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CONTEXTUAL BATTING AND BOWLING IN LIMITED OVERS CRICKET

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Cricket is a sport for which many batting and bowling statistics have been proposed. However, a feature of cricket is that the level of aggressiveness adopted by batsmen is dependent on match circumstances. It is therefore relevant to consider these circumstances when evaluating batting and bowling performances. This paper considers batting performance in the second innings of limited overs cricket when a target has been set. The runs required, the number of overs completed and the wickets taken are relevant in assessing the batting performance. We produce a visualization for second innings batting which describes how a batsman performs under different circumstances. The visualization is then reduced to a single statistic "clutch batting" which can be used to compare batsmen. An analogous approach is then provided for bowlers based on the symmetry between batting and bowling, and we define the statistic "clutch bowling".

Key words: Ball-by-ball data, Duckworth-Lewis-Stern resource table, One-day cricket, Twenty20 cricket.

1. Introduction

Imagine the following scenario: It is the second innings of a limited overs cricket match (either one-day or Twenty20). There are 3 overs remaining, 7 wickets have been taken and the batting team requires R additional runs to win the match. During the next over, the batsman of interest scores 5 runs. How has the batsman performed?

Clearly, the answer to the question is that it depends on the number of runs R required to win the match. If $R = 10$, the batsman has done his job, and his team is in a good position to win the match. However, if $R = 40$, the batsman has underperformed, and the chance that his team will win has diminished considerably.

The evaluation of batting performance is therefore contextual. Yet, context is not considered when using traditional batting statistics. This paper attempts to incorporate context in the evaluation of batting and bowling. The basic idea is that prior to every ball bowled, there is a ratio of runs required

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to resources available that describes the contextual urgency of the second innings chase. After the ball is bowled, the ratio changes. Therefore, performance is measured according to the change in the ratio. A batsman has performed well if there is a decrease in the ratio.

Swartz (2017) provides a review of the various measures that have been proposed to assess batting and bowling performance in cricket. These measures range from simple statistics such as batting and bowling averages and strike and economy rates to WAR (wins above replacement) type measures that are based on match simulation. Player evaluation metrics also differ in their intent, varying from an economic focus (Karnik 2010) to graphical visualizations (van Staden 2009). However, a commonality of all of the proposed measures is that they do not incorporate context in terms of the runs required, the over and the wickets taken. For example, a player's batting average is obtained by dividing his total runs scored over all matches by his total number of dismissals. Therefore, batting average fails to account for any of the three contextual features.

The *pressure index* (PI) defined by Shah and Shah (2014) and later modified by Bhattacharjee and Lemmer (2016) captures aspects of context. The pressure indices are calculated during the second innings and they attempt to describe the changing circumstances of matches. A dificulty with both measures is that the second innings always commence with PI = 100.0 (or unity), and therefore the indices do not distinguish between the difficulty of attaining large targets versus the difficulty of attaining small targets at the beginning of the second innings. Both papers mention that the pressure index may be used to evaluate batting performance.

In Section 2, we introduce our approach for the assessment of contextual batting and contextual bowling. We produce a visualization that describes performance against a range of contexts. In the case of batting, the graphical display is then reduced to a single statistic "clutch batting" that can be used to compare batsmen in challenging situations. An analogous approach is then provided for bowlers based on the symmetry between batting and bowling. In Section 3, clutch batting and clutch bowling are investigated for prominent cricketers based on data from one-day international (ODI) cricket and Twenty20 (T20) cricket. The results provide insight into aspects of batting and bowling that are not captured by traditional statistics. We also provide some insights on the differences between domestic and international play, and T20 versus one-day cricket. In Section 4, we provide some concluding remarks.

2. Contextual performances

2.1 Data

A key element of our approach is that it requires ball-by-ball data. Ball-by-ball data is not common in cricket as most analyses are based on summary statistics as presented in match scorecards. We have developed a parser of match commentary logs that provides detailed ball-by-ball data including the batsman, the bowler, the over, the number of wickets taken and the outcome of the ball. Commentary logs for high level domestic matches and international matches for teams belonging to the International Cricket Council (ICC) are available from the website www.cricinfo.com. The parser has been carefully verified and we believe that it has close to 100% accuracy. The parser was first used in an application to determine optimal batting orders in ODI cricket (Swartz et al. 2006).

Second innings data were collected for 395 ODI matches and 625 domestic Twenty20 and Twenty20 International matches. The domestic matches consisted of those from the Indian Premier League

(IPL) and the Big Bash League (BBL) that took place between April 2015 to October 2019. We excluded all matches that were reduced in length due to delays; this resulted in a loss of 10.8% of the ODI matches and 4.5% of the Twenty20 matches. In this dataset, 169,251 balls were bowled.

2.2 Contextual batting

A batsman's approach in the second innings (his degree of aggressiveness versus cautiousness) is dependent on context. As noted earlier, context is a function of (1) the runs required, (2) the overs remaining and (3) the wickets taken. How then should we quantify context in terms of these three elements in the second innings of a limited overs cricket match?

We begin with the interplay between overs and wickets. A batsman can be more aggressive when there are fewer overs remaining and can be more aggressive when fewer wickets have been taken. Fortunately, the interplay between overs and wickets is described via the Duckworth-Lewis-Stern (DLS) resource table. Although some details of the construction of the DLS table are propriety, the estimation of resources is based on run scoring from historical matches. In one-day cricket, a batting team begins their innings with 100% of their resources available (i.e. 50 overs and 10 wickets at their disposal). When the team has used up all of their overs or 10 wickets have been taken, the innings are complete and they have 0% of their resources remaining. For intermediate values of overs and wickets, the DLS table gives the appropriate resource percentage. In the case of T20 cricket, a simple transformation of the resources from the one-day table gives the T20 resource percentage. The Duckworth-Lewis method (Duckworth and Lewis 1998, 2004) was introduced in the context of resetting targets in interrupted one-day cricket matches. Frank Duckworth and Tony Lewis have since ceded the management of the system to Steven Stern where the resource table has been updated to account for recent changes in scoring (Stern 2016). In the Appendix, we provide additional information on the DLS system and an abbreviated Duckworth-Lewis table based on the Standard Edition found at www.icc-cricket.com.

For the purposes of our investigation, what is important to note is that DLS resources provide a measure that is proportional to run scoring capability. It therefore follows that at any particular juncture of the second innings, the ratio r of runs required (for victory) to the resources available describes the contextual urgency of the second innings chase.

The ratio of runs required to resources available r is a key statistic in our work. Using the combined ODI/Twenty20 dataset, Figure 1 provides a histogram of r based on all of the balls bowled in the second innings. It is instructive to be able to calibrate r. In the ODI matches in our dataset, the average number of runs scored in the first innings is 263. Therefore, at the beginning of the second innings of ODI matches, the average value of the ratio is $r = 263/100 = 2.63$. For reference, there is an average of 157.0 runs scored in the first innings of the T20 matches, and we note that $157.0/56.6 = 2.78$ (see the T20 standardization in the Appendix). In the combined ODI/Twenty20 dataset, it is also interesting to note that the batting side was never able to win if $r > 9.17$ at any point in the second innings. Further, when $r > 3.33$, the batting side won only 25% of the time, and when $r > 2.80$, the batting side won only 50% of the time. Therefore, we will define highly challenging batting contexts as those for which $r \in (2.80, 3.33)$. Only 33,282 second innings balls were bowled in this challenging scenario.

The motivation for our approach is based on well-established concepts in limited overs cricket; the runs required in the chase and the resources available. For every ball that a batsman faces,

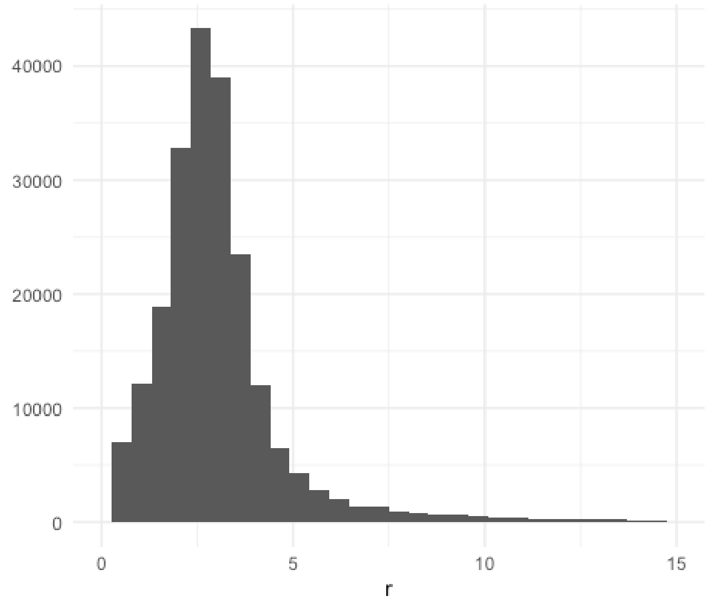

Figure 1. Histogram of r based on all second innings balls in the combined ODI/Twenty20 dataset.

we therefore have his ratio r_0 before the ball is bowled and his ratio r_1 after the ball is bowled. For example, if there is a target of 250 runs at the beginning of the second innings in an ODI match, then we have a starting ratio $r_0 = 250/100 = 2.5$. If the batsman scores a run on the first ball, then referring to the DLS table, $r_1 = 249/99.8 = 2.495$. If instead, no runs were scored on the first ball, $r_1 = 250/99.8 = 2.505$. In the case where a wicket was obtained on the first ball, $r_1 = 250/93.4 = 2.677$.

Therefore, the ordered pairs $(r_0, r_0 - r_1)$ over all balls that a batsman has faced describes the batsman's performance with respect to the contextual difficulty of the chase. On a particular ball, the quantity r_0 describes the difficulty of the chase with larger values of r_0 corresponding to more challenging chases. The quantity $r_0 - r_1$ describes the contribution by the batsman based on the outcome of the ball where $r_0 - r_1 > 0$ corresponds to improving his team's situation.

However, there is a difficulty with the interpretation of $r_0 - r_1$. Towards the end of the second innings when resources are limited, it is possible that the ratios r_0 and r_1 can be relatively large. In this case, $r_0 - r_1$ can vary greatly with respect to a given ball. In fact, r_1 is undefined if the ball in question is the last ball of the innings or if it results in the 10th wicket (since the remaining resources are nil). To adjust for this, and to compare apples to apples, we make two modifications. First, we introduce the arbitrary cutoff that when resources are less than 10% we do not include the batting outcome. Second, we introduce the statistical technique of standardization. We disregard the rare events corresponding to scoring three runs and five runs, and for a given ball, we calculate the 7 outcome possibilities:

$$
\begin{array}{rcl}
r_0 - r_1(0) & - & \text{the result of } r_0 - r_1 \text{ if 0 runs are scored,} \\
r_0 - r_1(1) & - & \text{the result of } r_0 - r_1 \text{ if 1 runs are scored,} \\
r_0 - r_1(2) & - & \text{the result of } r_0 - r_1 \text{ if 2 runs are scored,} \\
r_0 - r_1(4) & - & \text{the result of } r_0 - r_1 \text{ if 4 runs are scored,} \\
r_0 - r_1(6) & - & \text{the result of } r_0 - r_1 \text{ if 6 runs are scored,} \\
r_0 - r_1(w) & - & \text{the result of } r_0 - r_1 \text{ if a wicket falls,} \\
r_0 - r_1(e) & - & \text{the result of } r_0 - r_1 \text{ if an extra occurs.}
\end{array}
$$

We then define

$$s^2 = [\ (r_0 - r_1(0) - 0)^2 + \cdots + (r_0 - r_1(e) - 0)^2\ ]\ /\ 6$$

and replace the observed $r_0 - r_1$ with the standardized quantity

$$s(r_0 - r_1) = \frac{r_0 - r_1}{s}\ . \tag{1}$$

Therefore, using (1), the plot of $(r_0, s(r_0 - r_1))$ over all balls that a batsman has faced describes the batsman's performance with respect to the contextual difficulty of the chase. The points are then smoothed to provide a trend for the batsman. This smoothed curve is referred to as the batsman's *contextual batting function*. It describes performance over a range of contextual circumstances. When one batsman's curve dominates (i.e. lies above) another batsman's curve, the first batsman is the better batsman in all contexts.

Note that in the case of extras such as byes, leg-byes, wide-balls and no-balls, we credit the extra runs to the batsman. Although a case may be made that these extra runs are not a function of batting performance, they occur while the batsman is on-strike. Perhaps the batsman should receive credit for the extras as the bowler takes the strengths of the batsman into account during the delivery. In Section 2.2, we propose an analogous visualization for bowlers; in this case, it is evident that extras ought to be charged against bowlers. Therefore, we retain symmetry in the visualization by also giving credit to batsmen for extras. Extras occur at the rate of 5.1% in Twenty20 cricket (Davis, Perera and Swartz 2015).

Consider Figure 2 which displays the points $(r_0, s(r_0 - r_1))$ and the contextual batting function (ODI and T20) for the high profile batsman Steve Smith who was the former captain of Australia. The function is provided over the range of contexts $r_0 \in (0, 4)$. We observe that Smith bats infrequently in some contexts, and has not batted at all when $r_0 > 4$. This is partly explained by noting that Australia is a strong cricketing nation and rarely falls behind by huge margins during matches. We also note that some contexts (e.g. $r_0 < 2.80$) correspond to more comfortable chases which are not as interesting. It appears that for most contexts, Smith's contextual batting function lies above the par line $s(r_0 - r_1) = 0$ which suggests that he improves his team's situation in these chases. Figure 2 also illustrates a difficulty in visualization; when the points are plotted, it is difficult to compare the contextual batting function with the par line. We also observe that wickets are very damaging when

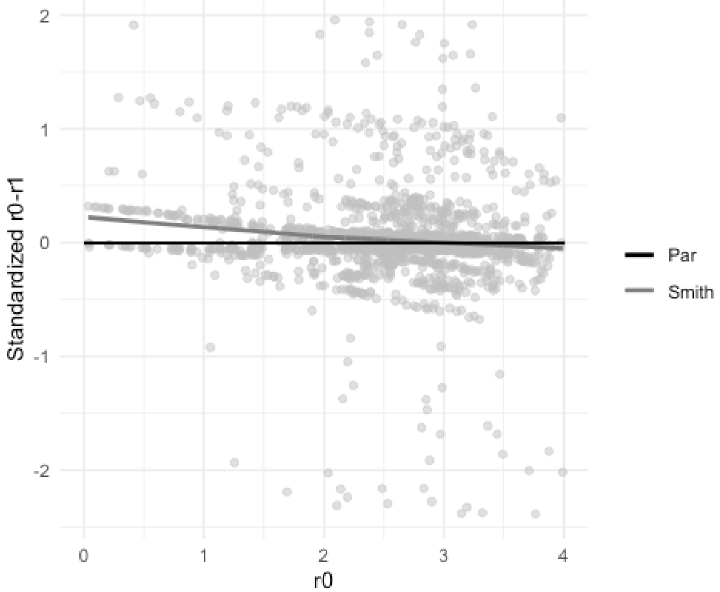

Figure 2. The points $(r_0, s(r_0 - r_1))$ and the resulting contextual batting function for Steve Smith over the contextual range $r_0 \in (0, 4)$.

assessing contextual batting performance; the large negative points in Figure 2 correspond to wickets and these points pull the contextual batting curve downwards.

2.3 A summary statistic for contextual batting

The contextual batting function describes a complete picture of how a batsman performs against a range of contexts. When comparing two batsmen, one batsman is superior if his curve dominates (lies above) the other curve. However, it will not always be the case that one curve dominates the other and therefore interpretation of contextual batting functions is necessary. For example, it could be the case that a batsman is very good at pushing through a win when a win is expected but is unable to produce a huge number of runs when his team is trailing badly. In this case, his contextual batting function would lie above the line $s(r_0 - r_1) = 0$ for smaller values of r_0 and lie below the line $s(r_0 - r_1) = 0$ for larger values of r_0. In fact, many batsmen will have functions that take this general shape with crossover points on the line $s(r_0 - r_1) = 0$.

Although the contextual batting function provides a description of batting performance across a range of contexts, the general public is more at ease with simple univariate statistics that are directly comparable. We will therefore propose a single statistic *clutch batting* which is a summarization of the contextual batting function when matches are highly challenging (i.e. $r_0 \in (2.80, 3.33)$). Clutch batting provides overall evaluation of second innings batting in challenging chases.

In Figure 3, we illustrate the clutch batting statistic with reference to Steve Smith. Smith's contextual batting function is restricted to the challenging range $r_0 \in (2.80, 3.33)$. This allows us to narrow in on his performance in the more interesting matches where there is a challenging chase. We compare Smith's performance against the par line $s(r_0 - r_1) = 0$ where a player is doing just

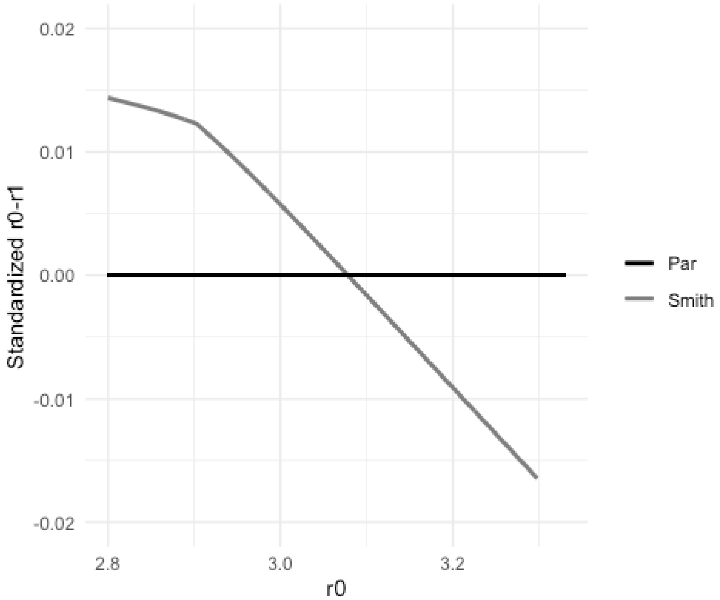

Figure 3. The contextual batting plot for Steve Smith over the challenging range $r_0 \in (2.80, 3.33)$.

enough to maintain the difficulty of the chase. Interestingly, Smith does not seem to help his team in the most difficult contexts (e.g. $r_0 > 3.05$) where his team is struggling. We also note that there is a downward slope to his contextual batting curve. This makes sense from a cricketing perspective since it becomes increasingly difficult to overcome a losing position as r_0 increases.

If we denote the contextual batting function as $f(r_0)$, then the clutch batting statistic is defined as

$$\begin{aligned} \mathrm{C_{bat}} &= \left(\int_{2.80}^{3.33} (f(r_0) - 0)\, dr_0 \right) 100 \\ &= \left(\int_{2.80}^{3.33} f(r_0)\, dr_0 \right) 100, \end{aligned} \tag{2}$$

where 100 is a scaling factor that is introduced to make the statistic more appealing. Therefore, (2) involves an area calculation involving the contextual batting function and the par line. Accordingly, $\mathrm{C_{bat}}$ is an overall measure of batting performance in challenging situations where larger values of $\mathrm{C_{bat}}$ denote greater proficiency. In Smith's case, his clutch batting statistic is 0.46 which suggests that overall, Smith improves his team's situation in challenging chases.

2.4 Contextual bowling performance

In cricket, there is an inherent symmetry between batting and bowling. Whereas a batsman attempts to score runs and avoid wickets, the bowler attempts to limit runs and take wickets. Therefore, the previous development of contextual batting can be modified to provide an analysis of contextual bowling. As before, during the second innings, we study the ratio of the runs required by the batting team (to win the match) to the resources available. Opposite to batsmen, a bowler attempts to increase the ratio on each delivery of the ball.

In clutch batting, we defined $r_0 \in (2.80, 3.33)$ as highly challenging contexts corresponding to a win probability interval $(0.25, 0.50)$ for the batting side. We likewise define $r_0 \in (2.27, 2.80)$ as highly challenging contexts corresponding to a win probability interval $(0.25, 0.50)$ for the bowling side. We therefore define the clutch bowling statistic as

$$\mathrm{C}_{\mathrm{bowl}} = \left(\int_{2.27}^{2.80} -f(r_0)\, dr_0 \right) 100, \tag{3}$$

where the negative sign has been introduced since we wish positive values of the statistic to be associated with clutch bowling.

An attractive feature of the clutch batting statistic (2) and the clutch bowling statistic (3) is that batsmen and bowlers can be assessed on the same scale.

3. Data analyses

3.1 Details of implementation

As previously emphasized, we use combined data from both ODI cricket and T20 cricket during the period April 2015 through October 2019. The synthesis of the two formats is possible due to the introduction of the runs to resource ratio r that describes and standardizes the contextual difficulty of the chase at any point during the second innings in limited overs cricket.

An issue related to clutch batting and clutch bowling is that we limit the analysis of batsmen and bowlers to those who have faced/delivered sufficient balls. This provides us with reliable statistics that are not heavily influenced by the results of only a few batting and bowling outcomes. We set the minimum number of balls faced/delivered to 300. This leaves us with 24 batsmen and 19 bowlers under consideration. With 12 full member nations in the International Cricket Council (ICC), our study is therefore restricted to a small number of prominent batsmen and bowlers on each ICC team.

The shape of the contextual batting and bowling curves are impacted by smoothing. We prefer curves that are not too "wiggly" since we do not believe there are practical reasons why batting and bowling performances should oscillate over the range r of contextual urgency. Smoothing is carried out in the R programming language using the *loess* function (Cleveland 1979). The parameters *span* and *degree* determine the characteristics of smoothing in loess. The parameter span $\in (0, 1)$ controls the smoothing neighbourhood where larger span means that more nearby data influence the fit. The parameter degree > 0 specifies the order of the smoothing polynomials where higher order polynomials permit more wiggle in the fitted curve. In our application, we have set span $= 1$ and degree $= 1$.

Once the loess function has been determined, the calculation of the clutch batting statistic (2) and the clutch bowling statistic (3) require numerical integration to obtain the areas beneath the loess curve. This is done using the *uniroot* and *integrate* functions in R. The function *uniroot* finds the roots of the contextual curves, and *integrate* obtains the corresponding areas between the roots.

To get a sense of the reliability of the clutch batting and clutch bowling statistics, we associate standard errors to the statistics. This is implemented through a bootstrapping procedure where for each batsman and bowler, we resample (with replacement) the balls faced/delivered from their individual dataset. From the resampled data, the clutch batting/bowling statistic is calculated, and this resampling procedures is repeated $M = 10,000$ times. From the M simulated statistics, a standard error is calculated.

3.2 Clutch batting analysis

In Table 1, we present the clutch batting statistic 24 prominent batsmen in limited overs cricket who have faced at least 300 balls. For comparison purposes, we also present the batting average, the strike rate and the survival rate (i.e. balls per dismissal) of van Staden (2009) where large values of the three statistics are all indicative of good batting. An immediate reaction is that clutch batting correlates positively but not strongly with batting average (average number of runs scored per wicket) where the sample correlation coefficient is 0.34. The correlation between clutch batting and strike rate is 0.70 and the correlation between clutch batting and survival rate is -0.34. This suggests that clutch batting detects an aspect of performance that resembles features of the strike rate. Clutch batting and the survival rate appear to have little in common. Note that to make fair comparisons, we have calculated the common statistics based on the same timeframe considered in our dataset.

We see from Table 1 that the best clutch batsman is Jason Roy of England followed by his countryman Jos Buttler. Whereas Roy and Buttler are known as solid batsmen, they are spectacular in situations when their team is in desperate need of runs. Perhaps this partly explains England's good run of form in recent years. We also observe that the remarkable Virat Kohli of India is also a top clutch batsman. Shai Hope of the West Indies is situated at the bottom of the table. He does not pull his team from the brink in desperate chase situations. We do note that Hope's statistic was based on only 331 balls and has a standard error of 0.95.

Another observation from Table 1 is that the bootstrap standard error is large. This is caused by large values of $|s(r_0 - r_1)|$ which impact clutch batting. These impactful observations correspond to scoring sixes and dismissals. We note that the standard errors tend to decrease with greater numbers of at-bats. Given the large standard errors, we can only make broad inferences concerning the differentiation between batsmen.

3.3 Clutch bowling analysis

In Table 2, we present the clutch bowling statistic for 19 prominent bowlers in limited over cricket who have delivered at least 300 balls. For comparison purposes, we also present the strike rate, the bowling average and the economy rate where low values of the three statistics are all indicative of good bowling. An immediate reaction is that clutch bowling correlates moderately with bowling strike rate (average number of balls bowled per wicket) where the sample correlation coefficient is -0.51 The correlation between clutch bowling and bowling average is -0.54 and the correlation between clutch bowling and economy rate is -0.72. This suggests that clutch bowling is detecting an aspect of performance that resembles features of the economy rate. Note that to make fair comparisons, we have calculated the common statistics using the same timeframe considered in our dataset. As with clutch batting, we observe that the bootstrap standard error is high and this makes it difficult to differentiate between bowlers. We note that the range $(-2.84, 3.26)$ of the clutch bowling statistics in Table 2 is similar to the range $(-1.75, 2.40)$ of the clutch batting statistics in Table 1. The similarity is a consequence of the symmetry in the definitions of clutch bowling and clutch batting.

Looking at particular players, we observe that both Rashid Khan and Mujheeb Ur Rahman of Afghanistan are strong clutch bowlers. This comes as no surprise as they are the top two T20 bowlers

Table 1. Clutch batting C_{bat} and other statistics for 24 batsmen who have faced at least 300 balls in high level limited overs cricket matches. For comparison purposes, batting average was calculated over the same data collection period.

Batsman	Country	Balls	C_{bat} (Std Err)	Bat Avg	Strike Rate	Surv Rate
JJ Roy	England	416	2.40 (0.79)	41.5	116.6	31.2
JC Buttler	England	470	2.15 (0.91)	40.6	138.3	31.5
AB de Villiers	South Africa	325	2.04 (0.99)	48.4	146.2	34.7
CH Gayle	West Indies	374	1.81 (1.08)	35.6	130.9	28.7
Q de Kock	South Africa	534	1.68 (0.64)	47.1	110.9	36.2
S Dhawan	India	507	1.50 (0.89)	38.3	116.4	32.7
V Kohli	India	659	1.00 (0.49)	66.7	114.8	49.3
RG Sharma	India	812	0.68 (0.52)	49.5	112.4	39.0
AJ Finch	Australia	608	0.52 (0.51)	44.5	115.8	34.1
SPD Smith	Australia	399	0.46 (0.75)	41.8	101.1	39.3
SR Watson	Australia	319	0.20 (1.17)	24.4	137.3	20.8
BA Stokes	England	317	0.14 (0.71)	46.3	107.3	33.1
S Al Hasan	Bangladesh	329	0.02 (0.84)	41.7	99.6	36.4
LRPL Taylor	New Zealand	369	0.01 (0.64)	52.3	92.2	57.2
KS Williamson	New Zealand	676	0.01 (0.56)	52.4	97.5	44.4
TWM Latham	New Zealand	306	−0.54 (0.69)	43.0	88.8	45.4
E Lewis	West Indies	472	−0.72 (0.99)	27.1	108.5	27.9
PR Stirling	Ireland	312	−0.94 (1.03)	36.6	94.8	37.2
HM Amla	South Africa	303	−0.98 (1.05)	38.3	102.4	49.4
S Sarkar	Bangladesh	339	−1.32 (1.15)	35.4	108.8	27.3
F du Plessis	South Africa	338	−1.32 (1.07)	44.3	106.4	46.4
WU Tharanga	Sri Lanka	316	−1.38 (1.07)	37.8	91.9	37.9
AM Rahane	India	388	−1.41 (1.12)	35.3	107.5	34.3
SD Hope	West Indies	331	−1.75 (0.95)	33.1	78.7	57.8

according to the current ICC rankings. Perhaps it is a surprise that the South African fast bowler, Kagiso Rabada sits as the second worst clutch bowler in Table 2. We also obtained the clutch bowling statistic of Lasith Malinga of Sri Lanka ($C_{bowl} = -0.24$) who only delivered 278 balls over the time period. Malinga is of particular interest due to his reputation as an incredible "death" bowler. The clutch bowling statistic suggests that Malinga's reputation is perhaps overrated.

3.4 Data synthesis

One of the bold assumptions that we have made in the paper involves the synthesis of data. In forming the clutch statistics, we used data from both domestic cricket and international cricket. In addition, we combined T20 data and one-day data. Of course, our intention was to provide the best measures of clutch performance statistics through utilizing as much data as possible.

To investigate these assumptions, we first investigated batting averages corresponding to the 24 batsmen in Table 1 using the same timeframe. We observed that six of the batsmen (Latham, Stirling, Tharanga, Hope, Sarkar and Taylor) did not compete domestically in T20. We therefore excluded these batsmen from the following analysis. We then separated the T20 batting averages by calculating

Table 2. Clutch bowling C_{bowl} and other statistics for 19 bowlers who have delivered at least 300 balls in high level limited overs cricket matches. For comparison purposes, strike rate was calculated over the same data collection period.

Bowler	Country	Balls	C_{bowl} (Std Err)	Strike Rate	Bowl Avg	Econ Rate
R Khan	Afghanistan	680	3.26 (0.64)	20.9	16.0	5.2
M Ur Rahman	Afghanistan	418	2.07 (1.03)	28.5	21.0	4.7
MJ Henry	New Zealand	330	0.95 (1.13)	33.2	30.7	5.8
MJ Santner	New Zealand	373	0.00 (0.72)	35.9	29.6	5.3
M Nabi	Afghanistan	624	−0.02 (0.60)	35.3	24.9	5.3
PJ Cummins	Australia	304	−0.10 (0.75)	33.0	25.0	5.7
M Rahman	Bangladesh	467	−0.10 (0.68)	28.5	21.8	5.9
TA Boult	New Zealand	364	−0.13 (0.67)	28.1	24.8	6.1
YS Chahal	India	351	−0.14 (0.87)	23.0	22.6	6.3
I Tahir	South Africa	465	−0.19 (0.54)	26.4	21.6	5.7
I Wasim	Pakistan	323	−0.21 (0.88)	35.7	27.3	5.2
S Al Hasan	Bangladesh	591	−0.33 (0.61)	33.6	31.2	5.8
JJ Bumrah	India	341	−0.35 (0.81)	21.0	21.5	5.8
M Mortaza	Bangladesh	620	−0.46 (0.39)	41.7	37.6	5.6
A Zampa	Australia	371	−0.56 (0.51)	29.9	29.5	6.1
TG Southee	New Zealand	362	−0.62 (0.63)	36.7	34.7	6.6
B Kumar	India	534	−0.74 (0.78)	33.9	25.7	6.1
K Rabada	South Africa	346	−1.02 (0.63)	38.8	21.9	5.5
MP Stoinis	Australia	364	−2.84 (0.86)	36.4	33.6	7.2

a domestic batting average x and an international batting average y for the remaining 18 batsman. Using a simple linear regression of y versus x, a lack of difference between the two competitions would imply an intercept $\beta_0 = 0.0$ and a slope $\beta_1 = 1.0$. We obtained estimates (standard errors) of 25.98 (15.15) and 0.15 (0.42) for the intercept and slope, respectively. This suggests that there may be slight differences in the scoring patterns between the two competitions.

The calculation of the proposed clutch statistics are dependent on the runs to resource ratio r introduced in Section 2. As we have combined T20 and ODI datasets, it is important to check that r is invariant to the two formats. In Figure 4, we have overlaid the histograms of r calculated for all second innings balls for the two datasets. We observe that the two histograms have roughly the same shape and this suggests that amalgamation of the two datasets may be appropriate. It could be the case that the r_0 values for ODI are slightly larger.

4. Discussion

The proposed clutch batting and clutch bowling statistics are not intended to usurp traditional and popular statistics such as batting average and bowling strike rate. Rather, these statistics were introduced to provide insight on an aspect of performance that had not been previously investigated. Specifically, we are interested in how batsmen and bowlers perform in the second innings when their teams are in difficult situations. Hence, the clutch batting and clutch bowling statistics are contextual. The methods presented here may be regarded as proof of concept; should the approach gain traction, it may be sensible to separate datasets according to the competition level and the format of cricket.

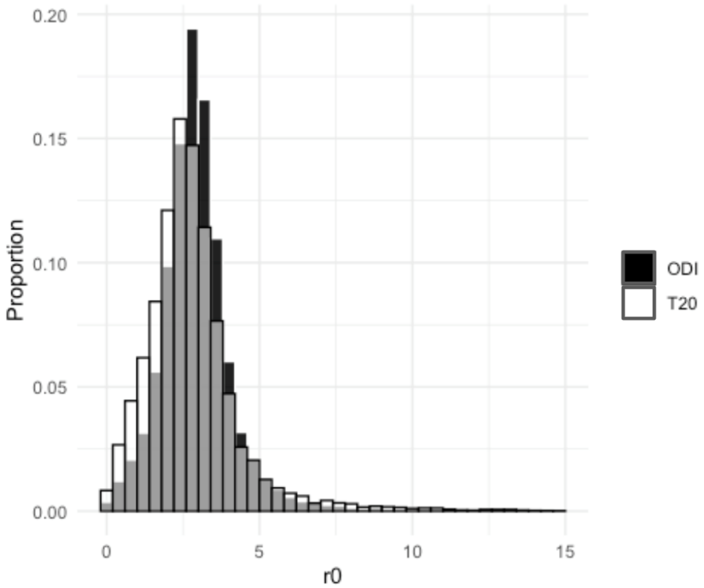

Figure 4. Frequency histograms of r based on all second innings balls displayed for the ODI and Twenty20 datasets.

The data analyses have demonstrated that performance in difficult contexts does not correlate highly with overall performance measures. From the point of view of tactics, the clutch batting and clutch bowling statistics may provide teams with useful information to determine optimal batting and bowling orders in difficult contexts.

There are various ways in which our ideas concerning contextual performance may be explored in future research. For example, one could study different contexts as described by the runs to resource ratio r_0. Also, it is possible to narrow or expand data collection timeframes under consideration. Alternatively, one could define statistics that weight recent performances more highly. Contextual performance in sport is clearly an important and understudied subject area that deserves greater attention.

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Appendix: Additional information on DLS

To get a sense of the use of the DLS method, consider the abbreviated Standard Edition of the Duckworth-Lewis-Stern table presented in Table 3. Imagine that Team A is batting and scores 250 runs on completion of its innings. It then rains prior to the resumption of the second innings. When Team B comes to bat, they are only allotted 30 overs. Using the old method of run rates, Team B would need to score $250(30/50) + 1 = 151$ runs in order to win the match. The obvious problem with the run rate approach is that Team B can bat more aggressively since their 10 wickets are spread

Table 3. Abbreviated version of the Duckworth-Lewis resource table (2014–2015 Standard Edition). The table entries indicate the percentage of resources remaining in a match with the specified number of wickets lost and overs available.

	Wickets Lost										
Overs Available	0	1	2	3	4	5	6	7	8	9	10
50	100.0	93.4	85.1	74.9	62.7	49.0	34.9	22.0	11.9	4.7	0.0
40	89.3	84.2	77.8	69.6	59.5	47.6	34.6	22.0	11.9	4.7	0.0
30	75.1	71.8	67.3	61.6	54.1	44.7	33.6	21.8	11.9	4.7	0.0
20	56.6	54.8	52.4	49.1	44.6	38.6	30.8	21.2	11.9	4.7	0.0
10	32.1	31.6	30.8	29.8	28.3	26.1	22.8	17.9	11.4	4.7	0.0
5	17.2	17.0	16.8	16.5	16.1	15.4	14.3	12.5	9.4	4.6	0.0
1	3.6	3.6	3.6	3.6	3.6	3.5	3.5	3.4	3.2	2.5	0.0
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

throughout 30 overs rather than 50 overs. Therefore, the target of 151 runs is lower than what might be considered fair. However, using the DLS approach, Table 1 indicates that with 30 overs remaining and zero wickets lost, Team B retains 75.1% of its resources. Therefore, the target is rounded up to $250(0.751) \rightarrow 188$ runs. The large difference between 151 runs and 188 runs indicates how unpalatable it was for matches to be determined by run rates. The ICC Playing Handbook describes other scenarios in which D/L can be used to reset targets in interrupted matches.

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