Assessing Player Performance in Cricket

Borooah, Vani

Ulster University

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Chapter 7
Assessing Player Performances

7.1 Introduction

This chapter assesses the performance of men and women cricketers in international cricket in terms of batting and bowling. Batters and bowlers in cricket are most usually ranked according to their respective batting and bowling averages. Batting averages in cricket are calculated by dividing the number of runs scored by the number of innings played, excluding not-out innings from the number. Bowling averages in cricket are calculated by dividing the number of runs conceded by the number of wickets taken.

Judged by batting averages, Donald Bradman was the greatest of all Test batsmen: he retired in 1948 with a career average of 99.94, achieved over 52 Tests and 80 innings, towering over the batsman with the next highest career average, Steve Smith's 61.8, achieved over 77 Tests and 139 innings. Women have played far fewer Test matches than men: between 1934 and 2021, there were only 141 women's Test Matches in contrast to the 2,433 men's Test Matches between 1876 and 2021. But, even in the context of the small number of Test Matches played by women, it is interesting to note that, when attention is focused on those who played at least 10 Tests, the Australian batter Joanne Broadbent had a career average of 109.25 after eight innings in 10 Tests. Just behind her, another Australian batter, Denise Annetts — 13 innings in 10 Tests — ended her career with an average of 81.9.

In terms of Test Match bowling performance, and concentrating on men who played at least 20 Test Matches, William Barnes of England bowled 2,289 balls in 21 Tests for a career average of 15.55; he is followed by Sydney Barnes (no relation), also of England, who averaged 16.43 after bowling 7,873 balls in 27 Tests. Focusing on women who played at least 10 Tests, the player with the lowest bowling average was the Australian, Elizabeth Wilson, who, after bowling 2,885 balls in 11 Tests, averaged 11.81; she is followed by Mary Duggan of England who averaged 13.49 after bowling 3,734 balls in 17 Test Matches.[1]

[1] Elizabeth (Betty) Wilson was the first cricketer to score a century and take 10 wickets in the same match https://www.theguardian.com/sport/blog/2014/jan/10/betty-wilson-womens-ashes-australia-cricket (accessed 9 September 2021).

The preceding paragraphs showed that, in terms of Test Match cricket, women have performed as well as, if not better than, men, with Donald Bradman's career batting average of 99.94 being eclipsed by Joanne Broadbent's 109.25 and Elizabeth Wilson's career bowling average of 11.81 outclassing William Barnes' 15.55. However, since there have been, to date, only 141 women's Test Matches, it would be invidious to assess women's cricketing performance based on this form of cricket. Consequently, the analysis in this chapter focuses on women's One Day Internationals (WODI), of which there have been 1,206 between the first WODI, on 23 June 1973, and (at the time of writing) the latest, on 7 September 2021; and on men's One Day Internationals (MODI), of which there have been 4,319 between the first MODI, on 5 January 1971, and the latest (again at the time of writing) on 8 September 2021.

The assessment of batting and bowling performance raises the general question of whether batting or bowling averages are the best means of judging the worth of cricketers. Ranking batters and bowlers by their averages does not consider variations in performance across matches: a batter with a high career average might intersperse high with low scores; another might have a lower average but much greater consistency in their scores. Thus it is possible to compile a high average while, at the same time, displaying considerable inconsistency in performance. In incorporating the issue of consistency into the assessment of the batter, this chapter, borrowing from the methods of inequality analysis, evaluates batters by combining two criteria: *career average* and *career consistency*. This type of problem, involving tension between an average and its distribution, is well known in welfare economics and in the analysis of inequality.

Anand and Sen (1997), in a paper prepared for the 1995 *Human Development Report*, pointed out that a country's non-economic achievements were likely to be unequally distributed between subgroups of its population: for example, in terms of gender equality, which was the focus of their concern, metrics such as the female literacy rate or female life expectancy were often lower than those for males. In the face of such inter-group inequality, they argued that a country's achievement with respect to a particular outcome should not be judged exclusively by its mean level of achievement (for example, by the average literacy rate for a country) but rather by the mean level *adjusted to take account of inter-group differences in achievements*. Anand and Sen (ibid.) proposed a method, based on Atkinson's (1970) work on the relation between social welfare and inequality, for making such adjustments and they termed the resulting indicators *equity sensitive indicators*. They further suggested that assessing country achievements based on such equity sensitive indicators rather than mean level of achievement would allow a comparison between two countries, one of which had a lower mean achievement level, but a more equitable distribution of achievement, than the other.[2] The first contribution of this chapter is to apply these ideas to evaluating batting performances in cricket.

The chapter's second contribution is to quantify the values of a bowler's economy rate and strike rate to their team. This quantification borrows from the utilitarian approach to welfare economics whereby social welfare can the represented by the sum of individual utilities. The application of this to assessing bowling performance focuses on two aspects of bowling: a bowler's economy rate (average number of runs conceded per over) and their strike rate (average number of balls bowled per wicket), the product of the two being their bowling average. An increase in the economy rate or in the strike rate increased the team's *disutility* and the sum of these two disutilities constituted the team's *ill-fare*. By considering a specific form for the disutility function, defined as the logarithms of the economy and strike rates, this chapter computes the proportionate contribution, in ODI matches, of women and men bowlers to their team's ill-fare.

7.2 Consistency in Batting Performance: Conceptual Issues

In his seminal paper on income inequality, Atkinson (1970) argued that we (society) would be prepared to accept a reduction in average income, *provided the lower income was equally distributed*, from a higher average income which was unequally distributed.[3] The size of this reduction depends upon our degree of 'inequality aversion' which Atkinson measured by the value of a (inequality aversion) parameter: the larger the parameter's value, the greater would be the degree of inequality aversion. This idea can be applied to evaluating batting performance.

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[2] Anand and Sen (1997) compared the Honduras (with an average literacy rate of 75%, distributed between men and women as 78% and 73%) with China (with an average literacy rate of 80%, distributed between men and women as 92% and 68%) and asked which country should be regarded as having the 'better' achievement regarding literacy: China with a higher overall rate or the Honduras with greater gender equality?

[3] In the language of economics, the two situations would yield the same level of social welfare, that is, be 'welfare equivalent'.

Suppose that, over their career, a batter had scores of $X_1, X_2, ...X_N$ runs in *N* innings and these scores resulted in a career average of $\bar{X}$. Suppose that team managers were averse to inconsistency in the performance of their batters where, depending upon the specific management, the degree of *inconsistency aversion* could vary from ‘no aversion’, to ‘mild aversion’, to ‘moderate aversion’, to ‘strong aversion’. If management had no aversion to inconsistency, then the only thing that would concern it would be a batter’s average and it would be indifferent to the distribution of the batter’s innings’ scores that underpinned this average. On the other hand, if management was, to some degree, ‘inconsistency averse’, then compared to the present situation, they might be equally happy with a batter having a smaller batting average provided their scores were more equitably distributed across the innings. In other words, management might be prepared to sacrifice a higher average to obtain greater consistency in scores.

This idea of a trade-off between the average and its distribution leads very naturally to the concept of ‘an equally distributed equivalent’ (EDE) score, denoted X^E. The EDE score is the number of runs which, if scored by a batter in every innings (that is, equally distributed over all their innings), would yield the *same* level of ‘utility’ to management as the batter’s actual average, unequally distributed. In management’s eyes, X^E and $\bar{X}$ are ‘equivalent’ in terms of team welfare: the former offers a lower average but a better distribution, the latter a better average but a worse distribution. It follows, therefore, that $X^E \leq \bar{X}$. The size of these reductions, as measured by $\bar{X} - X^E$, depends on management’s aversion to inconsistency: the lower the degree of inconsistency aversion, the smaller will be the difference and, in the extreme case, in which there is no aversion to inconsistency, there will be no difference between the average score, $\bar{X}$, and the EDE score, X^E.

A Diagrammatic Analysis

It may be useful to present the analysis of the preceding paragraphs in diagrammatic terms. Figure 7.1 portrays a world of two innings (*R* and *S*) that are required to ‘share’ a given average score, $\bar{X}$, in terms of their individual scores, X_R and X_S. The horizontal axis of Figure 7.1 measures X_R and the vertical axis measures X_S. The two scores are related to the aggregate score by the ‘sharing’ equation: $\bar{X} = (X_R + X_S)/2$ and this is represented in Figure 7.1 by the ‘sharing possibility line’, *MN*. The point *V*, on *MN*, lies on the 45^0-line passing through the origin and, so, *V* is the point at which $X_R = X_S$.

<Figure 7.1>

Given the mean score, $\bar{X}$, the observed distributional outcome may be viewed as a mapping of $\bar{X}$ to a point on *MN* which establishes X_R and X_S. Different outcomes will locate at different points of *MN*. Those that locate closer to the point *V* (for example, *B*) will embody greater consistency across innings than those (like *A*) which locate further away.

Suppose that the utility of a batter to management depended on the runs scored, the higher the score the larger the utility. Then management's utilities from scores of X_R and X_S can, for a utility function *U(.)*, be represented by $U(X_R)$ and $U(X_S)$ and welfare, *Q*, from a batter's overall scores can be taken as the sum of the two utilities:[4]

$$Q = U(X_R) + U(X_S) \tag{7.1}$$

Now suppose that utility $U(X_R)$ and $U(X_S)$ increased with a rise in the batter's score *but at a diminishing rate*: this is the property of diminishing marginal utility. Then welfare, *Q*, would be maximised when the batter had the same score in every one of their innings or, in other words, the batter's scores were equally distributed across their innings. To see this, suppose that the score of a 'low scoring' innings, *S*, was raised by, say, 10 runs with a corresponding decrease in the score of a 'high scoring' innings, *R*. Then management welfare would rise by dint of the former but fall because of the latter. However, by the property of diminishing marginal utility, the former rise in utility, from a 10-run increase, would exceed the fall in utility from a 10-run decrease. Consequently, welfare, *Q*, would rise. Welfare would continue to rise for 'equal run' transfers from low to high scoring innings and would be maximised when no further such transfers were possible: this would occur when the batter made the same score in both innings, *R* and *S*.

The curves QQ and Q′ Q′ in Figure 7.1 represent indifference curves associated with the welfare function of equation (7.1): holding the level of welfare constant in equation (7.1), each

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[4] In the language of welfare economics, the welfare function is *additively decomposable* in the individual utilities.

indifference curve traces the X_R, X_S combinations which yield that constant level of welfare, the higher curve (QQ) representing a greater level of welfare than the lower curve (Q′ Q′). These ‘welfare indifference curves’ are superimposed upon the sharing possibility line.[5] Since the utility functions $U(.)$ in equation (7.1) are assumed to embody the property of diminishing marginal utility, welfare is maximised when $X_R = X_S$ that is, when scores are the same in each innings. Consequently, *V*, the point at which the indifference curve, *QQ*, is tangential to the sharing possibility line, *MN*, is the point at which welfare is maximised. In practice, however, the actual outcome of the batter's scores is at the point *A* at which the score is higher in *R* (X_R=*OF*) and lower in *S* (X_S=*AF*). The outcome at point *A* is *welfare equivalent* to that at point *C*, at which the score is the same in *R* and *S* ($X_R = X_S = CD$), because both *A* and *C* are on the same indifference curve, Q′ Q′, thus yielding the same amount of welfare. *CD* is then defined as theEDE score in relation to the higher average, but unequally distributed, score at point *A*.

7.3 Empirical Results on Batting Performance in ODI Matches

Tables 7.1 and 7.2 show the batting performances of, respectively, the top 20 female and male batters in ODI cricket who have played at least 20 ODI matches and who are currently playing. Heading the list for women is Meg Lanning of Australia with an average of 53.76 from 3,925 runs in 85 matches (85 innings); next in line are Mithali Raj of India, with an average of 51.80 from 7,304 runs in 217 matches (196 innings), and Ellyse Perry of Australia with an average of 51.78 from 3,107 runs in 115 matches (92 innings). Heading the list for men is Rassie van der Dussen of South Africa, with an average of 65.56 runs from 1,049 runs in 29 matches (23 innings); he is followed by Virat Kohli of India, with an average of 59.07 runs from 12,169 runs in 254 matches (245 innings), and by Babar Azam of Pakistan with an average of 56.92 runs from 3,985 runs in 83 matches (81 innings).

<Tables 7.1 and 7.2>

[5] An indifference curve shows the different combinations of X_R, X_S which yield the same level of welfare. It is obtained by holding *Q* constant in equation (7.1) and solving for the different X_R, X_S which yield this value of *Q*.

These tables show that the batting average of men is approximately 10 runs higher than that of women: the lowest batting averages for women and men are, respectively, 31 (Sophie Devine of New Zealand) and 40.43 (Ben Stokes of England) while the highest batting averages for women and men are, respectively, 53.76 (Meg Lanning of Australia) and 65.56 (Rassie van der Dussen of South Africa). Comparing two stalwarts of ODI cricket, Mithali Raj and Virat Kohli of India, both have played a comparable number of innings — Raj's 196 to Kohli's 245 — and their averages — Raj's 51.8 to Kohli's 59.07 — are just seven runs apart. The fact that ODI batting averages for women are lower than those for men must be set alongside the fact that average team scores were considerably lower in women's (164 runs) than in men's (216 runs) ODI matches. Given this disparity in team scores, the difference in batting averages between the leading women and men batters is surprisingly small.

<Tables 7.3 and 7.4>

Tables 7.3 and 7.4 set alongside the conventional batting averages, shown above, the EDE scores for, respectively the top 20 women and men batters identified in the earlier tables. As discussed earlier, the EDE scores embody management's aversion to inconsistency and this aversion is reflected in the fact that the EDE score, X^E, is less than or equal to the batting average, $\bar{X}$. As a result of this aversion, management is prepared to trade a higher average of runs, unequally distributed across the innings, for a smaller but more equitably distributed score. The EDE score is arrived at when a smaller score, equally distributed across the innings, gives the same amount of welfare as the current average and its attendant distribution. As previously discussed, the gap between the EDE score and the average will depend upon the degree of inequality aversion: an absence of any aversion will mean that there is no gap ($X^E = \bar{X}$) and the gap will increase as the degree of aversion increases from say, 'mild', to 'medium', to 'high'.

The EDE scores reported in Tables 7.3 and 7.4 assume that management has a *mild* aversion to inequality. This is made more precise in the box, below. These tables show that when inconsistency in batting performance is taken into consideration, the original ranking of batters, based on batting averages, changes considerably. For example, Table 7.3 shows that Ellyse Perry of Australia dropped from number 3 in the rankings to number 8 (a fall of five places) while the South African Laura Wolvaardt rose from number 6 to number 2 (a rise of four places).

Similarly, Table 7.4 shows that Babar Azam of Pakistan, who was number 3 in an average-based ranking rose to number 1 when inconsistency in batting performance was accounted for, while Quinton de Kock of South Africa rose from number 14 in the original ranking to number 8 in the new ranking (a rise of six places) and Shreyas Iyer of India rose from number 15 in the original ranking to number 6 in the new ranking (a rise of nine places). At the other end of the spectrum, Rohit Sharma of India fell from 7 in the original ranking to number 16 in the revised ranking (a fall of nine places) while Imam-ul-Haq of Pakistan fell from 6 in the original ranking to number 10 in the revised ranking (a fall of four places).

Box 7.1: A Welfare-based Measure of Batting Inconsistency

Let $\overline{X}$ and X^E represent, respectively a player's batting average and their equally distributed equivalent (EDE) score. The EDE score is that score which, if scored in every innings, yields the same level of welfare as the existing distribution of scores. Consequently, $X^E \leq \overline{X}$. If $\varepsilon \geq 0$ represents an inequality parameter then Atkinson's (1970) inequality index applied to the distribution of the batter's scores in *N* innings, $X_1, X_2, \ldots X_N$ yields:

$$ATK(\varepsilon) = 1 - \left(X^E - \overline{X}\right) = 1 - \left[\sum_{k=1}^{N}\left(\frac{X_i}{\overline{X}}\right)^{1-\varepsilon}\right]^{1/(1-\varepsilon)} \qquad (7.3)$$

When $\varepsilon=0$, $X^E = \overline{X}$ and $ATK(\varepsilon) = 0$: management is indifferent as to how a given average score is distributed across a batter's innings. For $\varepsilon>0$, however, $X^E < \overline{X}$ and $ATK(\varepsilon)>0$. The higher the value of the inequality aversion parameter, ε, the smaller will be the value of X^E and greater will be the value of the inequality index, $ATK(\varepsilon)$.

Three special cases, contingent upon the value assumed by ε, may be distinguished:

1. *Medium inconsistency aversion*. When $\varepsilon = 1$, X^E is the *geometric mean* of the batter's scores: $X^E = \left[\prod_{i=1}^{N}\left(X_i\right)^N\right]^{1/N} < \overline{X}$.
2. *High inconsistency aversion*. When $\varepsilon = 2$, X^E is the *harmonic mean* of the batter's scores: $X^E = \left[\sum_{i=1}^{N}\frac{N}{X_i}\right]^{-1} < \overline{X}$.
3. *Mild inconsistency aversion*. When $\varepsilon=0.5$, X^E lies between the arithmetic mean *($\varepsilon=0$)* and the geometric mean *($\varepsilon=1$)*. This is the definition of inconsistency aversion that is used in deriving the results shown in Tables 7.3 and 7.4.

7.4 Empirical Results on Bowling Performance in ODI Matches

In analysing bowling performances in ODI cricket this chapter takes a different approach to the EDE score calculations used to analyse batting performance. This is the method of *additive logarithmic decomposition*. This is because in limited overs cricket there are several ways of assessing bowling performance. The first is through traditional *bowling averages* defined as runs conceded per wicket taken or algebraically as: $AVG = R/W$. Since, in limited overs cricket, not conceding runs is, arguably, as important as taking wickets, the second way of assessing bowling performance is through the *economy rate* defined as runs conceded per over or, algebraically as: $ECO = R/O$. The third way of assessing bowling performance is through the strike rate defined as overs bowled per wicket or algebraically as: $SR = O/W$.

From these definitions it follows that:

$$\begin{aligned} &AVG = R/W = (R/O)\times(O/W) = ECO \times SR \\ &\Rightarrow \log(AVG) = \log(ECO) + \log(SR) \end{aligned} \qquad (7.2)$$

The latter part of equation (7.2) shows that the logarithm of a bowler's average can be expressed as the sum (of the logarithms) of their economy and strike rates or, in other words, the bowling average is additively decomposable in logarithms.

In the utilitarian framework of equation (7.1), welfare is the sum of identical utility functions which embodied the property of diminishing marginal utility. Suppose that, in the context of bowling, management derived *disutility* from an economy rate and a strike rate such that the *higher* the economy and strike rates, the *greater* the level of disutility. These *disutility functions* can be represented by $V(ECO)$ and $V(SR)$. Then *ill-fare* (which is the obverse of *welfare*) may be represented as $P = U(ECO) + U(SR)$ such that the level of ill-fare, P, increases with a rise in either ECO or SR.[6] Following Bourguignon (1979), one can take $\log(ECO)$ and $\log(SR)$ as a particular representation of the disutility function $V(.)$. Then ill-fare $P = \log(ECO) + \log(SR) = \log(AVG)$ so that

[6] For example, a rise in unemployment reduces welfare and, as a corollary, raises ill-fare. See Borooah (2002) for an application of ill-fare to unemployment.

$\alpha = \left[\log(ECO)/\log(AVG)\right] \times 100$ and $\beta = \left[\log(SR)/\log(AVG)\right] \times 100$ indicate the percentage contributions that a bowler's economy and strike rates make to their team's ill-fare.

Tables 7.5 and 7.6 show the bowling performances of, respectively, the top 20 female and male bowlers in ODI cricket who have bowled at least 1,000 balls and who are either currently playing or have only recently retired. These tables show that the leading woman bowler in ODI cricket, Rajeshwari Gayakwad of India, had a lower average and a lower economy rate than her male counterpart, Rashid Khan of Afghanistan: 17.7 versus 18.57 for average and 3.38 versus 4.18 for economy. Not only that, but every female bowler shown in Table 7.5 had a lower average than her corresponding male counterpart in Table 7.6. For example, Jhulan Goswami of India, 10th on the list in Table 7.5, had an average of 21.47 and an economy rate of 3.39, compared to Shaheen Afridi's (10th on the list in Table 7.6) average of 24.62 and economy rate of 5.51.

The workload of female bowlers was also higher than that of men. Jhulan Goswami, during her (still ongoing) career, has bowled 9,219 balls — the highest number among women — while the highest number of balls bowled by a man was 8,557 by Ravindra Jadeja of India. What makes this difference in workload even more impressive is that firstly, Goswami is a fast bowler while Jadeja is a spinner and secondly, despite bowling more balls, Goswami had a lower average and a lower economy rate than Jadeja: 21.47 versus 25.32 for average and 3.29 versus 4.95 for economy.

A more general way of viewing gender disparities in workloads is to note that the two bowlers with the highest workloads were both women fast bowlers: Jhulan Goswami bowled 9,219, and Katherine Blunt bowled 6,290 balls. In contrast, the leading male fast bowlers who are currently playing and who have bowled more than 5,000 balls, sent down far fewer balls than their female counterparts: Mitchell Starc (Australia), Trent Boult (New Zealand), and Thisara Perera (Sri Lanka) bowled, respectively, 5,099, 5,117, and 5,900 balls.

<Table 7.7>

Table 7.7 shows the contribution that economy and strike rates made to team ill-fare using the methodology developed earlier. Among women, the contributions of the strike rate to ill-fare were highest for Katherine Blunt (England), Jhulan Goswami (India) and Stafanie Taylor (West Indies).

The strike rates of the first two bowlers contributed over 60% to their respective teams' ill-fare while, for Taylor, this contribution was nearly 60%. It is no coincidence that these three bowlers had some of the highest (that is, worst) strike rates relative to their economy rates: Brunt took a wicket every 40 balls but conceded only 3.5 runs per over; Goswami took a wicket every 39 balls and conceded only 3.3 runs per over; while Taylor took a wicket every 38 balls in conceding 3.4 runs per over. By contrast, the strike rate for Leigh Kasperek (New Zealand), which was 29, contributed only 48% to her team's ill-fare.

Bowlers who had both a high economy rate (going at over 4 runs per over) and a high strike rate (needing at least 5 overs before taking a wicket) present an interesting case. Ayabonga Khaka (South Africa) had an economy rate of more than 4 runs per over and a strike rate which had her taking a wicket after nearly 38 balls. In her case, her poor strike rate contributed 57% to her team's ill-fare with her poor economy rate contributing the remaining 43%.

The fact that the average scores in men's ODI matches were higher than in women's matches (216 versus 164 runs) meant that men had a higher economy rate than women. For example, Umesh Yadav (India), who is 20th on the list of bowlers in Table 7.6, had an economy rate of 6 runs per over compared to the 4.4 runs per over of Heather Knight (England), who is 20th on the list of bowlers in Table 7.5. At the same time, the strike rate of men was not dissimilar to that of women: Umesh Yadav and Heather Knight had strike rates of, respectively, 33.5 and 34.3 balls per wicket. The dissimilarity between women and men in the relative difference of their economy and strike rates meant that economy rates made a larger contribution to the ill-fare of men's teams than it did to women's teams and *ipso facto* strike rates made a larger contribution to the ill-fare of women's teams than it did to men's teams.

7.5 Conclusions

This chapter suggested a way by which the use of the 'batting average' to assess batting performance could be extended to encompass consistency and another way by which the contribution of bowlers to their teams' ill-fare, in terms of their economy and strike rates, might be evaluated. The suggested extension in terms of batters was to compute their equally distributed equivalent (EDE) score and to compare this to their batting average. In essence this meant that batting performance was assessed not just in terms of the average score but also in terms of the consistency of scores across a batter's innings. The weights given to these two components — average and consistency — depended on how averse team management was to inconsistency: the EDE score would depend upon whether they were not at all averse, mildly averse, medium averse, or strongly averse. In addition, for two batters with the same average, the more consistent batter would have a higher EDE score than the other. The results reported in this chapter show that the ranking of batters was sensitive to their degree of consistency across innings. For example, Ellyse Perry, who ranked third among the top 20 women cricketers currently playing ODI cricket, fell to eighth place when consistency was considered while Laura Wolvaardt, who was sixth in the ranking based on her average, rose to second place when the consistency of her scores was taken into account.

In evaluating bowling, the analysis focused on two aspects of bowling, the bowler's economy rate and strike rate, the product of the two being the bowler's average. An increase in the economy rate or in the strike rate increased the team's disutility. The interpretation offered in this chapter was in terms of a team's 'ill-fare' function which was the sum of the disutility from the economy and the strike rates. If one took the logarithm of the economy and the strike rates as a practical representation of the disutility functions, then the sum of the two disutilities was the log of the bowling average and represented team ill-fare. The proportionate contribution of a bowler's economy and strike rates to team ill-fare would depend upon the relative sizes of the two rates for the bowler.

It was shown that in women's ODI matches, the economy rate was small relative to the strike rate so that the latter made a greater contribution to team ill-fare than the former. For two bowlers — Jhulan Goswami and Katherine Brunt — this contribution exceeded 60%. In men's ODI matches, however, the economy rate was larger relative to the strike rate than in women's matches and, hence, the contribution of the strike rate to team ill-fare was dampened and that of the economy rate was elevated.

In proposing these extensions, one of the aims was to eliminate any element of subjectivity from the new measures. For example, a particular performance by a batter or a bowler may have had special value to their team because it was achieved in difficult circumstances. No attempt was made to adjust for such special circumstances, as that would have meant injecting an element of subjectivity into the assessment. Nor was any attempt made to adjust for the quality of the opposition which the top 20 ODI women and men players — batters and bowlers — faced. For example, runs scored or wickets taken against ‘strong’ sides must, surely, count for more than equivalent performances against weaker opposition. As Borooah and Mangan (2010) have written, ‘in any celestial judgement of batsmen these, and many more criteria, will all be used to arrive at St. Peter’s ranking of cricketers’. Until that day arrives, this chapter offers a modest proposal for redefining cricketing performance.

Table 7.1: Top 20 Batting Averages in Women's One-Day Internationals+

Player	Span	Matches	Innings	Not out	Runs	Highest Score	100s	50s	0s	Average
MM Lanning (AUS)	2011-2021	85	85	12	3925	152*	14	15	5	53.76
M Raj (IND)	1999-2021	217	196	55	7304	125*	7	58	6	51.8
EA Perry (AUS)	2007-2021	115	92	32	3107	112*	2	28	4	51.78
TT Beaumont (ENG)	2009-2021	77	69	9	2715	168*	7	13	4	45.25
SR Taylor (WI)	2008-2021	130	126	16	4929	171	6	36	5	44.8
L Wolvaardt (SA)	2016-2021	60	58	8	2186	149	2	19	5	43.72
S Mandhana (IND)	2013-2021	59	59	5	2253	135	4	18	2	41.72
NR Sciver (ENG)	2013-2021	73	64	12	2123	137	3	15	3	40.82
BL Mooney (AUS)	2016-2021	41	37	7	1170	100	1	8	2	39
AE Satterthwaite (NZ)	2007-2021	128	122	16	4125	137*	7	22	7	38.91
HC Knight (ENG)	2010-2021	107	102	23	3009	106	1	21	8	38.08
DB Sharma (IND)	2014-2021	61	54	13	1541	188	1	10	2	37.58
L Lee (SA)	2013-2021	91	89	7	3077	132*	3	21	12	37.52
D van Niekerk (SA)	2009-2021	104	81	23	2132	102	1	9	2	36.75
RL Haynes (AUS)	2009-2021	63	57	4	1937	118	1	15	6	36.54
PG Raut (IND)	2009-2021	73	73	7	2299	109*	3	15	6	34.83
H Kaur (IND)	2009-2021	107	89	15	2568	171*	3	12	4	34.7
AJ Healy (AUS)	2010-2021	79	68	11	1927	133	3	12	4	33.8
M du Preez (SA)	2007-2021	139	127	22	3443	116*	2	16	7	32.79
SFM Devine (NZ)	2006-2021	111	98	11	2697	145	5	13	4	31

+Only players who played at least 20 matches and who were still playing in 2021.
Last Match: West Indies versus South Africa at Coolidge, Antigua and Barbuda on 7 September 2021.
*Denotes not out
Source: ESPN Cricinfo. (www.espncricinfo.com)

Table 7.2: Top 20 Batting Averages in Men's One-Day Internationals[+]

Player	Span	Matches	Innings	Not Out	Runs	Highest Score	100s	50s	0s	Average
HE van der Dussen (SA)	2019-2021	29	23	7	1049	123*	1	9	0	65.56
V Kohli (INDIA)	2008-2021	254	245	39	12169	183	43	62	13	59.07
Babar Azam (PAK)	2015-2021	83	81	11	3985	158	14	17	3	56.92
SD Hope (WI)	2016-2021	83	78	10	3599	170	10	19	4	52.92
JE Root (ENG)	2013-2021	152	142	23	6109	133*	16	35	5	51.33
Imam-ul-Haq (PAK)	2017-2021	46	46	5	2023	151	7	10	3	49.34
RG Sharma (INDIA)	2007-2021	227	220	32	9205	264	29	43	13	48.96
KL Rahul (INDIA)	2016-2021	38	37	6	1509	112	5	9	2	48.67
LRPL Taylor (NZ)	2006-2021	233	217	39	8581	181*	21	51	9	48.2
JM Bairstow (ENG)	2011-2021	89	81	8	3498	141*	11	14	6	47.91
N Pooran (WI)	2019-2021	31	28	6	1044	118	1	8	2	47.45
Fakhar Zaman (PAK)	2017-2021	53	53	4	2325	210*	6	13	5	47.44
S Dhawan (INDIA)	2010-2021	145	142	8	6105	143	17	33	5	45.55
Q de Kock (SA)	2013-2021	124	124	6	5355	178	16	26	4	45.38
SS Iyer (INDIA)	2017-2021	22	20	1	813	103	1	8	0	42.78
KJ Coetzer (SCOT)	2008-2021	61	59	2	2435	156	4	17	5	42.71
MJ Guptill (NZ)	2009-2021	186	183	19	6927	237*	16	37	15	42.23
AD Mathews (SL)	2008-2021	218	188	48	5835	139*	3	40	15	41.67
DA Miller (SA)	2010-2021	136	117	35	3355	139	5	16	8	40.91
BA Stokes (ENG)	2011-2021	101	86	15	2871	102*	3	21	5	40.43

[+]Only players who played at least 20 matches and who were still playing in 2021.
Last Match: Sri Lanka versus South Africa at Colombo on 7 September 2021.
[*]Denotes not out
Source: ESPN Cricinfo.

Table 7.3: Top 20 Batting Averages in Women's One-Day Internationals Adjusted for Consistency+

Player	Span	Average	Equally Distributed Equivalent (EDE) score	Ranking Based on Average Score	Revised Ranking based on EDE Score	Change in Ranking
MM Lanning (AUS-W)	2011-2021	53.76	36.00	1	1	0
M Raj (IND)	1999-2021	51.8	30.44	2	3	-1
EA Perry (AUS)	2007-2021	51.78	25.62	3	8	-5
TT Beaumont (ENG)	2009-2021	45.25	29.89	4	4	0
SR Taylor (WI)	2008-2021	44.8	30.16	5	5	0
L Wolvaardt (SA)	2016-2021	43.72	30.46	6	2	+4
S Mandhana (IND)	2013-2021	41.72	29.87	7	6	+1
NR Sciver (ENG)	2013-2021	40.82	24.63	8	11	-3
BL Mooney (AUS)	2016-2021	39	26.47	9	7	+2
AE Satterthwaite (NZ)	2007-2021	38.91	25.04	10	9	+1
HC Knight (ENG)	2010-2021	38.08	22.82	11	15	-4
DB Sharma (IND)	2014-2021	37.58	21.37	12	17	-5
L Lee (SA)	2013-2021	37.52	24.67	13	10	+3
D van Niekerk (SA)	2009-2021	36.75	20.93	14	18	-4
RL Haynes (AUS)	2009-2021	36.54	24.30	15	12	+3
PG Raut (IND)	2009-2021	34.83	23.98	16	13	+3
H Kaur (IND)	2009-2021	34.7	22.97	17	14	+3
AJ Healy (AUS)	2010-2021	33.8	19.53	18	20	-2
M du Preez (SA)	2007-2021	32.79	21.58	19	16	+3
SFM Devine (NZ)	2006-2021	31	20.21	20	19	+1

+Only players who played at least 20 matches and who were still playing in 2021.
Source: ESPN Cricinfo (www.crickinfo.com)

Table 7.4: Top 20 Batting Averages in Men's One-Day Internationals Adjusted for Consistency[+]

Player	Span	Average	Equally Distributed Equivalent (EDE) score	Ranking Based on Average Score	Revised Ranking based on EDE Score	Change in Ranking
HE van der Dussen (SA)	2019-2021	65.56	39.78	1	2	-1
V Kohli (INDIA)	2008-2021	59.07	38.08	2	3	-1
Babar Azam (PAK)	2015-2021	56.92	40.48	3	1	+2
SD Hope (WI)	2016-2021	52.92	36.56	4	4	0
JE Root (ENG)	2013-2021	51.33	34.19	5	5	0
Imam-ul-Haq (PAK)	2017-2021	49.34	32.66	6	10	-4
RG Sharma (INDIA)	2007-2021	48.96	29.38	7	16	-9
KL Rahul (INDIA)	2016-2021	48.67	30.46	8	12	-4
LRPL Taylor (NZ)	2006-2021	48.2	30.33	9	14	-5
JM Bairstow (ENG)	2011-2021	47.91	33.39	10	7	+3
N Pooran (WI)	2019-2021	47.45	30.25	11	15	-4
Fakhar Zaman (PAK)	2017-2021	47.44	30.95	12	13	-1
S Dhawan (INDIA)	2010-2021	45.55	33.24	13	9	+4
Q de Kock (SA)	2013-2021	45.38	33.28	14	8	+6
SS Iyer (INDIA)	2017-2021	42.78	33.55	15	6	+9
KJ Coetzer (SCOT)	2008-2021	42.71	31.37	16	11	+5
MJ Guptill (NZ)	2009-2021	42.23	27.91	17	17	0
AD Mathews (SL)	2008-2021	41.67	23.92	18	19	-1
DA Miller (SA)	2010-2021	40.91	21.33	19	20	-1
BA Stokes (ENG)	2011-2021	40.43	25.59	20	18	+2

[+]Only players who played at least 20 matches and who were still playing in 2021.
Source: ESPN Cricinfo.

Table 7.5: Top 20 Bowling Averages in Women's One-Day Internationals[+]

Player	Span	Matches	Balls	Runs	Wickets	Best Figures	Average	Economy Rate	Strike Rate
RS Gayakwad (IND)	2014-2021	45	2354	1328	75	5/15	17.7	3.38	31.3
D van Niekerk (SA)	2009-2021	106	4548	2627	137	5/17	19.17	3.46	33.1
LM Kasperek (NZ)	2015-2021	36	1778	1174	61	6/46	19.24	3.96	29.1
JL Jonassen (AUS)	2012-2021	74	3420	2257	113	5/27	19.97	3.95	30.2
S Luus (SA)	2012-2021	88	2841	2133	106	6/36	20.12	4.5	26.8
A Mohammed (WI)	2003-2021	131	5810	3349	166	7/14	20.17	3.45	35
S Ismail (SA)	2007-2021	110	5348	3261	154	6/10	21.17	3.65	34.7
E Bisht (IND)	2011-2021	62	3339	2078	97	5/8	21.42	3.73	34.4
SR Taylor (WI)	2008-2021	130	5441	3114	145	4/17	21.47	3.43	37.5
J Goswami (IND)	2002-2021	189	9219	5067	236	6/31	21.47	3.29	39
S Ecclestone (ENG)	2016-2021	31	1669	1054	49	4/14	21.51	3.78	34
M Schutt (AUS)	2012-2021	65	3071	2163	99	4/18	21.84	4.22	31
S Pandey (IND)	2014-2021	55	2472	1644	75	4/18	21.92	3.99	32.9
KL Cross (ENG)	2013-2021	32	1413	993	44	5/24	22.56	4.21	32.1
Poonam Yadav (IND)	2013-2021	52	2724	1758	75	4/13	23.44	3.87	36.3
KH Brunt (ENG)	2005-2021	129	6290	3697	156	5/18	23.69	3.52	40.3
M Kapp (SA)	2009-2021	118	5229	3200	134	4/14	23.88	3.67	39
EA Perry (AUS)	2007-2021	115	5146	3724	152	6/22	24.5	4.34	33.8
A Khaka (SA)	2012-2021	69	3237	2170	86	4/40	25.23	4.02	37.6
HC Knight (ENG)	2010-2021	108	1719	1262	50	5/26	25.24	4.4	34.3

[+]Only players who bowled at least 1,000 balls and who were still playing in 2021.
Average = Runs/Wickets; Economy = Runs/Overs; Strike Rate = (Overs ×6)/Wickets
Source: ESPN Cricinfo.

Table 7.6: Top 20 Bowling Averages in Men's One-Day Internationals[+]

Player	Span	Matches	Balls	Runs	Wickets	Best Figures	Average	Economy	Strike Rate
Rashid Khan (AFG)	2015-2021	74	3732	2601	140	7/18	18.57	4.18	26.6
Mujeeb Ur Rahman (AFG)	2017-2021	43	2333	1543	70	5/50	22.04	3.96	33.3
JH Davey (SCO)	2010-2019	31	1301	1082	49	6/28	22.08	4.99	26.5
MA Starc (AUS)	2010-2021	99	5099	4379	195	6/28	22.45	5.15	26.1
Hamid Hassan (AFG)	2009-2019	38	1734	1330	59	5/45	22.54	4.6	29.3
Mustafizur Rahman (BNG)	2015-2021	68	3347	2900	127	6/43	22.83	5.19	26.3
L Ngidi (SA)	2018-2021	29	1392	1304	54	6/58	24.14	5.62	25.7
Nadeem Ahmed (HKG)	2004-2018	25	1327	932	38	4/26	24.52	4.21	34.9
Simi Singh (IRL)	2017-2021	33	1410	908	37	5/10	24.54	3.86	38.1
Shaheen Shah Afridi (PAK)	2018-2021	28	1419	1305	53	6/35	24.62	5.51	26.7
Imran Tahir (SA)	2011-2019	107	5541	4297	173	7/45	24.83	4.65	32
TA Boult (NZ)	2012-2021	93	5117	4261	169	7/34	25.21	4.99	30.2
M Morkel (SA)	2007-2018	117	5760	4761	188	5/21	25.32	4.95	30.6
RD Jadeja (IND)	2009-2021	168	8557	7024	188	5/36	25.32	4.95	45.5
JJ Bumrah (IND)	2018-2021	67	3523	2736	108	5/27	25.33	4.65	32.6
DW Steyn (SA)	2005-2019	125	6256	5087	196	6/39	25.95	4.87	31.9
CR Woakes (ENG)	2011-2021	106	5016	4567	155	6/45	29.46	5.46	32.3
NLTC Perera (SL)	2009-2021	166	5900	5740	175	6/44	32.8	5.83	33.7
AU Rashid (ENG)	2009-2021	112	5573	5251	159	5/27	33.02	5.65	35
U Yadav (IND)	2010-2021	75	3558	3565	106	4/31	33.63	6.01	33.5

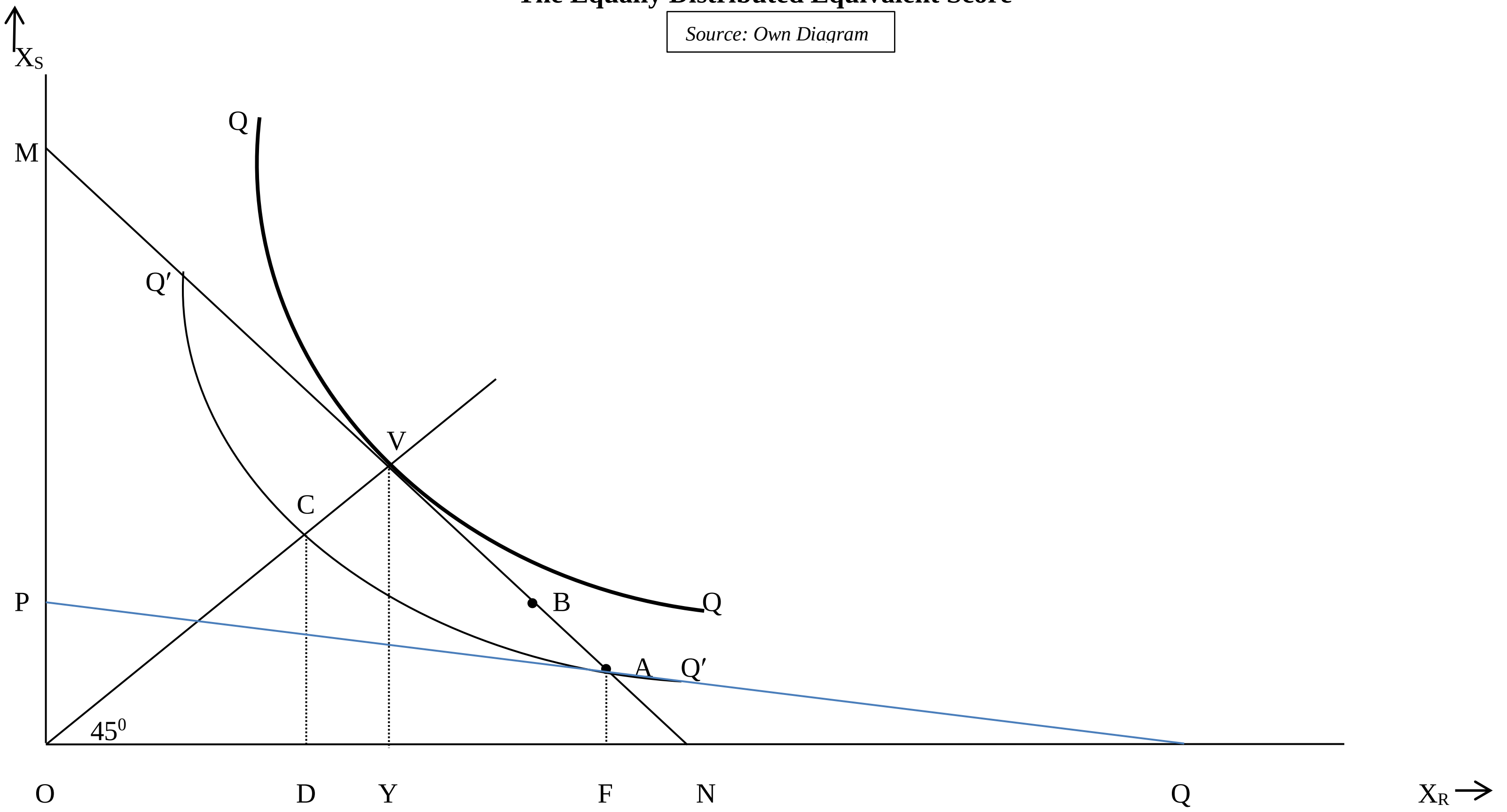
[+]Only players who bowled at least 1,000 balls and who were still playing in 2021 or were recently retired.
Average = Runs/Wickets; Economy = Runs/Overs; Strike Rate = (Overs ×6)/Wickets
Source: ESPN Cricinfo.

Table 7.7: Contributions of the Economy and Strike Rates to Overall Team Ill-lfare in ODI Matches

Player (Women)	Contribution of the Bowler's Economy Rate to Ill-fare (%)	Contribution of the Bowler's Strike Rate to Ill-fare (%)	Player (Men)	Contribution of the Bowler's Economy Rate to Ill-fare (%)	Contribution of the Bowler's Strike Rate to Ill-fare (%)
RS Gayakwad (IND)	42.44	57.56	Rashid Khan (AFG)	48.99	51.01
D van Niekerk (SA)	42.09	57.91	Mujeeb Ur Rahman (AFG)	44.54	55.46
LM Kasperek (NZ)	46.57	53.43	JH Davey (SCO)	51.97	48.03
JL Jonassen (AUS)	45.95	54.05	MA Starc (AUS)	52.71	47.29
S Luus (SA)	50.12	49.88	Hamid Hassan (AFG)	49.04	50.96
A Mohammed (WI)	41.25	58.75	Mustafizur Rahman (BNG)	52.70	47.30
S Ismail (SA)	42.45	57.55	L Ngidi (SA)	54.27	45.73
E Bisht (IND)	42.98	57.02	Nadeem Ahmed (HKG)	44.95	55.05
SR Taylor (WI)	40.21	59.79	Simi Singh (IRL)	42.22	57.78
J Goswami (IND)	38.88	61.12	Shaheen Shah Afridi (PAK)	53.34	46.66
S Ecclestone (ENG)	43.39	56.61	Imran Tahir (SA)	47.86	52.14
M Schutt (AUS)	46.72	53.28	TA Boult (NZ)	49.87	50.13
S Pandey (IND)	44.85	55.15	M Morkel (SA)	49.54	50.46
KL Cross (ENG)	46.15	53.85	RD Jadeja (IND)	44.12	55.88
P Yadav (IND)	42.92	57.08	JJ Bumrah (IND)	47.59	52.41
KH Brunt (ENG)	39.79	60.21	DW Steyn (SA)	48.65	51.35
M Kapp (SA)	40.99	59.01	CR Woakes (ENG)	50.21	49.79
EA Perry (AUS)	45.92	54.08	NLTC Perera (SL)	50.53	49.47
A Khaka (SA)	43.12	56.88	AU Rashid (ENG)	49.54	50.46
HC Knight (ENG)	45.94	54.06	U Yadav (IND)	51.05	48.95

Figure 7.1
The Equally Distributed Equivalent Score

Source: Own Diagram



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