Competitive Balance

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Chapter 4
Competitive Balance

4.1 Introduction

People follow sport — either as spectators or through newspapers, television, radio, and the internet — for essentially two reasons: first, to witness thrilling displays of skill by individual players, and second, to participate in the uncertainty of a close contest in which the tension of an unpredictable outcome is maintained into the game's dying moments. This last factor is particularly important for league sports where a commonly held view is that the long-term sustainability of sporting leagues, in terms of both retaining the interest of their fans and generating income from games, depends upon the degree of unpredictability in the outcome of matches or, in other words, the *competitive balance* (hereafter, CB) in the league.

The importance attached to CB is predicated on the belief that it is uncertainty about the outcomes of sporting contests that attracts spectators and persuades fans to follow a game through the media. In a perfectly balanced competition, each team would have an equal chance of winning each match and, therefore, of winning the championship or the league. By contrast, the absence of CB would mean that the outcomes of sporting contests would be predictable and, in consequence, the numbers following those contests would decline.[1] This was termed the 'league standing effect' by Neal (1964): if a league lacked competitive balance, then fan interest in the weaker teams would decline and, eventually, this would also lead to a withering of interest in the stronger teams. Quirk and Fort (1997) attributed the demise of the All-American Football Conference to a lack of CB.

Indeed, the most colourful example of the importance of CB has been provided by the Nobel-prize winning economist Amartya Sen in his book, *Home in the World: A Memoir* (Sen, 2021). Soccer in Calcutta (now Kolkata) is infused with a long-standing rivalry between two local teams: Mohun Bagan and East Bengal. In the 1940s of Sen's youth, supporters of Mohun Bagan celebrated a victory by feasting on a particular type of fish, *ruhi*, while supporters of East Bengal, when their team won, feasted on a different type of fish, *hilsa*. Consequently, depending on which team won, the post-match

[1] See *inter alia* Zimbalist (2002); Szymanski (2003, 2007); and Michie and Oughton (2004).

price of *ruhi* or *hilsa* shot up in response to a sudden surge of demand. The curious thing is that fishmongers in Calcutta did not lay in extra supplies of *ruhi* or *hilsa* to take advantage of the demand surge that they knew would occur. That they did not do so was because, in common with the rest of Calcutta, they did not know which of the two evenly matched teams would win. That is competitive balance encapsulated in the price of fish!

The importance of CB to a league's success gives rise to the question of how CB should be measured (Humphreys, 2002; Michie and Oughton, 2004; Avila-Cano *et al*., 2021). The general theme that underpins these measures is that of *inequality analysis*. In the context of a league — which is the subject of this chapter — the more equitable the inter-team distribution of the total number of points associated with the games' outcomes, the greater will be its CB.

However, the identification of competitive balance with inter-team inequality in the distribution of league points raises several ancillary questions. First, and foremost, how should inequality be measured? One of the drawbacks of existing analyses of CB is that they do not fully mine the rich vein of methodology that the study of inequality provides. To use the language of Cowell (1995), many of the measures that are currently used came about more or less by accident, with concepts borrowed from statistics being pressed into service as tools of inequality measurement.

Second, if there is a lack of competitive balance in a league, can one identify its source? Is there considerable CB *within* subgroups of teams in the league but relatively little CB *between* teams in the subgroups? Or does the lack of CB permeate the league in its entirety and affect all the teams? One of the problems with measures of CB is that they treat the league as a single unit and do not pay heed to the subgroups of teams within the league. Consequently, CB in the league considered in its entirety may be low but CB within subgroups of teams may be high as, say, the top teams fight to be promoted and the bottom teams fight to avoid relegation.

Third, given that the teams in a league enjoy different degrees of success, as measured by their end of season points, what is the *effective* number of teams in a league? In essence, calculating the effective number of teams in a league involves assigning a scalar value to a vector of inter-team distribution of points. At one extreme, this scalar value will (should) equal the number of teams that play in the league. This will occur when points are distributed equally among the teams. However, when the points are distributed unequally between the teams, the effective number of teams will be less than the actual number of teams.

The focus of most research on CB has been on sports leagues in the USA, particularly in baseball (Lenton, 2015). Characteristically these are closed leagues in which promotion and relegation do not figure and, in this respect, they differ from European leagues in which both promotion and relegation play an important role. The franchise teams of the Indian Premier League (IPL), Australia's Big Bash League (BBL) and Women's Big Bash League (WBBL), and the Hundred in England, however, share the US characteristic of being closed leagues in which teams play a fixed number of matches without facing either the threat of demotion or the promise of promotion.[2] This chapter examines CB in the context of such cricket leagues.[3] In doing so, it proposes a general measure of competitive balance based on the Generalised Entropy (GE) approach (due to Theil, 1967) to measuring inequality and shows how this might be used to study CB, both within and between subgroups of teams in a league.

4.2 Background

In a sports league consisting of N teams, each team plays every other team *twice* during a season: home and away. There are $N \times (N-1)$ independent games: team 1 plays the other $N-1$ teams twice; team 2 plays the other $N-2$ teams twice (excluding team 1, whom it has already played); team 3 plays the other $N-3$ teams twice (excluding teams 1 and 2, whom it has already played); and so on. Leagues comprising eight teams — such as India's IPL, and the BBL and WBBL in Australia — result in 56 round-robin games with each team playing 14 pre-qualifying matches. If, as is usually the case, a team is awarded two points for a win, one point for a tie or no-result, and zero points for a defeat then the maximum and minimum number of points a team can obtain are, respectively, 28 (a team wins all its matches) and zero (a team loses all its matches). If W_X is the total number of matches

[2] Other characteristics of these cricket leagues which mirror those of sports leagues in the USA are salary caps and the draft system.
[3] In this respect the analysis of this chapter differs from that of Mondal *et al.* (2021) who examine CB in the context of international cricket. The problem with their analysis, as they themselves recognise, is that international cricket teams play an unequal number of matches, some countries have not played each other for a long time (for example, India and Pakistan), and South Africa was excluded from international cricket from 1970 until 1991.

won by team X at the end of the round-robin then $V_X=2\times W_X$ is its total number of points, where V_X is a number between 0 and 28 (inclusive).

In the absence of ties and no-results, each team, under *perfect* CB, would be expected to win the same number of matches, that is with eight teams, each team should win seven matches and earn 14 points.[4] On the other hand, imperfect CB implies an unequal division of wins between the teams, the degree of imperfection increasing with the degree of inequality. Suppose the eight teams were ranked in descending order of the points they obtained (say team *1* with the maximum, and team *8* with the minimum, points). Then inequality would be greatest — competition would be most unbalanced — if all the results were perfectly predictable: team 1 wins all its 14 matches, $V_1 = 28$; team 2 wins 12 matches, $V_2 = 24$; and so on until the last team loses all its games and finishes without any points, $V_8 = 0$.

Suppose that v_X is the share of team X in the total number of points where these shares, over all the eight teams, sum to one. Since each of the 56 round-robin matches results in a win, the total number of points is 112 and, computed over the eight teams, the average number of points is 14. Then, under perfect CB, each team secures the average number of points by winning 7 of its 14 matches and receiving 14 points with a share of 1/8 in the total number of points (v_X=1/8). When CB is most imperfect, team 1's share in the total number of points is $v_1=28/112=0.25$ since it wins all is 14 matches; team 2's share in the total number of points is $v_2=24/112=0.21$ since it wins 12 matches; team 3's share in the total number of points is $v_3=20/112=0.18$ and so on until team 8 whose share in the total number of points is zero. These points are elaborated in a more general context in the mathematical box below.

[4] In T20 games, ties are resolved by a 'super over' and bad weather interruptions are resolved using the Duckworth-Lewis method.

Box 4.1: Formal Representation of Matches and Points

In a sports league consisting of N teams, each team plays every other team *twice* in a season: home and away. Suppose that, for every game that it plays, a team is awarded p_w points for a win, p_T points for a tie or no-result, and 0 points for a loss: $p_w \geq 2p_T$. Suppose, in a season, a proportion α of games have a winner (loser) and $(1-\alpha)$ end in a tie or no-result. Consequently, in a season, the total number of wins (W) and ties (T) result in a total (Z) of points awarded in the league:

$$\begin{aligned} Z &= p_w W + 2p_T T = p_w \alpha N(N-1) + 2p_T(1-\alpha)N(N-1) \\ &= N(N-1)\left[p_w\alpha + 2p_T(1-\alpha)\right] = N(N-1)[(p_w - 2p_T)\alpha + 2p_T] \end{aligned} \quad (4.1)$$

Suppose that in a season, team i wins W_i games and that T_i of its games end in a tie or no-result. Then team i's end-of-season points are: $V_i = p_w W_i + p_T T_i$. Since each team plays $2(N-1)$ games, the maximum and minimum points a team can obtain in a season are, respectively, $2p_w(N-1)$ and 0. Consequently, $0 \leq V_i \leq 2p_w(N-1)$.

If $\alpha=1$ (that is, all the $N(N-1)$ matches are won/lost, then, under perfect CB, each team would be expected to win the same number of games: $W_1 = W_2 = ...W_N = N(N-1)/N$. So, under perfect competitive balance, each team would be expected to end the season with the same number of points: $V_1 = V_2 = ...V_N = p_w(N-1)$. On the other hand, imperfect CB implies that the total number of wins would be unequally divided between the teams, the degree of imbalance increasing with the degree of inequality.

Suppose the teams were ranked in descending order of the points they obtained (say team *1* with the maximum, and team N with the minimum, points). Then inequality would be greatest — competition would be most unbalanced — if all the results were perfectly predictable: team 1 wins all its *2(N-1)* games, $V_1 = 2p_w(N-1)$; team 2 wins all its *2(N-2)* games, $V_2 = 2p_w(N-2)$; and so on till, say, team r, $V_r = 2p_w(N-r)$; the N^{th} team loses all its games and finishes without any points, $V_N = 2p_w(N-N) = 0$.

Let the points share of the i^{th} team be denoted by $v_i \geq 0$, $v_i = V_i / T = V_i / N\overline{V}$, where $\overline{V}$ is the average number of points computed over all the teams and $\sum_{i=1}^{N} v_i = 1$. Then under perfect competitive balance, $v_i = 1/N$ and when competition is most unbalanced, $v_i = [2p_w(N-i)]/[p_w N(N-1)] = 2(N-i)/N(N-1), i = 1...N$. So, when competition is most unbalanced, the points share of the teams would be: *2/N* for team 1; $[2(N-2)]/[N(N-1)]$ for team 2; till $[2/[N(N-1)]$ for team *N-1* and 0 for team N.

4.3 Properties of Inequality Indices and Measures of Inequality

The measurement of competitive balance, as argued above, is synonymous with the measurement of inequality and a 'good' measure of inequality should satisfy certain properties:[5]

1. The *weak principle of transfers* (also known as the Pigou-Dalton property): an egalitarian transfer of points (that is, from a stronger to a weaker team) causes the value of the inequality index to fall and a regressive transfer of points (that is, from a weaker to a stronger team) causes it to rise.
2. *Scale independence:* if everyone's quantity (points, income etc.) increased by the same *proportion*, inequality would remain unchanged.[6]
3. *Population homogeneity:* if the population of *N* teams is replicated, then inequality in this larger population of $2 \times N$ teams would remain unaltered.
4. *Decomposability*: if the population is divided into mutually exclusive groups, a decomposable inequality measure is one which can be expressed as the weighted average of inequality existing *within* subgroups and inequality existing *between* them. More specifically, *additive decomposability* allows total inequality to be expressed as the *sum* of within-subgroup and between-subgroup inequalities.

Not all inequality measures proposed in the literature satisfy all the above properties and only a special class of inequality measures satisfy the fourth property, that of additive decomposability. One of the most popular ways of measuring inequality is the *Gini coefficient* which is computed as follows:

a. First add up *the absolute value* of the differences in points between the teams. Here, the difference in points between teams *X* and *Y* are added twice: first as *X*-*Y* and then as *Y*-*X*. Note also, the difference in points between *X* with itself (zero) is also included. Consequently, there are N^2 differences.

[5] See Coulter (2018, chapter 2) for a discussion of these properties.
[6] For example, if under a new system, the points were awarded as four for a win, two for a tie or no-result, and zero for a loss, then each team's points would double but inequality would remain unchanged.

b. Then compute the average of these differences as the sum, computed above, divided by N^2.

c. Lastly, express this average as a ratio of twice the average number of points awarded in the league. The resulting ratio is the Gini coefficient. The average in the denominator is multiplied by 2 to overcome the problem of double counting differences in the numerator.

So, *G=0.45* implies that the *difference in points between two teams chosen at random* will be 90% of the average number of points: if $\bar{V}$ =14, this difference will be 13 points. On the other hand, *G=0.2* implies that the *difference in points between two teams chosen at random* will be 40% of the average number of points, that is 6 points. Consequently, higher values of the Gini coefficient are associated with higher levels of inequality.

It is also possible to compute from the Gini coefficient a measure of welfare (*W)* due to Sen (1976). The idea behind this measure, represented by $W = \bar{V}(1-G)$, is that welfare rises with increases in the average number of points, $\bar{V}$, but falls as inequality in the distribution of points rises. There is thus a trade-off between the welfare-enhancing property of the average number of points and the welfare-diminishing property of inequality in the points distribution and it is this trade-off that Sen's (1976) welfare measure seeks to capture.

The Gini coefficient embodies the first three desirable properties of inequality indices, set out above, but it does not satisfy the last property, that of decomposability. The Gini coefficient is not decomposable in the sense defined above and has seldom been used for this purpose (Bourguignon, 1979). To analyse decomposition through the lens of decomposability one must turn to entropy-based indices.

Box 4.2: Mathematical Representation of the Gini coefficient

If N is the number of teams, V_i is the points of the i^{th} team, and $\bar{V}$ is the average of the total number of points computed over the N teams, the Gini coefficient is defined as:

$$G = \frac{1}{2N^2\bar{V}} \underbrace{\sum_{i=1}^{N}\sum_{j=1}^{N} |V_i - V_j|}_{\text{Sum of absolute differenes}}$$

In other words, the Gini coefficient is computed as half the mean of the difference in points between pairs of teams, divided by the average number of points ($\bar{V}$).

4.4 Entropy-based Inequality Indices

The term entropy, as used in thermodynamics, means the degree of disorder or randomness in the system; in terms of inequality analysis, it means deviations from perfect inequality (Bellù and Liberati, 2006). The basic building block of entropy-based inequality measures is deviations of the outcomes of individuals (in respect of points for teams, incomes for households) from the mean outcome. This deviation is expressed as the *average* of the difference between individual outcomes and the mean outcome. For N individuals, this can be expressed more succinctly as:

$$\frac{1}{N}\left[\left(\frac{V_1}{\bar{V}}\right)+\left(\frac{V_2}{\bar{V}}\right)+\ldots+\left(\frac{V_N}{\bar{V}}\right)\right]=\frac{1}{N}\sum_{i}^{N}\left(\frac{V_i}{\bar{V}}\right) \qquad (4.2)$$

where V_i is the individual, and $\bar{V}$ is the average, outcome. For two special cases, discussed below, it is the logarithmic difference of the team points from the mean, $\frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{V_i}{\bar{V}}\right)$, that is used. Entropy is introduced into the analysis by raising the term in equation (4.2) to the power of a non-negative number, $\theta \geq 0$, to give: $\frac{1}{N}\sum_{i}^{N}\left(\frac{V_i}{\bar{V}}\right)^{\theta}$. The number θ is then the entropy parameter.

Interpretation of the Entropy Parameter

How is this parameter to be interpreted? All inequality indices should embody property 1, above, for inequality indices: the *weak principle of transfers*. In the case under discussion, this principle (also known as the Pigou-Dalton property: Dalton, 1920) requires that a transfer of points from a 'stronger' to a 'weaker' team should cause the value of the inequality index to fall. But by *how much* the value of the inequality index will fall, following this 'egalitarian' points transfer, will depend upon the value of the parameter, θ. The value of θ, therefore, measures the 'transfer sensitivity' of the inequality index: the *larger* the value of θ, the *greater* will be the fall in inequality, following an egalitarian transfer of points from a stronger to a weaker team. In that sense, the parameter θ represents the analyst's aversion to inequality: the greater the value of θ, the greater the league's aversion to competitive imbalance reflected in a willingness to sacrifice larger amounts of the points of strong teams in favour of weak teams.

Some Entropy-based Inequality Measures

Specific entropy-based measures can be obtained by assigning specific values to the entropy parameter θ. The most usual values are: $\theta=0, 1$, and 2. When $\theta=0$, the entropy index (EI) is simply the mean logarithmic deviation (MLD):

$$MLD = EI(0) = \frac{1}{N}\sum_{i}^{N} \underbrace{\log\left(\frac{V_i}{\overline{\overline{V}}}\right)}_{\text{logarithmic deviation}} \tag{4.3}$$

When $\theta=1$, the resulting entropy index, known as the Theil index (Theil, 1967), *weights* the individual logarithmic deviations from the mean with everyone's share of the total:

$$\text{Theil Index} = EI(1) = \frac{1}{N}\sum_{i=1}^{N} \underbrace{\left(\frac{V_i}{\overline{\overline{V}}}\right)}_{\text{weights}} \times \underbrace{\log\left(\frac{V_i}{\overline{\overline{V}}}\right)}_{\text{logarithmic deviation}} \tag{4.4}$$

When $\theta=2$, the resulting entropy index is equivalent to the *Herfindahl* index of concentration:

$$\text{Herfindhal Equivalent} = EI(2) = \frac{N}{2}\left[\underbrace{\sum v_i^2}_{\text{Herfindahl Index}} - \frac{1}{N}\right] \tag{4.5}$$

where v_i is the share of the individual in the total. The Herfindahl index (Hirschman, 1964) is a popular measure of concentration, used in the industrial economics literature, to measure the degree of competition in a market and is defined as the sum of squares of the firms' market shares: $\sum_{i=1}^{N} v_i^2$. The minimum value of the Herfindahl Index occurs when each firm has an equal share in the total so that $v_i=1/N$, $\sum_{i=1}^{N} v_i^2 = 1/N$ and $EI(2)=0$. Its maximum value occurs when a single firm completely dominates the market, leaving nothing for the other firms: $v_1=1, v_2=0 \ldots v_N=0$ implying that the Herfindahl index = 1 and $EI(2) = N \times (N-1)/2$.

Decomposability

Entropy-based inequality measures are important because, as Shorrocks (1980) showed, only inequality indices belonging to the family of Entropy Indices are additively decomposable. The method of inequality decomposition divides overall inequality into two parts: 'between-group' and 'within-group'' inequality. The technical details of how this is achieved are shown in Box 4.3 below with the intuition behind these details set out in the main text here. When the decomposition is *additive*, overall inequality can be written as the *sum* of within-group and between-group inequality:

$$\underbrace{I}_{\text{overall ineqality}} = \underbrace{A}_{\text{within-group inequality}} + \underbrace{B}_{\text{between-group inequality}} \tag{4.6}$$

Suppose there are two groups: a high-performing group, *H* and a low-performing group, *L* with four teams in each group. Then the following steps are needed to compute within-group inequality, that is, the term *A* above, and between-group inequality, the term *B* above.

1. First compute inequality separately for groups *H* and *L* using an entropy index. This entails choosing a value of θ. If $\theta=0$, inequality is calculated using the MLD index (see 4.3, above); if $\theta=1$, inequality is calculated using the Theil index (see 4.4, above); if $\theta=2$, inequality is calculated using a variant of the Herfindahl index (see 4.5, above). The choice of θ will depend on the league's aversion to inequality or, equivalently, to competitive imbalance: the greater the aversion, the higher the value of θ chosen. The empirical work of this chapter is based on $\theta=0$ which expresses mild inequality aversion. Call the resulting values of inequality for groups *H* and *L*, respectively, I_H and I_L.
2. Then construct the weighted average of I_H and I_L using weights w_H and w_L. Then within-group inequality (the term *A*, above) is: $A = w_H \times I_H + w_L \times I_L$. The weights depend upon the choice of θ. In general, if there are *N* teams divided into *K* groups with N_k teams in each group, Shorrocks (1980) showed that the general form of the weights is: $w_k = \frac{N_k}{N} \times \left(\frac{V_k}{\bar{V}}\right)^{\theta}$.

   If $\theta=0$, $w_k = \frac{N_k}{N}$, that is, the number of teams in group in *k*, N_k, as a proportion of the total number of teams, *N*. If there are eight teams ($N=8$) with four teams in each of the *H* and *L* groups, ($N_k=4$), then $w_H=w_L=1/2$.

   If $\theta=1$, $w_k = \frac{N_k}{N} \times \left(\frac{V_k}{\bar{V}}\right)$, that is, the number of points obtained by group *k*, $N_k \times V_k$, as a proportion of the total number of league points, $N \times \bar{V}$. If group H and L receive, respectively two-thirds and one-third of the total number of points, then $w_H=2/3$ and $w_L=1/3$.

3. The between-group calculation is computed by setting, for every group, all the team scores in a group to that group's average score and then computing inequality using one of the entropy indices. The resulting value is the between-group contribution, *B*. So, if the average score of groups *H* and *L* are, respectively, $\bar{V}_H$ and $\bar{V}_L$, all the four team scores in group *H* are set equal to $\bar{V}_H$, all the four team scores in group *L* are set equal to $\bar{V}_L$ and inequality is computed as *B*.

When inequality is additively decomposed then one can say that the basis on which the individual teams were subdivided (say, high/low scoring teams) contributed [(B/I)×100] % to overall inequality, the remaining inequality, [(A/I)×100] %, being due to inequality *within* the team subgroups.

Inequality decomposition thus provides a way of analysing the extent to which inter-team inequality in points is 'explained' by the factor (or a set of factors) used to assemble them into groups. If, indeed, inequality can be 'additively decomposed' then, as Cowell and Jenkins (1995) have shown, the proportionate contribution of the between-group component (B) to overall inequality is the income inequality literature's analogue of the R^2 statistic used in regression analysis: the size of this contribution is a measure of the amount of inequality that can be 'explained' by the factor (or factors) used to subdivide the sample.

Box 4.3: Mathematical Representation of Entropy Indices

Suppose a random variable *x* can take values $x_1 ... x_N$ with probabilities $p_1 ... p_N$, $0 \le p_i \le 1$, $\sum p_i = 1$.

Hence the *information content* h_i of observing *x* take the value x_i can be regarded as a decreasing function of p_i: if p_i is large/small, then it would not/would be a surprise if $x = x_i$ and so the 'information content', h_i of the observation would be small/large (Renyi, 1965). A measure of the 'expected amount of information' or *entropy* conveyed by the observations, $x_1 ... x_N$ is $e = \sum p_i h(p_i)$.

A formulation of the function *h(.)* in terms of a parameter β is:

$$h(z) = \frac{1 - z^{\beta}}{\beta} \text{ if } \beta \neq 0 \text{ and } h(z) = -\log(z) \text{ if } \beta = 0 \qquad (4.7)$$

The family of information-theoretic measures is obtained by subtracting the actual entropy of the distribution of point shares across the *N* teams, $v_1 ... v_N$, from the maximum possible value of this entropy which obtains when every team gets an equal share of points ($v_i = 1/N, \forall i$). This family is derived from the definition of *h(.)* in equation (4.6) and is defined as:

$$\begin{aligned} H(\beta) &= \frac{1}{1+\beta}\left[\sum_{i=1}^{N} \frac{1}{N} h\left(\frac{1}{N}\right) - \sum_{i=1}^{N} v_i h(v_i)\right] \\ &= \frac{1}{\beta+\beta^2}\sum_{i=1}^{N} v_i \left[v_i^{\beta} - N^{-\beta}\right] = \frac{1}{\beta+\beta^2}\left(\sum_{i=1}^{N} v_i^{1+\beta} - N^{-\beta}\right) \end{aligned} \qquad (4.8)$$

The family of information-theoretic measures, $H(\beta)$ in equation (4.7), does not satisfy the principle of population homogeneity because of the presence of the term $N^{-\beta}$. However, dividing through by N^{β} ensures the property is satisfied.

Box 4.3 (continued)

The generalised entropy measure family of measures is defined by the parameter θ and written:

$$EI(\theta) = \frac{1}{N}\frac{1}{\theta^2-\theta}\left[\sum_{i=1}^{N}\left(\left[\frac{V_i}{\overline{\overline{V}}}\right]^{\theta}-1\right)\right]$$
$$= \frac{1}{\theta^2-\theta}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{V_i}{\overline{\overline{V}}}\right)^{\theta}-1\right], \text{ if } \theta \neq 0,1 \tag{4.9}$$

$$\text{Theil Index} = EI(1) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{V_i}{\overline{\overline{V}}}\right)\times\log\left(\frac{V_i}{\overline{\overline{V}}}\right) \tag{4.10}$$

$$MLD = EI(0) = \frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{V_i}{\overline{\overline{V}}}\right) \tag{4.11}$$

The EI measure in equation (4.8) can be derived from the information theoretic measure of equation (4.7) by setting $\theta = 1+\beta$ in equation (4.7) and normalising for the population principle by multiplying equation (4.7) by N^{β}.

4.5 T20 Franchise Teams in Australia, England, and India

The methodology set out in the previous sections was applied to measuring competitive balance in the following closed T20 leagues: the Indian Premier League, the Australian Big Bash and Women's Big Bash Leagues, and the English Women's Kia Super League (KSL) which ran for four seasons starting in 2016 and ending in 2019.[7]

The Indian Premier League

The IPL, which was established in 2008 by the Board of Cricket Control India (BCCI) has, so far, completed 13 consecutive annual tournaments with the 14th tournament, which began in April 2021, yet to be completed because of the second COVID wave in India. The tournament is usually played over six weeks during April and May in various locations in India, with the exceptions of the 2020 tournament which was played in September in the United Arab Emirates, because of COVID, and the

[7] The Kia Super League was replaced in 2020 by the 50-over Rachel Heyhoe Flint Trophy supplemented by the T20 Charlotte Edwards Cup. Both involve eight teams playing round-robin matches followed by knock-out matches.

2009 tournament which was played in South Africa because of the Indian General Election in that year.

The IPL usually involves eight teams — Chennai Super Kings, Delhi Capitals, Kolkata Knight Riders, Mumbai Indians, Punjab Kings, Rajasthan Royals, Royal Challengers Bangalore, Sunrisers Hyderabad — but, exceptionally, there were nine teams in 2013, the additional team being Pune Warriors India, and in 2011, there were 10 teams, the additional teams being Pune Warriors India and Kochi Tuskers Kerala. Sunrisers Hyderabad is a 2014 reincarnation of the earlier Hyderabad franchise, Deccan Chargers.

With eight teams, each team played 14 round-robin (that is, pre-qualifying) matches obtaining two points for a win, one for a tie or no-result, and nothing for a defeat. In 2013, each of the nine teams played 16 round-robin matches. In 2011, when there were 10 teams, it was felt that the 90 round-robin matches that the original format would entail, would be excessive. Thus, in order to retain the original number of 14 round-robin matches per team, the teams were divided into two groups of five (the allocation determined randomly) so that each team: (i) played the other four times in their group twice — home and away — resulting in eight games; (ii) played four teams in the other group once and the remaining team in the other group twice, resulting in six games. In total, therefore each of the 10 teams in 2011 played 14 games at the round-robin stage.

After the round-robin matches had been completed, the top four teams in the points table (a tie involving an equal number of points being resolved by the Net Run Rate) proceeded to the playoffs. In these playoffs, the third and fourth ranked teams played an *eliminator* match, with the loser eliminated from the tournament, while the first and second ranked teams played a *qualifying* match, with the winner proceeding to the final of the tournament. There was then another *qualifying* match between the winner of the eliminator and the loser of the first qualifier with the winner of this qualifier becoming the second finalist. The last match of the IPL, the finals, was between the winners of the first and second qualifiers and the winner of this match was declared the IPL champion for that year.

The Big Bash and Women's Big Bash Leagues

The Big Bash League for men was started in 2011 by Cricket Australia and featured eight city-based franchises: Sydney Sixers and Sydney Thunder; Melbourne Renegades and Melbourne Stars; Brisbane Heat; Adelaide Strikers; Perth Scorchers; and Hobart Hurricanes. The points structure was the same as that of the IPL: two points for a win, one for a tie or no-result, and nothing for a defeat. At its inception in 2011, each of the eight BBL teams played seven matches, with each team playing the others once; between 2012 and 2016 each team played eight matches — six of the other teams once and the remaining team twice. In 2017, each team played 10 matches; and from 2018, the BBL adopted the IPL format of each team playing the others twice, resulting in 14 matches for each team. After the round-robin matches were completed, there began a series of matches to determine the BBL champion. From 2019, this began with an *eliminator* match between the fourth and fifth teams in the points table ranking with the losing team eliminated from the competition. There then followed a *qualifier* match between the first and second teams in the table ranking with the winner proceeding to the final. Then, there was a *knockout* between the team that was third in the table ranking and the winner of the eliminator. After that, there was a *challenger* match between the loser of the qualifier and the winner of the knockout. Lastly, the final was contested between the winner of the qualifier and the winner of the knockout. So, the BBL had five post-robin matches compared to the IPL's four.

The Women's Big Bash League, which started in 2015, also under the aegis of Cricket Australia, was the successor to the Australian Women's Twenty20 Cup which ran from 2007 to 2014, and comprised the same franchise teams as the BBL. The matches are all played in various Australian venues from December till February and the teams comprise current and former players from the Australian national team supplemented by up to three overseas signings.[8]

From its inception, the WBBL adopted the IPL format of each team playing the other teams twice — home and away — for a total of 14 matches per team, with two points for a win, one for a tie or no-result, and nothing for a defeat. The WBBL schedule is intensive. Unlike the IPL which schedules only one game per day and two on Saturday and on Sunday, the WBBL features two games

[8] Except that, because of COVID restrictions, all the 2020 matches were played in Sydney.

Monday–Friday, and four matches played on Saturday and on Sunday. After the conclusion of the round robin matches, the top four teams in the table ranking play semi-finals followed by the final. This contrasts with the eliminator, qualifying, knockout, challenger format of the BBL described above.

The Kia Super League

The England and Wales Cricket Board's (ECB) T20 Kia Super League ran from 2016 to 2019, being replaced in 2021 by the ECB's Hundred competition and the T20 Charlotte Edwards Cup. The KSL comprised six teams with each team hosted or partnered by a county team or a university: Lancashire Thunder (hosted/partnered by Lancashire County Cricket Club); Loughborough Lightning (hosted/partnered by Loughborough University); Southern Vipers (hosted/partnered by Hampshire/Berkshire/Dorset/Isle of Wight/Oxfordshire/Sussex/Wiltshire Cricket Clubs and Solent University); Surrey Stars (hosted/partnered by Surrey County Cricket Club); Western Storm (hosted/partnered by Somerset/Gloucestershire County Cricket Clubs and Exeter University); Yorkshire Diamonds (hosted/partnered by Yorkshire Cricket Club).

Each of the teams played the other five teams once in 2016 and 2017 and twice in 2018 and 2019. During the round-robin matches, each team received two points for a win and an additional point if their run rate was 25% higher than that of their opponents. After the round-robin matches had been concluded there followed a 'finals day' in which the second and third placed teams in the league table played a semi-final, with the winner facing the first placed team in a final.

4.6 Competitive Balance in T20 Franchise Teams

This section puts empirical flesh on the framework for measuring CB in respect of the four closed leagues — IPL, BBL, WBBL, and KSL — described in the preceding analysis. The central themes of the chapter so far have been, firstly, that CB is synonymous with inequality such that the more inequitable the inter-team distribution of total points, the greater will be the imbalance in competition and, conversely, competition will be balanced when there is an equitable inter-team distribution of total points. In the results presented below, the overall CB in a league is measured using the Gini coefficient, described earlier.

The second theme of this chapter is that even if competition in unbalanced in the league considered in its entirety, it may still be the case that competition is balanced for groups of teams within the league. This hypothesis can be tested by examining the contributions of within-group and between-group to overall inequality. If the between-group contribution is high then this suggests that, even in the face of high overall inequality or lack of CB in the league, there could still be CB within groups of teams in the league. As discussed earlier, going down the path of decomposing inequality into within- and between-group components requires that inequality be measured using an entropy index, the specific form of which is determined by assigning a specific value to θ, the entropy parameter. In the analysis of this section, the value of θ is set to zero or, in other words, it is the MLD index of equation (4.3) that is used.

Table 4.1 provides the inequality analysis for the IPL, BBL, WBBL, and KSL. Examining the averages of the Gini values over the time periods that the leagues were functioning suggests that competition was most balanced (CB was highest) in the IPL with Gini=0.148 and least balanced (CB was lowest) in the KSL with Gini=0.245. In the Australian leagues, CB was higher in the WBBL than in the BBL with Gini coefficients of, respectively, 0.160 and 0.175. So, comparing the leagues with the highest and lowest CB — respectively, the IPL and the KSL — a Gini=0.148 for the IPL implies that the difference in points between two teams chosen at random will be 29.6% of the average number of points (that is, 4 points for an average of 14) while a Gini=0.245 for the KSL implies that the difference in points between two teams chosen at random will be 49% of the average number of points (that is, 7.4 points for an average of 15).[9] Comparing the men's and women's Australian leagues, a Gini=0.175 for the BBL implies that the difference in points between two teams chosen at random will be 35% of the average number of points (that is, 4 points for an average of 11) while Gini=0.160 for the WBBL implies that the difference in points between two teams chosen at random will be 32% of the average number of points (that is, 4.5 points for an average of 14).

<Table 4.1>

[9] Remembering that in the KSL additional points were awarded for a suitably high run rate.

Examining movements in CB over time, competition has become more balanced in the men's leagues — the IPL and the BBL — as the leagues have grown older. For the IPL, the Gini coefficient was 0.219 when it started in 2008 but the last three tournaments show Gini values of 0.111, 0.114, and 0.076 for, respectively, the years 2018, 2019, and 2020. By contrast, with the passage of time, competition has become more unbalanced in the women's leagues: the WBBL and the KSL. The WBBL began with Gini=0.107 when it started in 2015 but this value has climbed steadily since then, reaching a peak of Gini=0.212 in 2019 before falling to Gini=0.141 in 2020. The KSL began with Gini=0.289 when it started in 2016 and this had increased to Gini=0.299 by 2019 when the KSL was wound up.

The decomposition of inequality by subgroups was examined in the context of two groups: for the eight-team IPL, BBL, and WBBL, the first group comprised the four teams that finished highest, and the second group comprised the four teams that finished lowest in the round-robin points table; for the KSL, with six teams, the first and second groups comprised the three highest and three lowest ranked teams, respectively. Overall inequality in points earned by the teams in each of these leagues was measured by the MLD index (equation 4.3) and this could then be expressed as the sum of within-group and between-group inequality (respectively, terms *A* and *B* of equation (4.6)).

Table 4.1 shows that the average between-group contributions, expressed as a percentage of total inequality in points, was 51.2% for the IPL, 64.4% for the BBL, 48.8% for the WBBL, and 61.5% for the KSL.[10] Remembering that the between-group contribution is a measure of the capacity of the factor, or factors, used to divide the sample to explain overall inequality (Cowell and Jenkins, 1995), between half and two-thirds of inequality in the distribution of points in these four leagues could be explained by a division of the leagues' teams into 'top' and 'bottom' teams. Thus, between half and two-thirds of imbalance in competition in these four leagues could be attributed to imbalance *between* the groups of the 'top' and 'bottom' four teams — 'top' and 'bottom' three for the KSL — with the remainder attributed to imbalance in competition *within* these groups. Nor were these results

[10] In terms of equation (4.6), this is $\frac{B}{I}\times 100$

greatly changed when, instead of using the MLD index (that is, setting $\theta=0$), the Theil and Herfindahl indices were used (that is, setting $\theta=1$ and $\theta=2$, respectively).[11]

4.7 Competitive Balance by Source of Points

Competitive balance, in terms of the inter-team distribution of a league's total points, can also be examined in terms of the source of these points in respect of: (i) home matches; (ii) away matches. One may, therefore, ask how much of the overall inequality in the distribution of points between the league's teams stems from inequality in the distribution of points from home venue, neutral venue, and opposition venue games. This is analogous to identifying the sources of income (wages, dividends, benefits etc.) and enquiring about the proportions of overall income inequality that could be explained by inequality in the distribution of its different components.

Shorrocks (1982) showed that the proportionate contribution s^j of income component j to overall inequality was given by: $s^j = \frac{\text{covariance}(\mathbf{y}^j, \mathbf{y})}{\text{variance}(\mathbf{y})}$, where: and were, respectively, the vector of values of income component j (say, wages) and total income across the N income earners and $\sum s^j = 1$. The decomposition rule embodied in the above equation is unique and invariant in that it 'avoided one of the major problems encountered in applied work on distributions: that of having constantly to qualify results by stating that they hold only for the particular index selected' (Shorrocks, 1982, p. 205).

The following steps are required to implement Shorrocks' (1982) methodology in respect of points earned from home and away matches:

1. Compute the covariance between the number of points earned by the league's teams from home/away matches and their total number of points. Represent these as *cov(home points, total points)* and *cov(away points, total points)*.
2. Compute the variance of the total points of the teams and represent this as *var(total points)*

[11] The use of $\theta=2$ implies that the competitive imbalance (inequality) was measured using the coefficient of variation. The coefficient of variation embodies the property of being *transfer neutral*: three points transferred from the top team to the team ranked second would improve competitive balance (reduce inequality) by as much as a transfer of three points from the second-lowest ranked team to the lowest ranked team.

3. Then the percentage contributions of inter-team inequality in home and in away points, to inter-team inequality in total points, are computed as:

$$s^{\text{home}} = \frac{\text{cov(home points, total points)}}{\text{var(total points)}} \text{ and } s^{\text{away}} = \frac{\text{cov(away points, total points)}}{\text{var(total points)}}$$

The contributions s^{home} and s^{away} were computed for two leagues: the IPL and the Caribbean Premier League (CPL). It was not possible to compute the home/away contributions for the BBL, the WBBL, and the Kia Super League because matches in most of these leagues were played at neutral venues, that is, they were 'away' matches. For example, of the roughly 82 matches played in the WBBL from its inception in 2015 until 2021, almost all were away matches played at neutral venues. Similarly, of the 30 matches played in the KSL between its inception in 2016 and its termination in 2019, nearly 23 were played as away matches at neutral venues. It was only the IPL and the CPL that had a significant demarcation between home and away (that is, played at the opposition's venue) matches.

The CPL is a T20 cricket competition founded by Cricket West Indies (CWI) in 2013. It comprises six teams — Barbados Tridents, Guyana Amazon Warriors, Jamaican Tallawahs, St. Kitts and Nevis Patriots, St. Lucia Zouks, Trinbago Knight Riders — and while most of the CPL venues are in the Caribbean, one of the venues is in Florida. Each of the teams has a well-defined 'home ground — for example, Kensington Oval, Sabina Park, and Queen's Park Oval are the home grounds of, respectively, the Barbados Tridents, the Jamaican Tallawahs, and the Trinbago Knight Riders — and there is a clear distinction between home and away matches.

Applying Shorrocks' (1982) analysis to the contribution of inter-team inequality in home and away wins to overall inequality in inter-team wins showed that, for the CPL, the distribution of home wins contributed 31%, and the distribution of away wins contributed 69%, to overall inequality in wins. For the IPL, the contributions of home and away wins were much more muted: the distribution of home wins contributed 49%, and the distribution of away wins contributed 51%, to overall inequality in wins.

4.8 Conclusions

This chapter examined the issue of how competitive balance should be measured against the backdrop of four T20 cricket leagues — the IPL, the BBL, the WBBL, and the KSL — where the first two leagues pertained to men's, and the last two to women's, cricket. The argument of this chapter was that the insights provided by the methods of inequality analysis — in this case, those of generalised entropy — deepened our understanding of competitive balance and provided valuable insights into the implications of a lack of balance.

It was found that when the teams comprising the four leagues were divided by their round-robin points into the top and bottom halves of the league, half to two-thirds of the leagues' competitive imbalance could be attributed to between-group imbalance. This confirms the conjecture that, in its present form, the various T20 leagues are segmented into several (effectively) non-competing groups: the group of top teams who aspire to proceed to the qualifying stages with the aim of winning the league championship, and the group of the bottom teams whose aim, at least for the current year, is simply to be part of the league. The competitive aspects of the league take place *within* groups of teams and competitive imbalance results from disparities in personnel and resources between the teams. When within-group competition is high then, despite the lack of competition between teams in the different groups, a sporting league may still be successful.

The use of entropy methods to analyse competitive balance raises the question of what is the effective number of teams in a league? In essence, calculating the effective number of teams in a league is analogous to calculating the effective number of parties in an electoral system: it involves assigning a scalar value to the inter-team distribution of points.[12] At one extreme, with perfect equality and with all the teams getting an equal number of points, the effective number of teams is the actual number of teams in the league. As equality diminishes (equivalently, inequality increases), the effective number of teams falls. Consequently, when points are distributed unequally between the teams, the effective number of teams will be less than the actual number of teams. League success does not require effective competition between *all* the teams in the league. However, should a league seek to move towards more balanced competition between *all* its teams, an analysis of the effective number of teams suggests that a possible solution might be a reduction in the number of teams in the league.

[12] The concept of the effective number of parties is used in the analysis of electoral systems where votes are unequally distributed between parties: see Laasko and Taagepera (1979) and Borooah (2013).

Table 4.1: Inequality Analysis for T20 Cricket Franchise Teams

	Indian Premier League (IPL)+		**Big Bash League (BBL)+**		**Women's Big Bash League (WBBL)+**		**Kia Super League++**	
	Gini	Between Group Inequality* (%)	Gini	Between Group Inequality* (%)	Gini	Between Group Inequality* (%)	Gini	Between Group Inequality* (%)
2020	0.076	59.5	0.106	49.2	0.141	56.2		
2019	0.114	67.9	0.165	49.5	0.212	52.1	0.299	32.0
2018	0.111	79.6	0.127	54.3	0.194	45.3	0.204	65.0
2017	0.176	63.2	0.200	63.2	0.196	44.6	0.188	72.5
2016	0.121	53.1	0.117	73.9	0.112	52.2	0.289	76.3
2015	0.129	35.3	0.203	74.7	0.107	42.2		
2014	0.205	43.2	0.203	86.1				
2013	0.194	46.1	0.285	58.0				
2012	0.134	15.5	0.134	49.9				
2011	0.142	72.9	0.205	86.7				
2010	0.116	36.9						
2009	0.145	48.6						
2008	0.219	44.2						
Average	*0.148*	*51.2*	*0.175*	*64.4*	*0.160*	*48.8*	*0.245*	*61.5*

+ The standard format for the IPL, BBL, and WBBL is eight teams, each playing 14 matches. In IPL 2013 and IPL 2011, however, there were, respectively, nine and 10 teams. In 2011, each BBL team played seven matches; between 2012 and 2016, each BBL team played eight matches; in 2017, each BBL team played 10 matches; and, from 2018, each BBL team played 14 matches. The eight WBBL teams have always played 14 matches each.
++ The KSL had six teams with each team playing five matches in 2016 and 2017 and 10 matches in 2018 and 2919.
*Percentage of total inequality (as measured by the Mean Logarithmic Deviation (MLD) index) that could be explained by inequality *between* the two groups of the top and the bottom four teams. For IPL 2013, the groups were the top four and bottom five teams and, for IPL 2011, the groups were the top and bottom five teams.
Source: Own calculations using Stephen Jenkins' **ineqdeco** command in Stata.

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