedabad, March 4, 2021.

First match for women: Australia versus England, Brisbane, 28 December 1934; last match for women: Australia versus England, Taunton, July 18, 2019.

Source: Ric Finlay, Tastats (tastats.com.au)

Table 2.2: Win/Loss Ratios from Batting First or Second: Men's Test Matches

	Toss Was Won				
Country	**Number of Matches**	**Number Matches in Which Team Batted First**	**Win-Loss Ratio**	**Matches in Which Team Bowled First**	**Win-Loss Ratio**
Australia	420	336 (80.0)	1.98	84 (20.0)	2.05
England	506	409 (80.8)	1.56	97 (19.2)	0.91
India	272	215 (79)	1.46	57 (21)	0.45
New Zealand	222	127 (57)	0.4	95 (43)	1.23
Pakistan	208	142 (68)	1.11	66 (32)	1.30
South Africa	211	162 (76.8)	1.16	49 (23.2)	2.64
West Indies	287	181 (63.1)	0.94	37 (36.9)	1.03
Toss was Lost					
Australia	414	105 (25.4)	2.26	309 (74.6)	1.34
England	528	126 (23.8)	1.28	402 (76.2)	1.03
India	278	53 (19.1)	0.46	225 (79.9)	0.92
New Zealand	224	88 (39.2)	0.96	136 (60.8)	0.36
Pakistan	228	64 (28.2)	0.79	164 (71.8)	1.04
South Africa	232	53 (22.8)	2.75	179 (77.2)	0.67
West Indies	265	67 (25.3)	0.96	198 (74.7)	0.75

First match for men: Australia versus England, Melbourne, 15 March, 1877; last match for men: India versus England, Ahmedabad, March 4, 2021.

First match for women: Australia versus England, Brisbane, 28 December 1934; last match for women: Australia versus England, Taunton, July 18, 2019.

Figures in parentheses are percentages

Source: Ric Finlay, Tastats (tastats.com.au)

Table 2.3: Win/Loss Ratios from Batting First or Second: Women's Test Matches

	Toss Was Won				
Country	**Number of Matches**	**Number Matches in Which Team Batted First**	**Win-Loss Ratio**	**Matches in Which Team Bowled First**	**Win-Loss Ratio**
Australia	28	23 (82.1)	3.5	5 (17.9)	3W 0L
England	54	43 (79.6)	1.3	11 (20.4)	3.0
India	18	13 (72.2)	3.0	5 (27.8)	1W 0L
New Zealand	20	19 (95)	0.17	1 (5)	0W 0L
Toss was Lost					
Australia	46	9 (19.6)	0.5	37 (80.4)	1.5
England	41	7 (17.1)	0.33	34 (82.9)	2.0
India	18	5 (27.8)	0.0	13 (72.2)	0.33
New Zealand	25	5 (20.0)	1W 0L	20 (80.0)	0.0

First match for men: Australia versus England, Melbourne, 15 March, 1877; last match for men: India versus England, Ahmedabad, March 4, 2021.

First match for women: Australia versus England, Brisbane, 28 December 1934; last match for women: Australia versus England, Taunton, July 18, 2019.

Figures in parentheses are percentages

Source: Ric Finlay, Tastats (tastats.com.au)

Table 2.4: Probabilities of Winning After Winning the Toss: Test Matches

	Men						
	Australia	England	India	New Zealand	Pakistan	South Africa	West Indies
Number of Tests	834	1,034	550	446	435	443	552
Number of Tests Won	394	377	162	105	140	167	177
P(A)	*0.47*	*0.36*	*0.29*	*0.24*	*0.32*	*0.38*	*0.32*
Number of Tosses Won	420	506	272	222	208	211	287
P(T)	*0.50*	*0.49*	*0.49*	*0.50*	*0.48*	*0.48*	*0.52*
Number of Wins After Winning Toss	213	191	85	56	68	93	98
P(T|A)	*0.54*	*0.51*	*0.52*	*0.53*	*0.49*	*0.56*	*0.55*
Updating Factor: $\left[P(T \mid A)/P(T)\right]$	1.08	1.04	1.06	1.06	1.02	1.17	1.06
P(A|T)	*0.51*	*0.37*	*0.31*	*0.25*	*0.33*	*0.44*	*0.34*
	Women						
	Australia	England	India	New Zealand			
Number of Tests	74	95	36	45			
Number of Tests Won	20	20	5	2			
P(A)	*0.27*	*0.21*	*0.14*	*0.04*			
Number of Tosses Won	28	54	18	20			
P(T)	*0.38*	*0.57*	*0.50*	*0.44*			
Number of Wins After Winning Toss	10	11	4	1			
P(T|A)	*0.50*	*0.55*	*0.8*	*0.50*			
Updating Factor: $\left[P(T \mid A)/P(T)\right]$	*1.32*	*0.96*	*1.6*	*1.14*			
P(A|T)	*0.36*	*0.20*	*0.22*	*0.05*			

First match for men: Australia versus England, Melbourne, 15 March, 1877; last match for men: India versus England, Ahmedabad, March 4, 2021.

First match for women: Australia versus England, Brisbane, 28 December 1934; last match for women: Australia versus England, Taunton, July 18, 2019.

P(A) is the prior probability that that the team will win a Test Match

P(T|A) is the proportion of wins in which the country won the toss

P(A|T) is the posterior probability of a win after the result of the toss has been observed

The updating factor from prior to posterior probability is $P(A)\times P(T \mid A)/P(T)$

P(T) is the probability of winning the toss as derived from the data for each country.

Source: Own calculations based on data from Ric Finlay, Tastats (tastats.com.au)

Table 2.5: Probabilities of Winning After Winning the Toss: One Day Internationals

	Men						
	Australia	England	India	New Zealand	Pakistan	South Africa	West Indies
Number of Matches	955	755	993	775	933	628	828
Number of Matches Won	579	380	516	354	490	386	404
P(A)	*0.61*	*0.50*	*0.52*	*0.46*	*0.53*	*0.61*	*0.49*
Number of Tosses Won	485	372	516	380	469	324	388
P(T)	*0.51*	*0.49*	*0.52*	*0.50*	*0.50*	*0.52*	*0.47*
Number of Wins After Winning Toss	288	190	277	169	245	198	189
P(T|A)	*0.50*	*0.50*	*0.54*	*0.48*	*0.50*	*0.51*	*0.47*
Updating Factor: $\left[P(T \mid A) / P(T)\right]$	0.98	1.02	1.04	0.96	1.0	0.98	1.0
P(A|T)	*0.60*	*0.51*	*0.54*	*0.44*	*0.53*	*0.60*	*0.49*
	Women						
	Australia	England	India	New Zealand	Pakistan	South Africa	West Indies
Number of Matches	332	351	272	344	168	199	177
Number of Matches Won	261	206	151	171	48	100	80
P(A)	*0.79*	*0.59*	*0.56*	*0.50*	*0.29*	*0.50*	*0.45*
Number of Tosses Won	174	189	127	162	87	98	82
P(T)	*0.52*	*0.54*	*0.47*	*0.47*	*0.52*	*0.49*	*0.46*
Number of Wins After Winning Toss	136	103	66	77	31	51	38
P(T|A)	*0.52*	*0.50*	*0.44*	*0.45*	*0.65*	*0.51*	*0.48*
Updating Factor: $\left[P(T \mid A) / P(T)\right]$	1.0	0.93	0.94	0.96	1.25	1.04	1.07
P(A|T)	*0.79*	*0.55*	*0.53*	*0.48*	*0.36*	*0.52*	*0.48*

First match for men: Australia versus England, Melbourne, 5 January 1971; last match for men: Pakistan versus South Africa at the Centurion on 7 April 2021

First match for women: England versus International XI 23 June 1973; last match for women: New Zealand versus England at Dunedin University on 28 February 2021

P(A) is the prior probability that that the team will win an ODI

P(T|A) is the proportion of wins in which the country won the toss

P(A|T) is the posterior probability of a win after the result of the toss has been observed

The updating factor from prior to posterior probability is $P(A) \times P(T \mid A) / P(T)$

P(T) is the probability of winning the toss as derived from the data for each country.

Source: Own calculations based on data from Ric Finlay, Tastats (tastats.com.au)

Table 2.6: Probabilities of Winning After Winning the Toss: T20 Internationals

	Men						
	Australia	England	India	New Zealand	Pakistan	South Africa	West Indies
Number of Matches	136	131	142	145	170	131	130
Number of Matches Won	71	68	91	73	105	73	58
P(A)	*0.52*	*0.52*	*0.64*	*0.50*	*0.62*	*0.56*	*0.45*
Number of Tosses Won	70	64	65	72	89	62	67
P(T)	*0.51*	*0.49*	*0.46*	*0.50*	*0.52*	*0.47*	*0.52*
Number of Wins After Winning Toss	34	33	41	34	57	34	32
P(T|A)	*0.48*	*0.49*	*0.45*	*0.47*	*0.54*	*0.47*	*0.55*
Updating Factor: $\left[P(T \mid A) / P(T)\right]$	0.94	1.0	0.98	0.94	1.04	1.0	1.06
P(A|T)	*0.49*	*0.52*	*0.63*	*0.47*	*0.64*	*0.56*	*0.48*
	Women						
	Australia	England	India	New Zealand	Pakistan	South Africa	West Indies
Number of Matches	141	148	123	129	120	114	135
Number of Matches Won	95	107	67	75	48	51	73
P(A)	*0.67*	*0.72*	*0.54*	*0.58*	*0.40*	*0.45*	*0.54*
Number of Tosses Won	66	78	53	72	57	56	68
P(T)	*0.47*	*0.53*	*0.43*	*0.56*	*0.48*	*0.49*	*0.50*
Number of Wins After Winning Toss	47	60	29	46	26	28	36
P(T|A)	*0.49*	*0.56*	*0.43*	*0.61*	*0.54*	*0.55*	*0.49*
Updating Factor: $\left[P(T \mid A) / P(T)\right]$	1.04	1.06	1.0	1.09	1.13	1.12	0.98
P(A|T)	*0.70*	*0.76*	*0.54*	*0.63*	*0.45*	*0.50*	*0.53*

First match for men: Australia versus New Zealand, Auckland, 17 February 2005; last match for men: Pakistan versus Zimbabwe, Harare, April 25, 2021.

First match for women: New Zealand versus England, Hove, 5 August 2004; last match for women: New Zealand versus England, Wellington, March 5, 2021.

P(A) is the prior probability that that the team will win a T20 International

P(T|A) is the proportion of wins in which the country won the toss

P(A|T) is the posterior probability of a win after the result of the toss has been observed

The updating factor from prior to posterior probability is, $P(A) \times P(T \mid A) / P(T)$

P(T) is the probability of winning the toss as derived from the data for each country.

Source: Own calculations based on data from Ric Finlay, Tastats (tastats.com.au)

Table 2.7: The Probabilities of Winning Under Different Toss Winning/Losing and Batting/Bowling First Scenarios: Men's Test Matches[+]

	Probability of Winning: Won the Toss/Batted First	Probability of Winning: Won the Toss/Bowled First	Difference in Probabilities
Australia	0.664	0.672	-0.008
England	0.609	0.476	0.134*
India	0.594	0.310	0.283*
New Zealand	0.285	0.552	-0.266*
Pakistan	0.525	0.565	-0.040
South Africa	0.538	0.725	-0.187*
West Indies	0.484	0.507	-0.023
	Probability of Winning: Lost the Toss/Batted First	Probability of Winning: Lost the Toss/Bowled First	Difference in Probabilities
Australia	0.693	0.573	0.120*
England	0.561	0.507	0.054
India	0.316	0.478	-0.162*
New Zealand	0.491	0.265	0.226*
Pakistan	0.442	0.514	-0.072
South Africa	0.733	0.400	0.333*
West Indies	0.490	0.429	0.062
	Probability of Winning: Won the Toss/Batted First	Probability of Winning: Lost the Toss/Batted First	Difference in Probabilities
Australia	0.664	0.693	-0.029
England	0.610	0.561	0.049
India	0.594	0.316	0.278*
New Zealand	0.285	0.491	-0.205*
Pakistan	0.525	0.442	0.083
South Africa	0.539	0.733	-0.196*
West Indies	0.484	0.490	-0.006
	Probability of Winning: Won the Toss/Bowled First	Probability of Winning: Lost the Toss/Bowled First	Difference in Probabilities
Australia	0.672	0.573	0.098*
England	0.476	0.507	-0.031
India	0.310	0.478	-0.168*
New Zealand	0.552	0.265	0.287*
Pakistan	0.565	0.514	0.051
South Africa	0.725	0.400	0.325*
West Indies	0.507	0.429	0.078

[+] Only matches for which there was a win/loss result.

First match for men: Australia versus England, Melbourne, 15 March, 1877; last match for men: India versus England, Ahmedabad, March 4, 2021.

[*] Significant at 5% level.

Source: Own calculations based on data from Ric Finlay, Tastats (tastats.com.au)

Table 2.8: Win-Loss outcomes in (pre-eliminator) Men's Big Bash League 2020 Matches

	Sydney Sixers	Perth Scorchers	Sydney Thunder	Brisbane Heat	Adelaide Strikers	Hobart Hurricanes	Melbourne Stars	Melbourne Renegades
Played	14	14	14	14	14	14	14	14
Wins	9	8	8	7	7	7	5	4
Losses	5	5	6	7	7	7	8	10
No result*	0	1	0	0	0	0	1	0
Probability of observed wins under the "pure luck" hypothesis (%)	12.2	15.7	18.3	20.9	20.9	20.9	15.7	6.1
Probability of observed wins under the "ability-based luck" hypothesis (%)	21.8	22.3	21.2	20.9	20.9	20.9	22.3	23.1
θ: Proportion of the probability of observed wins due to ability/inability (%)	44.0	29.6	13.7	0	0	0	29.6	73.6
1-θ: Proportion of the probability of observed wins due to luck (%)	56.0	70.4	86.3	100	100	100	70.4	26.4

* Match abandoned

Source: Own calculations using data from www.espncricinfo.com

Table 2.9: Win-Loss outcomes in (pre-eliminator) Women's Big Bash League 2019 Matches

	Brisbane Heat	Adelaide Strikers	Perth Scorchers	Melbourne Renegades	Sydney Sixers	Sydney Thunder	Hobart Hurricanes	Melbourne Stars
Played	14	14	14	14	14	14	14	14
Wins	10	10	9	8	7	5	4	2
Losses	4	4	5	6	7	8	9	12
No result*	0	0	0	0	0	1	1	0
Probability of observed wins under the "pure luck" hypothesis (%)	6.1	6.1	12.2	18.3	20.9	15.7	8.7	0.56
Probability of observed wins under the "ability-based luck" hypothesis (%)	23.1	23.1	21.8	21.2	20.9	22.3	23.4	29.2
θ: Proportion of the probability of observed wins due to ability/inability (%)	73.6	73.6	44.0	13.7	0	29.6	62.8	98
$1-\theta$: Proportion of the probability of observed wins due to luck (%)	26.4	26.4	56	86.3	100	70.4	37.2	2

* Match abandoned

Source: Own calculations using data from www.espncricinfo.com

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