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Scoreboard pressure and batting performance in T20 cricket: A state-dependent DCCA approach

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Abstract

This study investigates the dynamic relationship between scoreboard pressure and batting outcomes in Indian Premier League (IPL) run chases using Detrended Fluctuation Analysis (DFA) and Detrended Cross-Correlation Analysis (DCCA). Required run rate (RRR) is used as a measure of scoreboard pressure, while runs scored and wicket occurrence represent dimensions of batting response. We first examine long-range dependence and scale-dependent cross-correlations at the franchise level. The analysis is then extended by estimating DCCA coefficients within consecutive blocks defined by match conditions, characterized by innings phase, RRR, and wickets remaining. Regression, bootstrap, spline, and segmented-regression methods are subsequently used to examine how the resulting pressure wicket dependence varies with the state of the chase. The results show that the DCCA relationship between RRR and wicket occurrence is not static. Specifically, the initial negative pressure wicket association tends to weaken as RRR increases, with the RRR effect remaining stable under bootstrap resampling. Nonlinear analysis provides some evidence of further reduction at very high required run rates, although the estimated breakpoint is subject to substantial uncertainty. Overall, the findings demonstrate that combining DCCA with match-state information provides a useful framework for characterizing evolving dependence structures in event-level sports data.

Keywords Detrended Cross-Correlation Analysis, Detrended Fluctuation Analysis, Indian Premier League, Required Run Rate, Sports Analytics, T20 Cricket

1. Introduction

Understanding how athletes and teams respond to increasing competitive pressure is an important problem in sports analytics. Pressure need not produce a one-sided improvement in performance. Experimental evidence shows that sufficiently large stakes can impair performance (Ariely et al., 2009), while field studies in professional sport document performance deterioration in high-pressure situations (Dohmen, 2008; Cao et al., 2011; Böheim et al., 2019). At the same time, the sports psychology literature suggests that “choking under pressure” may arise due to several reasons, including changes in attention and concerns about self-presentation (Mesagno and Beckmann, 2017). Related work on professional volleyball shows that pressure may also produce relatively subtle performance declines even when severe choking is not observed (Bozhinov and Grote, 2019). These findings motivate the study of performance as a dynamically changing response to the competitive environment rather than as a fixed characteristic of an athlete or team.

Professional sport provides a particularly useful setting for studying such relationships because it generates repeated high stakes decisions in environments where actions, outcomes, and the prevailing state of play can often be observed directly. Penalty-kick data have been used to test strategic behavior among professional athletes (Huerta, 2003) and to examine whether professionals choke when the importance of success or social pressure increases

(Dohmen, 2008). More recent work on penalty shootouts has considered how cognitive biases and the ordering of attempts may influence performance under pressure (Da Silva and Matsushita, 2024). In basketball, Cao et al. (2011) show that free-throw performance declines as game situations become more pressurized, particularly when the score margin is small and little time remains. Such studies show the value of event level sporting data for investigating how performance changes with the evolving state of competition.

T20 cricket provides an especially attractive setting for such an analysis. During the second innings, the batting side faces a known target while its available resources decline continuously in terms of both deliveries and wickets. Statistical research on cricket has long recognized the importance of jointly accounting for runs, overs, and wickets. For example, resource based approaches to interrupted matches explicitly model the changing value of overs and wickets, and adaptations of the Duckworth–Lewis framework to T20 cricket demonstrate that the scoring and resource structure of the shorter format differs from that of one-day cricket (Bhattacharya et al., 2011). There has been a growing quantitative research on competitive balance and performance across formats in cricket (Mondal et al., 2023).

More directly relevant to the present study, Mallawa Arachchi et al. (2024) propose a pressure index specifically for the team batting second in T20 cricket. Their framework quantifies pressure at each stage of a chase using RRR together with the resources remaining and constructs an index that can be compared both within and across matches. This work provides important evidence that scoreboard pressure in a T20 chase can be represented quantitatively using the evolving target requirement and batting resources. The objective of the present study is different. Rather than constructing a scalar measure of pressure itself, we take RRR as an observable measure of scoreboard demand and investigate how the dependence structure between this pressure variable and batting outcomes evolves during the chase.

In a run chase, RRR changes after almost every delivery and therefore provides a natural observable representation of the mathematical demand imposed by the scoreboard. Its implications however depend strongly on the accompanying match state. An RRR of eight with nine wickets remaining early in an innings portrays a very different competitive environment from an RRR of eight with only two wickets remaining near the end. Thus, the relationship between scoreboard pressure, runs scored, and wicket occurrence is inherently sequential and state-dependent. The resulting series may also exhibit trends, nonstationarity, and dependence across multiple time scales. Conventional correlation coefficients that summarize association globally may therefore provide an incomplete description of these dynamics.

DFA, introduced by Peng et al. (1994), provides a framework for detecting scaling behavior and long-range correlations in nonstationary time series. Subsequent methodological work has emphasized its usefulness for distinguishing long-range temporal dependence from local trends (Hardstone et al., 2012). Building on DFA, Podobnik and Stanley (2008) introduced DCCA to identify power-law cross-correlations between two simultaneously observed nonstationary series. Zebende (2011) subsequently proposed the DCCA cross-correlation coefficient, ρ_{DCCA} , which provides a bounded and scale-dependent measure of the strength and direction of detrended cross-correlation. These methods are therefore well suited to sequential sporting processes where dependence may operate across different temporal scales.

An important development in the DCCA literature is the recognition that cross-correlation need not remain constant throughout a series. For example, Marinho et al. (2013) examine local correlation using DCCA-based measures. More explicitly, Guedes and Zebende (2019) introduce a sliding-window implementation of ρ_{DCCA} that measures cross-correlation as a function of both time and scale. The idea has subsequently been extended to multiple nonstationary series using a detrended multiple cross-correlation coefficient with sliding windows (Guedes et al., 2021). Thus, the existing methodological literature already allows cross-correlation structures to evolve locally over time.

The present study builds on this literature but adopts a different basis. Rather than defining local dependence solely through a mechanically moving chronological window, we condition DCCA estimation on cricket relevant match states. Two temporally adjacent segments of a run chase may represent very different competitive environments if their required run rates or remaining batting resources differ substantially. Conversely, observations from different matches may represent comparable states when the same combinations of scoreboard demand and resources are present. Defining the blocks in terms of match conditions therefore allows the analysis to reflect the actual situation of the chase.

Motivated by this, we develop a DCCA-based framework for examining pressure performance dependence in Indian Premier League (IPL) run chases. RRR is used as an observable measure of scoreboard pressure, while runs scored

and wicket occurrence represent two distinct dimensions of batting response. We first employ DFA to characterize temporal persistence in franchise level ball-by-ball scoring and then use DCCA to quantify the scale-dependent relationship between RRR and batting outcomes. This provides an initial aggregate characterization of pressure performance dependence across franchises.

The analysis is subsequently extended by estimating DCCA coefficients within consecutive blocks characterized by the prevailing match state. These states incorporate innings phase, RRR, and wickets remaining, thereby conditioning the dependence calculation jointly on scoreboard pressure and available batting resources. The resulting local DCCA coefficients are then treated as quantities of interest in their own right. Linear and interaction models are used to examine whether the pressure–wicket dependence varies systematically with match conditions, while bootstrap and spline methods are used to assess stability and nonlinearity. Finally, segmented regression is employed to investigate whether the relationship exhibits a possible change in slope. This final step is conceptually related to the wider structural change literature, in which unknown changes in regression relationships are identified from the data (Bai and Perron, 1998).

The empirical results indicate that the pressure–wicket dependence structure is not static. In particular, the initial negative DCCA association between RRR and wicket occurrence tends to weaken as RRR increases, and the RRR effect remains comparatively stable under bootstrap resampling. Nonlinear specifications further suggest that the relationship may flatten under very high RRRs. A segmented specification identifies a candidate transition near an RRR of 20.31. However, substantial uncertainty surrounding this estimate means that it should not be interpreted as a universal threshold. The stronger empirical conclusion is that the cross-correlation structure itself changes with the state and severity of the chase.

The contribution of this study is threefold. First, we provide a multiscale characterization of scoreboard pressure and batting outcomes in T20 cricket using DFA and DCCA. Second, while previous cricket research has constructed scalar pressure indices based on RRR and remaining resources (Mallawa Arachchi et al., 2024), and previous DCCA research has allowed cross-correlation to vary through moving windows (Guedes and Zebende, 2019), we combine these two perspectives by estimating dependence within cricket-specific states defined by scoreboard pressure, innings phase, and batting resources. Third, we model the resulting local DCCA coefficients to investigate whether the dependence structure itself changes systematically as scoreboard pressure increases. The analysis therefore shifts attention from measuring the level of pressure to characterizing the evolving statistical relationship between pressure and performance.

Importantly, RRR is interpreted throughout as scoreboard pressure rather than as a direct measure of psychological pressure. The broader literature documents choking and other behavioral responses to high stakes situations (Dohmen, 2008; Ariely et al., 2009; Cao et al., 2011; Mesagno and Beckmann, 2017; Da Silva and Matsushita, 2024), but the present analysis identifies statistical dependence in observed match outcomes and does not establish the psychological mechanism producing that dependence.

The remainder of the paper is organized as follows. Section 2 describes the IPL data and construction of the ball-by-ball variables with a preliminary DFA analysis. Section 3 presents the DCCA methodology and the initial franchise-level analysis. Section 4 develops the match-state-controlled DCCA framework. Section 5 investigates nonlinearities and potential threshold behavior. Section 6 discusses the main findings, followed by the limitations and future directions (Section 7), and the concluding remarks (Section 8).

2. Data and preliminary DFA analysis

This section describes the construction of the ball-by-ball time series used in the empirical analysis and provides a preliminary examination of temporal persistence in team scoring patterns using DFA. The purpose of the DFA analysis is to establish whether the scoring sequences exhibit non-random temporal dependence before examining their relationship with dynamically evolving scoreboard pressure through DCCA.

2.1. Data and sample construction

The empirical analysis uses historical ball-by-ball data from the IPL, covering matches played between April 2008 and May 2024. The dataset is publicly available through Kaggle and be accessed at Patrick (2024). The data consist of two complementary files. The match-level dataset contains information on 1,095 IPL matches, including the season, match date, participating teams, match winner, target score, and target overs. The delivery-level dataset contains

2, 60, 920 ball-by-ball observations and records, among other variables such as the batting and bowling teams, innings number, over and ball number, runs scored, extras, and wicket occurrences.

The two datasets are linked through a unique match identifier. Within each match and innings, deliveries are retained in their observed order, while match dates are used to arrange matches chronologically across IPL seasons. This preserves the temporal ordering required for the subsequent fluctuation and cross-correlation analyses.

Several IPL franchises underwent name changes during the sample period. To maintain a consistent franchise-level interpretation, historical names corresponding to the same franchise were harmonized prior to the analysis. Specifically, Delhi Daredevils and Delhi Capitals were treated as Delhi Capitals; Kings XI Punjab and Punjab Kings as Punjab Kings; Royal Challengers Bangalore and Royal Challengers Bengaluru as Royal Challengers Bangalore; and Rising Pune Supergiants and Rising Pune Supergiant as Rising Pune Supergiant. Franchises representing distinct organizations, such as Deccan Chargers and Sunrisers Hyderabad, were retained separately. Following this harmonization, the sample contains 15 distinct IPL franchises.

For franchise i , define $X_{i,t}$, $t = 1, \dots, N_i$ as the total number of runs recorded on the t^{th} chronological delivery faced by franchise i , and N_i denotes the total number of deliveries available for that franchise. Hence $\{X_{i,1}, X_{i,2}, \dots, X_{i,N_i}\}$ represents the chronological ball-by-ball scoring history of franchise i over the sample period.

For the subsequent analysis of scoreboard pressure, attention is placed on second-innings run chases. Let T_m denote the target in match m , $C_{m,t}$ the cumulative score immediately prior to delivery t , and $B_{m,t}$ the number of legal deliveries remaining immediately before that delivery. The number of runs required is

$$D_{m,t} = T_m - C_{m,t},$$

and the corresponding RRR is

$$RRR_{m,t} = \frac{6D_{m,t}}{B_{m,t}}, \quad B_{m,t} > 0. \quad (1)$$

The Current Run Rate (CRR) at the same point is obtained from the runs already scored and the number of legal deliveries completed. Together, CRR and RRR provide a simple representation of the evolving relationship between the batting team's realized scoring rate and the rate required to successfully complete the chase.

Figure 1 illustrates this behaviour using two representative IPL run chases with very similar targets but contrasting outcomes. The figure tracks the evolution of the CRRs and RRRs through the innings, while wicket events are marked as stars. The comparison demonstrates how scoreboard pressure can evolve substantially within a chase even when the initial target is similar. It also motivates treating RRR as a dynamically changing match-state variable rather than as a fixed characteristic of an inning.

2.2. The DFA

Before examining the relationship between scoring behavior and dynamically changing scoreboard pressure, we first investigate whether franchise level ball-by-ball scoring sequences themselves exhibit temporal persistence. DFA is used for this purpose because it characterizes scaling behavior while removing local trends from potentially nonstationary time series.

For a scoring sequence $\{X_t\}_{t=1}^N$, let

$$\bar{X} = \frac{1}{N} \sum_{t=1}^N X_t$$

denote its sample mean. The corresponding integrated profile is constructed as

$$Y(k) = \sum_{t=1}^k (X_t - \bar{X}), \quad k = 1, \dots, N. \quad (2)$$

The integrated profile is divided into non-overlapping windows of length n . Logarithmically spaced window sizes ranging from 10 deliveries to approximately $N/10$ are considered. Within each window ν , a linear trend $\hat{Y}_\nu(k)$ is fitted and subsequently removed.

The detrended variance within the ν^{th} window is

$$F_\nu^2(n) = \frac{1}{n} \sum_{k=1}^n \left[Y_\nu(k) - \hat{Y}_\nu(k) \right]^2.$$

Averaging across the N_n available windows gives the fluctuation function

$$F(n) = \left[\frac{1}{N_n} \sum_{\nu=1}^{N_n} F_\nu^2(n) \right]^{1/2}, \quad (3)$$

where N_n denotes the number of windows of length n .

For a process exhibiting scaling behavior, the fluctuation function follows

$$F(n) \propto n^H, \quad (4)$$

or, equivalently

$$\log F(n) = c + H \log n,$$

where H denotes the DFA scaling exponent, which is estimated as the slope of the linear relationship between $\log F(n)$ and $\log n$. Conventionally

$$\begin{cases} H < 0.5, & \text{anti-persistent behavior,} \\ H \approx 0.5, & \text{approximately uncorrelated behavior,} \\ H > 0.5, & \text{persistent behavior.} \end{cases} \quad (5)$$

Thus, an estimated value above 0.5 provides evidence that ball-by-ball scoring fluctuations possess temporal persistence over the scales under consideration.

2.3. Preliminary evidence of persistence

DFA was applied separately to the chronological scoring sequence of each of the 15 harmonized IPL franchises. Table 1 presents the resulting scaling exponents together with the corresponding number of deliveries.

The estimated scaling exponent exceeds 0.5 for every franchise, with values ranging from 0.5291 for Kochi Tuskers Kerala to 0.6055 for Royal Challengers Bangalore. Thus, evidence of persistence is observed throughout the IPL sample rather than being restricted to a small number of long-established franchises. At the same time, the estimated exponents are generally relatively close to 0.5, suggesting that the observed persistence is mild rather than particularly strong.

Figure 2 provides a graphical comparison of the estimated scaling exponents for all franchises. The dashed vertical line at $H = 0.5$ represents the benchmark associated with an approximately uncorrelated process. All estimated values lie to the right of this benchmark. The visualization also highlights cross-franchise heterogeneity: Royal Challengers Bangalore, Lucknow Super Giants, Gujarat Titans, and Sunrisers Hyderabad exhibit comparatively larger estimated scaling exponents, whereas Kochi Tuskers Kerala, Pune Warriors, and Rising Pune Supergiant lie considerably closer to the uncorrelated benchmark. The latter estimates should be interpreted with additional caution because these short-lived franchises contribute substantially fewer observations.

Robustness to innings boundaries:

The franchise-level DFA construction combines chronologically ordered deliveries across matches in order to obtain sufficiently long series for estimating scaling behavior. Such concatenation may create artificial adjacency between the final delivery faced by a franchise in one inning and the first delivery faced in its subsequent innings. To assess whether the observed persistence is driven by these artificial boundaries, DFA was recomputed using only fluctuation windows contained entirely within individual innings.

Using window sizes up to 60 deliveries, the resulting DFA exponents for the four longest-running franchises were 0.5609 for Mumbai Indians, 0.5490 for Kolkata Knight Riders, 0.5532 for Chennai Super Kings, and 0.5621 for Royal Challengers Bangalore. Although somewhat smaller than the corresponding estimates from the fully concatenated

series, each remains above 0.5. As an additional benchmark, randomly permuting the ball-by-ball scoring sequences resulted in DFA exponents close to 0.5. These checks suggest that the observed persistence is not solely an artifact of concatenating scoring sequences across innings.

Figure 3 provides a closer view of the scaling relationships for the four franchises with the longest histories. The fluctuation function is plotted against window size on logarithmic scales, together with the corresponding fitted linear relationships. The approximately linear log–log patterns provide visual support for the power-law representation in (4). The slopes are consistently positive and correspond to the estimated DFA exponents reported above. Importantly, the similarity in the overall scaling pattern across franchises suggests that the evidence of persistence is not being driven by a single team.

Taken together, Table 1 and Figures 2–3 provide evidence of mild but systematic temporal persistence in IPL ball-by-ball scoring sequences. The purpose of this preliminary analysis is not to rank franchises according to persistence, but to establish that the scoring process contains temporal structure warranting further investigation.

DFA is a univariate procedure, which quantifies the dependence structure within the scoring process itself but does not reveal whether this structure is related to changes in the prevailing match environment. Figure 1, illustrates that the constraints faced by a chasing team evolve continually throughout an innings. This motivates the transition to DCCA, through which the next section examines the relationship between ball-by-ball performance and dynamically changing scoreboard pressure.

3. The DCCA

The DFA results in Section 2 provide evidence of mild temporal persistence in franchise-level ball-by-ball scoring sequences. As stated before, DFA is inherently univariate and therefore cannot determine whether fluctuations in scoring behavior are systematically associated with the evolving constraints of a run chase. To examine this relationship, we use DCCA, which quantifies cross-dependence between two potentially nonstationary series after removing local trends.

3.1. Construction of the pressure–performance series

The DCCA analysis focuses on second-innings run chases, for which the target score is known. For each delivery t in match m , the prevailing match state is represented by $C_{m,t}, B_{m,t}, D_{m,t}, RRR_{m,t}$ as defined in Section 2.1. Because these variables are constructed immediately prior to delivery t , the measure of scoreboard pressure does not incorporate information generated by the current delivery itself.

Wide deliveries and no-balls are excluded when counting legal deliveries, while their contribution to the score is retained where appropriate.

For each delivery, let $R_{m,t}$ denote the total number of runs scored on that delivery. Wicket occurrence is represented by the binary variable

$$W_{m,t} = \begin{cases} 1, & \text{if a wicket is recorded on delivery } t, \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

The empirical analysis therefore considers two pressure–performance systems, $(RRR_{m,t}, R_{m,t})$ and $(RRR_{m,t}, W_{m,t})$. The first captures the relationship between scoreboard pressure and realized scoring, while the second captures the relationship between scoreboard pressure and wicket occurrence.

3.2. DCCA methodology

Consider two time series of equal lengths, $\{x_t\}_{t=1}^N$ and $\{y_t\}_{t=1}^N$. Let $\bar{x}$ and $\bar{y}$ denote their respective sample means. The corresponding integrated profiles are

$$X(k) = \sum_{t=1}^k (x_t - \bar{x}), \quad k = 1, \dots, N, \quad (7)$$

and

$$Y(k) = \sum_{t=1}^k (y_t - \bar{y}), \quad k = 1, \dots, N. \quad (8)$$

For a selected scale n , the integrated profiles are divided into windows of length n . Within each window ν , first-order polynomial trends are fitted separately to the two integrated profiles. Denote these local trends by $\hat{X}_\nu(k)$ and $\hat{Y}_\nu(k)$.

The detrended covariance within the ν^{th} window is

$$f_{DCCA}^2(\nu, n) = \frac{1}{n} \sum_{k=1}^n \left[X_\nu(k) - \hat{X}_\nu(k) \right] \left[Y_\nu(k) - \hat{Y}_\nu(k) \right]. \quad (9)$$

Averaging across the N_n available windows gives

$$F_{DCCA}^2(n) = \frac{1}{N_n} \sum_{\nu=1}^{N_n} f_{DCCA}^2(\nu, n). \quad (10)$$

The corresponding detrended variances of the two series are

$$F_{DFA,x}^2(n) = \frac{1}{N_n} \sum_{\nu=1}^{N_n} \frac{1}{n} \sum_{k=1}^n \left[X_\nu(k) - \hat{X}_\nu(k) \right]^2, \quad (11)$$

and

$$F_{DFA,y}^2(n) = \frac{1}{N_n} \sum_{\nu=1}^{N_n} \frac{1}{n} \sum_{k=1}^n \left[Y_\nu(k) - \hat{Y}_\nu(k) \right]^2. \quad (12)$$

This procedure removes local trends before evaluating covariance, thereby allowing cross-dependence to be examined without attributing common local trends directly to cross-correlation.

3.3. The DCCA cross-correlation coefficient

The magnitude and direction of detrended cross-correlation at scale n are quantified using the DCCA cross-correlation coefficient

$$\rho_{DCCA}(n) = \frac{F_{DCCA}^2(n)}{F_{DFA,x}(n)F_{DFA,y}(n)}. \quad (13)$$

The coefficient satisfies

$$-1 \leq \rho_{DCCA}(n) \leq 1.$$

Accordingly,

$$\begin{cases} \rho_{DCCA}(n) > 0, & \text{positive detrended cross-correlation,} \\ \rho_{DCCA}(n) \approx 0, & \text{weak or absent detrended cross-correlation,} \\ \rho_{DCCA}(n) < 0, & \text{negative detrended cross-correlation.} \end{cases}$$

It is important to distinguish this coefficient from the DCCA scaling exponent. If the detrended cross-covariance exhibits power-law scaling,

$$F_{DCCA}(n) \propto n^\lambda,$$

then λ characterizes the scaling behavior of the cross-covariance. It does not directly measure the magnitude or direction of the cross-correlation. Since the objective of the present study is to quantify the direction and strength of the relationship between scoreboard pressure and batting outcomes, the analysis focuses on $\rho_{DCCA}(n)$.

3.4. Choice of DCCA scale

Since $\rho_{DCCA}(n)$ is scale dependent, the scale must be specified before interpreting the pressure–performance relationship. In the primary analysis, we set $n = 30$ corresponding to approximately five overs of legal deliveries. This provides a natural medium-horizon representation of a T20 run chase: the window is sufficiently long to capture sustained changes in scoring behavior while remaining short enough to reflect evolving within-innings scoreboard conditions.

For franchise i , we therefore define

$$\rho_{\text{runs},i}(30) = \rho_{DCCA,i}(RRR, \text{Runs}; n = 30), \quad (14)$$

and

$$\rho_{\text{wickets},i}(30) = \rho_{DCCA,i}(RRR, \text{Wickets}; n = 30). \quad (15)$$

The first coefficient measures the detrended association between scoreboard pressure and realized scoring over approximately a five-over horizon. A positive value indicates that higher RRR tends to coincide locally with higher scoring after detrending, whereas a negative value indicates an inverse association.

The second coefficient measures the corresponding association between scoreboard pressure and wicket occurrence. Both coefficients are interpreted as measures of statistical dependence and not as evidence of a causal response to changes in RRR.

3.5. An exploratory composure index

To summarize the two dimensions of pressure response, the initial analysis combines the scoring and wicket coefficients through an exploratory Composure Index

$$C_i(30) = \rho_{\text{runs},i}(30) - \rho_{\text{wickets},i}(30). \quad (16)$$

The construction treats the run-scoring component as the favorable dimension and the wicket component as an offsetting dimension. A relatively larger value of $C_i(30)$ therefore represents a more favorable joint pressure–performance profile, while a smaller value represents a less favorable profile.

The index is deliberately interpreted in a comparative rather than psychological sense. In particular, terms such as “composure” are used as convenient labels for the statistical construction and should not be interpreted as direct measurements of player psychology.

3.6. Initial franchise-level results

The initial franchise-level DCCA analysis was conducted for Chennai Super Kings, Royal Challengers Bangalore, Kolkata Knight Riders, and Mumbai Indians. For each franchise, the DCCA procedure was applied separately to the RRR–runs and RRR–wickets pairs. The resulting coefficients were then combined according to (16) to obtain the exploratory Composure Index, $C_i(30)$. Table 2 reports the resulting index values for the four franchises.

All four franchises exhibit negative values of the exploratory index, although substantial cross-franchise heterogeneity is evident. Chennai Super Kings record the value closest to zero (-0.046), followed by Royal Challengers Bangalore (-0.217), Kolkata Knight Riders (-0.222), and Mumbai Indians (-0.273). Thus, within this initial comparison, Chennai Super Kings exhibits the largest value of the joint pressure–performance measure, whereas Mumbai Indians exhibits the smallest.

Figure 4 provides a graphical representation of these differences. The separation of Chennai Super Kings from the remaining franchises is particularly noticeable, whereas Royal Challengers Bangalore and Kolkata Knight Riders have very similar index values. Mumbai Indians records the most negative value among the four. The graphical comparison therefore reinforces the heterogeneity observed in Table 2.

The observed differences provide preliminary evidence that the joint association between scoreboard pressure, scoring, and wicket occurrence may vary across franchises. These estimates should, however, not be interpreted as fixed or intrinsic characteristics of the teams. Each franchise-level coefficient aggregates deliveries observed under widely different match conditions, including different stages of the innings, RRRs, and levels of remaining batting resources.

Moreover, the construction of $C_i(30)$ assigns an equal contribution to the scoring and wicket components. This assumption is restrictive because the consequence of a wicket need not remain constant throughout a run chase. For example, a wicket lost early in an inning with substantial batting resources remaining may have a very different implication from a wicket lost late in the innings under a high RRR.

The initial DCCA results should therefore be viewed as an exploratory benchmark. They establish that the pressure–performance relationship exhibits meaningful cross-franchise variation, while simultaneously highlighting the limitations of representing this relationship through a single static franchise-level quantity. These limitations motivate the state-dependent analysis developed in the subsequent section.

3.7. Limitations of the aggregate DCCA measure

Although the franchise-level index provides a convenient exploratory summary, it imposes two restrictive assumptions. First, (16) assigns an equal and constant contribution to the scoring and wicket components. There is no a priori reason why a unit change in the wicket-related DCCA coefficient should offset a unit change in the run-related coefficient.

Second, the aggregate analysis assumes that the pressure–performance relationship can be summarized meaningfully across heterogeneous match situations. The consequence of losing a wicket is unlikely to remain constant throughout a T20 chase. A wicket lost early in an inning with substantial batting resources remaining may have a very different implication from a wicket lost during the death overs when the RRR is high and few wickets remain.

More generally, the relationship between scoreboard pressure and batting outcomes may depend jointly on the current RRR, the phase of the innings, and the number of wickets remaining. Aggregating across these states can conceal such heterogeneity and potentially produce a franchise-level coefficient that does not accurately characterize any specific match situation.

The franchise-level DCCA analysis is therefore treated as an exploratory starting point rather than the final characterization of pressure response. The subsequent analysis relaxes the assumption of a static aggregate relationship and investigates whether the DCCA structure changes systematically with the prevailing state of the run chase.

4. State-dependent DCCA framework

The aggregate analysis in Section 3 provides evidence that the relationship between scoreboard pressure and batting outcomes differs across franchises. However, the construction of the Composure Index in (16) implicitly treats the contribution of wicket loss as constant across all match situations. This is a restrictive assumption in a T20 run chase, where the consequence of losing a wicket may depend strongly on the prevailing RRR, the stage of the innings, and the batting resources remaining.

This section therefore develops a state-dependent extension of the DCCA framework. Rather than treating the pressure–performance relationship as a fixed franchise characteristic, the proposed approach estimates it within locally homogeneous match states. This allows the association between scoreboard pressure and wicket occurrence to vary with the evolving geometry of the run chase.

4.1. From a static to a weighted composure measure

A natural generalization of the exploratory index in (16) is obtained by introducing a wicket-penalty parameter α . For franchise i , define

$$C_i(\alpha) = \rho_{\text{runs},i} - \alpha \rho_{\text{wickets},i}, \quad (17)$$

where $\alpha > 0$ represents the relative importance assigned to the wicket-related component. The original index corresponds to the special case $\alpha = 1$.

(17) makes an explicit assumption which was absent in the original construction. In particular, fixing $\alpha = 1$ assumes that the run-scoring and wicket components enter the index with equal magnitude. More generally, allowing α to vary provides a mechanism through which the relative cost of wicket loss can be estimated rather than imposed.

An initial attempt was therefore made to estimate a common value α^* using franchise-level match outcomes. The objective was to identify a value of α for which the resulting composure measure was most informative about

successful run chases. However, the estimated parameter proved highly unstable. Bootstrap estimation produced substantial dispersion, while relatively small perturbations in α resulted in large changes in the franchise rankings.

This instability is informative rather than merely computational. It suggests that there may be no single wicket-penalty parameter capable of summarizing the role of wickets across all run-chase situations. In particular, aggregating deliveries across heterogeneous match states can obscure the conditional nature of the relationship between pressure, scoring, and wicket loss. This motivates replacing the static parameter α with a state-dependent representation.

4.2. Definition of match state

Let the match state immediately prior to delivery t in match m be represented by

$$S_{m,t} = (P_{m,t}, RRR_{m,t}, W_{m,t}^R), \quad (18)$$

where $P_{m,t}$ denotes the phase of the innings, $RRR_{m,t}$ is the RRR defined in (1), and $W_{m,t}^R$ denotes the number of wickets remaining.

The innings phase is defined as

$$P_{m,t} = \begin{cases} \text{Early,} & 1 \leq \text{over} \leq 6, \\ \text{Middle,} & 7 \leq \text{over} \leq 15, \\ \text{Death,} & 16 \leq \text{over} \leq 20. \end{cases} \quad (19)$$

Thus, two deliveries are regarded as belonging to comparable match states when they occur under similar combinations of innings phase, RRR, and remaining batting resources.

This representation separates chronological match time from the underlying constraints of the chase. For example, two observations occurring in the same over need not represent comparable pressure states if their RRRs or available wickets differ substantially. Conversely, deliveries from different matches may represent similar states when the corresponding values of RRR and wickets remaining are comparable.

4.3. State-controlled DCCA

To estimate the local dependence structure, the second-innings data are partitioned into consecutive blocks corresponding to relatively similar match states. Only blocks containing at least 12 deliveries are retained, thereby ensuring a minimum amount of information for local detrending and cross-correlation estimation.

Let $\mathcal{B}_j$ denote the j th admissible block and let

$$n_j = |\mathcal{B}_j|$$

denote its length. For each block, the DCCA procedure described in Section 3.2 is applied to the locally observed series.

The state-specific scoring coefficient is

$$\rho_{\text{runs},j} = \rho_{\text{DCCA}}(RRR, \text{Runs} \mid \mathcal{B}_j), \quad (20)$$

while the corresponding wicket coefficient is

$$\rho_{\text{wickets},j} = \rho_{\text{DCCA}}(RRR, \text{Wickets} \mid \mathcal{B}_j). \quad (21)$$

Each local estimate is therefore associated with a state vector

$$Z_j = (\overline{RRR}_j, \overline{W}_j^R, P_j), \quad (22)$$

where $\overline{RRR}_j$ denotes the mean RRR within the block, $\overline{W}_j^R$ denotes the mean number of wickets remaining, and P_j denotes the corresponding innings phase.

The key distinction from the aggregate analysis is therefore

$$\rho_{\text{wickets}} \longrightarrow \rho_{\text{wickets}}(S). \quad (23)$$

Rather than interpreting the DCCA wicket coefficient as a fixed franchise-level quantity, it is now treated as a function of the prevailing match state.

4.4. Modeling the state-dependent wicket relationship

The resulting block-level estimates allow the variation in the wicket coefficient to be modeled statistically. As an initial specification, consider

$$\rho_{\text{wickets},j} = \beta_0 + \beta_1 \overline{RRR}_j + \beta_2 \overline{W}_j^R + \beta_3 I(P_j = \text{Early}) + \beta_4 I(P_j = \text{Death}) + \varepsilon_j, \quad (24)$$

where the middle phase serves as the reference category. This model tests whether variation in the local pressure–wicket relationship is explained by scoreboard pressure, remaining batting resources, and innings phase.

To allow the influence of RRR to depend on the available batting resources, an interaction specification is also considered, which is given as

$$\begin{aligned} \rho_{\text{wickets},j} = & \beta_0 + \beta_1 \overline{RRR}_j + \beta_2 \overline{W}_j^R + \beta_3 I(P_j = \text{Early}) + \beta_4 I(P_j = \text{Death}) \\ & + \beta_5 (\overline{RRR}_j \times \overline{W}_j^R) + \varepsilon_j. \end{aligned} \quad (25)$$

The interaction term allows the association between increasing scoreboard pressure and the wicket-related DCCA coefficient to differ according to the amount of batting resources still available.

4.5. Linear state-dependent results

Table 3 reports the estimates from the baseline state-dependent regression. The most prominent result is the positive and highly significant coefficient on mean RRR ($\hat{\beta}_1 = 0.0054$, $p < 0.001$). Since the baseline DCCA wicket coefficient is negative, the positive RRR coefficient implies that this negative relationship moves toward zero as the RRR increases. Mean wickets remaining also enters positively and significantly ($\hat{\beta}_2 = 0.0108$, $p = 0.001$).

In contrast, once RRR and remaining wickets are controlled for, the early and death-phase indicators are statistically insignificant. This suggests that the observed variation in the pressure–wicket relationship is more closely associated with the simultaneous scoreboard state than with the over number alone.

Table 4 reports the corresponding interaction model. After inclusion of the interaction term, mean RRR remains positive and statistically significant ($\hat{\beta}_1 = 0.0034$, $p = 0.024$). The estimated interaction coefficient is positive but does not attain conventional statistical significance ($p = 0.116$). Consequently, the data provide stronger evidence for a direct association between scoreboard pressure and the local DCCA wicket coefficient than for an interaction between pressure and remaining wickets.

Taken together, these results reject a simple interpretation of the wicket component as a constant franchise-level penalty. Instead, ρ_{wickets} varies systematically with the prevailing match state, particularly with RRR. At the same time, the linear specifications impose a constant marginal effect of RRR. The observed state dependence need not be linear, and the response may change more sharply once scoreboard pressure becomes sufficiently severe. This possibility motivates the nonlinear and threshold analysis considered in the next section.

5. Nonlinear and threshold analysis

The linear state-dependent models in Section 4 indicate that the local DCCA wicket coefficient becomes less negative as RRR increases. However, the assumption of a constant marginal effect may be restrictive. In particular, the relationship between scoreboard pressure and wicket-related dependence may change more rapidly at some levels of RRR than at others. We therefore examine nonlinear specifications, bootstrap uncertainty, and a possible structural breakpoint.

5.1. Spline-based nonlinear model

To allow the relationship between RRR and the DCCA wicket coefficient to vary flexibly, we replace the linear RRR term with a B-spline representation. The model is written as

$$\rho_{\text{wickets},j} = \beta_0 + \sum_{k=1}^4 \gamma_k B_k(\overline{RRR}_j) + \beta_W \overline{W}_j^R + \varepsilon_j, \quad (26)$$

where $B_k(\cdot)$ denotes the k^{th} basis function of a four-degree-of-freedom B-spline, $\overline{RRR}_j$ is the mean RRR within block j , and $\overline{W}_j^R$ denotes mean wickets remaining. Table 5 reports the corresponding coefficient estimates.

The estimated spline terms indicate that the relationship between RRR and ρ_{wickets} is not well represented by a simple monotonic linear trend. In particular, the fitted curve becomes more negative at low to moderate levels of RRR before subsequently increasing toward zero as scoreboard pressure becomes more severe. Mean wickets remaining continues to enter positively and significantly, consistent with the state-dependent results reported previously.

Figure 5 displays the fitted nonlinear relationship. The curve suggests a pronounced negative region for approximately moderate RRR values, followed by a gradual weakening of the negative DCCA coefficient as RRR increases. The change appears to accelerate beyond roughly the low-teens range of RRR. This graphical pattern motivates a more formal investigation of whether the relationship contains a structural breakpoint.

5.2. Bootstrap assessment of the linear state model

Because the local DCCA coefficients are obtained from contiguous match blocks of varying lengths and match conditions, sampling uncertainty is assessed using nonparametric bootstrap resampling. The interaction model in (25) is re-estimated over 1,000 bootstrap samples.

Table 6 reports the bootstrap means and 95% confidence intervals. The bootstrap interval for mean RRR excludes zero, $[0.0007, 0.0062]$, reinforcing the earlier result that increasing scoreboard pressure is associated with a weakening of the negative DCCA wicket coefficient. In contrast, the intervals for innings phase, mean wickets remaining, and the interaction term include zero in the bootstrap analysis. The evidence is therefore strongest for a systematic RRR effect rather than for a stable interaction between RRR and wickets remaining.

5.3. Segmented regression

The spline model is useful for identifying broad nonlinear patterns but does not directly estimate a transition point. To investigate whether the relationship changes slope at a particular level of scoreboard pressure, we fit a continuous segmented regression of the form

$$\rho_{\text{wickets},j} = \begin{cases} \beta_0 + \beta_1 R_j + \varepsilon_j, & R_j < c, \\ \beta_0 + \beta_1 c + \beta_2 (R_j - c) + \varepsilon_j, & R_j \geq c, \end{cases} \quad (27)$$

where $R_j = \overline{RRR}_j$ and c denotes the unknown breakpoint.

The estimated parameters are reported in Table 7. The point estimate places the breakpoint at an RRR of approximately 20.31. Below this value, the estimated slope is positive (0.0058), indicating that the negative DCCA wicket coefficient becomes progressively less negative as RRR rises. Above the estimated breakpoint, the fitted slope is close to zero (0.0003), suggesting little additional change in the coefficient at very high levels of RRR. Figure 6 presents the fitted piecewise relationship.

5.4. Uncertainty in the breakpoint

The estimated breakpoint should be interpreted cautiously. A 1000 sample nonparametric bootstrap yields the confidence intervals reported in Table 8.

The confidence interval for the breakpoint is wide, indicating substantial uncertainty about the precise location of any structural transition. Moreover, the confidence interval for the difference between the two slopes contains zero. Hence, although the point estimate and fitted curve suggest a flattening of the relationship at very high RRR, the available data do not provide strong statistical evidence for a uniquely identified breakpoint.

This uncertainty is consistent with the relative sparsity of contiguous match blocks observed at extremely high RRRs. Hence, $\hat{c} = 20.31$ is treated as a candidate transition point rather than as a precisely estimated universal pressure threshold.

5.5. Model comparison

Finally, the linear, spline, and segmented specifications are compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and adjusted R^2 . The results are presented in Table 9.

The segmented specification attains the lowest AIC and the largest adjusted R^2 , whereas the linear specification is preferred according to BIC. The differences in overall fit are modest, and the very small adjusted R^2 values indicate that match-state variables explain only a limited fraction of the total variation in local DCCA coefficients. The comparison therefore provides some support for nonlinear structure, but not sufficient evidence to conclude that the segmented model dominates the simpler linear specification.

Taken together, the nonlinear, bootstrap, and segmented analyses support a consistent qualitative result: the negative association between scoreboard pressure and the wicket-related DCCA coefficient weakens as required run rate increases. The evidence for a specific universal breakpoint is considerably weaker. The principal empirical finding is therefore the systematic attenuation of the pressure–wicket dependence, rather than the precise location of a threshold.

6. Discussion

The empirical results demonstrate that the relationship between scoreboard pressure and batting outcomes is inherently state dependent. While the initial franchise-level DCCA analysis reveals substantial heterogeneity across teams, a single aggregate coefficient cannot fully characterize the changing pressure–performance relationship within a run chase. In particular, the instability of a common wicket–penalty parameter motivates the transition from a static composure measure to a state-controlled DCCA framework.

The state-dependent analysis provides the clearest empirical finding of the study. After controlling for innings phase and remaining batting resources, the RRR is significantly associated with the local DCCA wicket coefficient. As RRR increases, the initially negative pressure–wicket association tends to move toward zero. Bootstrap analysis supports the stability of this RRR effect, whereas the evidence for separate innings-phase and RRR–wicket interaction effects is considerably weaker.

The nonlinear analysis further suggests that this attenuation may not occur uniformly over the entire range of scoreboard pressure. Both the spline and segmented specifications indicate a possible flattening of the relationship at very high RRRs. The segmented model identifies a candidate breakpoint near an RRR of 20.31; however, the wide bootstrap confidence interval and the statistically uncertain change in slope imply that this value should not be interpreted as a universal pressure threshold. The more robust conclusion is that the dependence structure itself changes with the severity of the chase.

From a methodological perspective, these findings illustrate an important advantage of combining DCCA with match-state information. Conventional aggregate DCCA summarizes dependence over an entire series, whereas the state-controlled framework permits the dependence structure to evolve with the underlying competitive environment. This provides a more flexible way of studying pressure–performance dynamics in event-level sports data, particularly when the relevant time series are nonstationary and exhibit long-range dependence.

Finally, the proposed measures should be interpreted as statistical descriptions of observed match dynamics rather than direct measures of psychological pressure or player composure. The results establish systematic changes in the cross-correlation structure of scoreboard pressure, scoring, and wicket occurrence; they do not by themselves identify the behavioral or psychological mechanisms responsible for these changes.

7. Limitations and future directions

Several limitations should be acknowledged. First, the state-dependent DCCA coefficients are estimated from contiguous match blocks, and their precision depends on the number and length of observations available within each state. This is particularly relevant at extreme RRRs, where relatively few sustained match blocks are observed. Consequently, the estimated breakpoint should be interpreted as exploratory rather than as a universal threshold.

Second, the construction of match states requires choices concerning innings phase, RRR categories, wickets remaining, and minimum block length. Although these choices provide an interpretable framework for conditioning the DCCA analysis, alternative state definitions may produce somewhat different results. Future work could examine the robustness of the findings to these design choices and develop data-driven approaches for identifying match states.

Third, the analysis is based on IPL run chases and therefore need not generalize directly to other competitions or formats of cricket. Validation using international T20 matches and other domestic leagues would provide an important robustness assessment.

Finally, the proposed framework identifies statistical dependence between scoreboard pressure and batting outcomes rather than psychological pressure itself, and the observed associations should not be given a causal interpretation. A natural methodological extension would be to develop a fully state-dependent DCCA procedure in which the cross-correlation structure is allowed to evolve continuously with the match state, rather than being estimated within discretely defined blocks.

8. Concluding remarks

This study develops a DCCA-based framework for examining the dynamic relationship between scoreboard pressure and batting outcomes in IPL run chases. The results show that this dependence cannot be adequately summarized by a single franchise-level measure. In particular, the state-controlled analysis indicates that the relationship between RRR and wicket occurrence changes systematically with the evolving conditions of the chase.

The principal empirical finding is that the initially negative DCCA pressure–wicket association tends to weaken as the RRR increases. Nonlinear and segmented analyses provide some evidence of further attenuation at very high pressure levels, although the estimated breakpoint near an RRR of 20.31 is subject to considerable uncertainty and should not be interpreted as a universal threshold.

Overall, the study demonstrates the usefulness of combining DCCA with match-state information for analyzing nonstationary and evolving dependence structures in event-level sports data. The framework provides a foundation for future work on continuously varying state-dependent DCCA methods and their application to other teams, competitions, and sporting environments.

Conflicts of interest

The authors declare that they have no competing interests.

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Data availability

The data underlying this article are available in Kaggle at <https://www.kaggle.com/datasets/patrickb1912/ipl-complete-dataset-20082020>.

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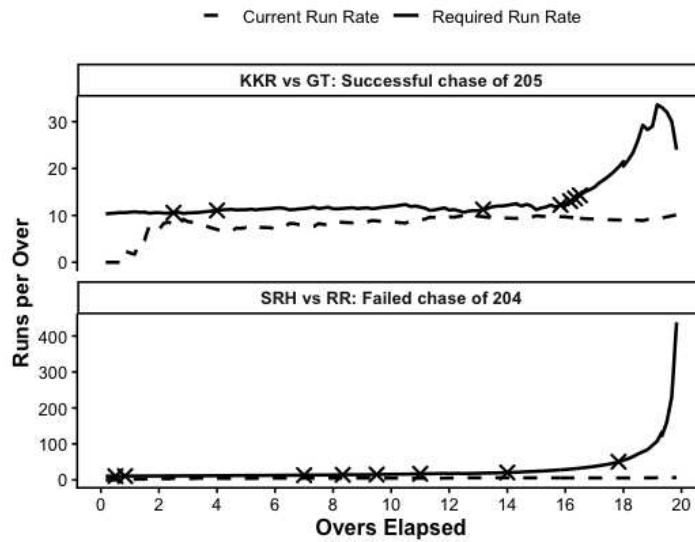


Figure 1 Evolution of CRR and RRRs in two representative IPL run chases with similar targets but contrasting outcomes. The curves show how realized scoring performance and scoreboard pressure evolve through the innings, while crosses denote wicket events.

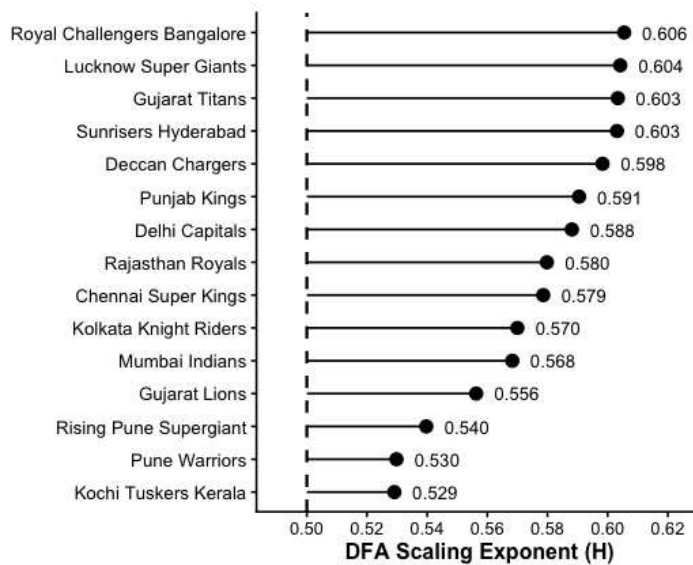


Figure 2 Estimated DFA scaling exponents across IPL franchises. The dashed vertical line at $H = 0.5$ denotes the benchmark for an approximately uncorrelated process. All estimated exponents exceed 0.5, indicating mild persistence in franchise-level ball-by-ball scoring sequences.

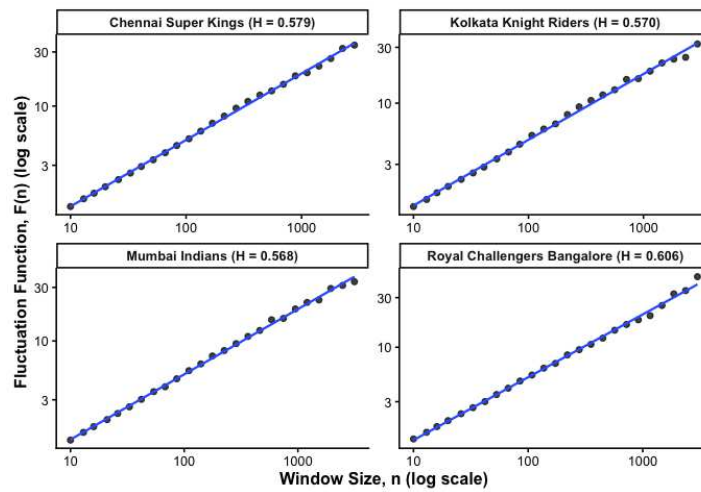


Figure 3 Log–log relationship between the DFA fluctuation function $F(n)$ and window size n for Mumbai Indians, Kolkata Knight Riders, Chennai Super Kings, and Royal Challengers Bangalore. The fitted slopes correspond to the estimated DFA scaling exponents H .

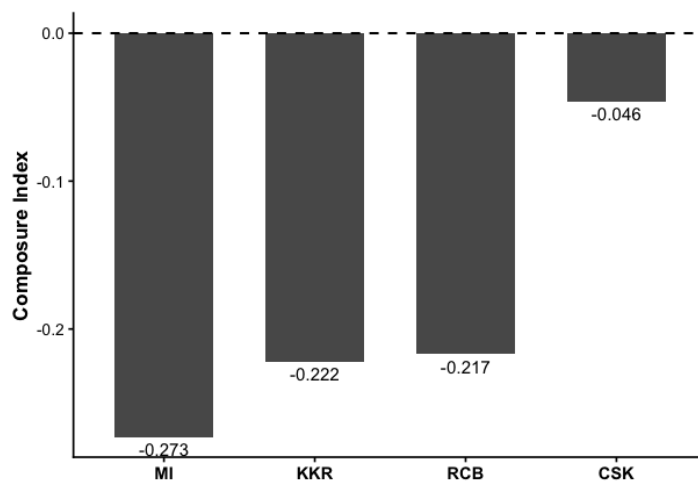


Figure 4 Exploratory franchise-level DCCA Composure Index at scale $n = 30$ deliveries. Values closer to zero represent a relatively larger joint pressure–performance measure. The index is used as a comparative statistical summary and is not interpreted as a direct psychological measure of composure.

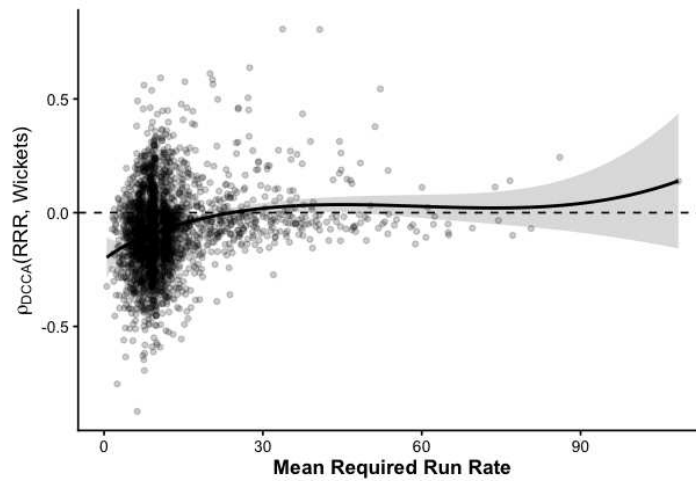


Figure 5 Spline-based relationship between mean RRR and the state-dependent DCCA wicket coefficient. The fitted curve illustrates nonlinear variation in the pressure-wicket dependence structure.

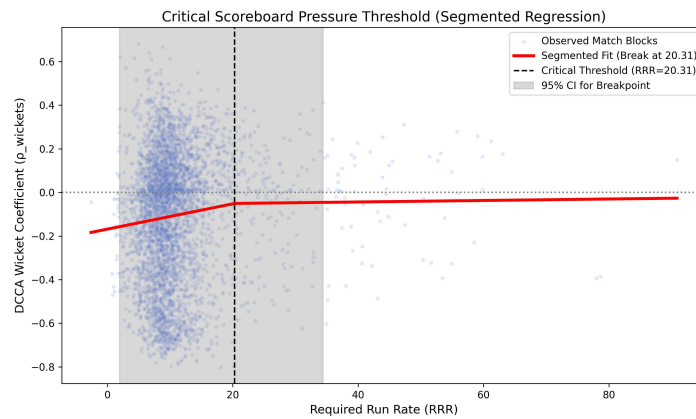


Figure 6 Segmented-regression fit between mean RRR and the state-dependent DCCA wicket coefficient. The vertical line denotes the estimated breakpoint at $\hat{c} = 20.31$.

Table 1. DFA scaling exponents for IPL franchises

Franchise	No. of Deliveries	H
Mumbai Indians	31,437	0.5683
Royal Challengers Bangalore	30,023	0.6055
Delhi Capitals	29,732	0.5881
Kolkata Knight Riders	29,514	0.5700
Punjab Kings	29,479	0.5905
Chennai Super Kings	28,651	0.5786
Rajasthan Royals	26,242	0.5798
Sunrisers Hyderabad	21,843	0.6031
Deccan Chargers	9,034	0.5983
Gujarat Titans	5,494	0.6034
Pune Warriors	5,443	0.5298
Lucknow Super Giants	5,400	0.6042
Gujarat Lions	3,566	0.5563
Rising Pune Supergiant	3,480	0.5397
Kochi Tuskers Kerala	1,582	0.5291

Table 2. Franchise-level DCCA Composure Index at scale $n = 30$

Franchise	$C_i(30)$
Chennai Super Kings	−0.046
Royal Challengers Bangalore	−0.217
Kolkata Knight Riders	−0.222
Mumbai Indians	−0.273

Table 3. State-dependent regression of the DCCA wicket coefficient

Variable	Estimate	Std. Error	t	p
Intercept	−0.2425	0.029	−8.314	< 0.001
Death phase	−0.0061	0.013	−0.482	0.630
Early phase	−0.0025	0.012	−0.213	0.831
Mean RRR	0.0054	0.001	6.486	< 0.001
Mean wickets remaining	0.0108	0.003	3.277	0.001

Table 4. State-dependent regression with RRR–wickets interaction

Variable	Estimate	Std. Error	t	p
Intercept	−0.2209	0.032	−6.852	< 0.001
Death phase	−0.0057	0.013	−0.451	0.652
Early phase	−0.0005	0.012	−0.044	0.965
Mean RRR	0.0034	0.002	2.261	0.024
Mean wickets remaining	0.0057	0.005	1.219	0.223
RRR $\times$ wickets remaining	0.0005	0.000	1.572	0.116

Table 5. Spline regression for the state-dependent DCCA wicket coefficient

Variable	Estimate	Std. Error	<i>t</i>	<i>p</i>
Intercept	−0.1024	0.127	−0.808	0.419
$B_1(\text{RRR})$	−0.2309	0.140	−1.647	0.100
$B_2(\text{RRR})$	0.2298	0.117	1.969	0.049
$B_3(\text{RRR})$	−0.0493	0.228	−0.217	0.829
$B_4(\text{RRR})$	−0.0107	0.244	−0.044	0.965
Mean wickets remaining	0.0151	0.003	5.580	< 0.001

Table 6. Bootstrap estimates for the state-dependent interaction model

Variable	Mean Estimate	Std. Error	95% CI Lower	95% CI Upper
Intercept	−0.2230	0.0316	−0.2850	−0.1586
Death phase	−0.0058	0.0119	−0.0282	0.0163
Early phase	−0.0006	0.0120	−0.0238	0.0236
Mean RRR	0.0035	0.0015	0.0007	0.0062
Mean wickets remaining	0.0059	0.0045	−0.0037	0.0143
RRR $\times$ wickets remaining	0.0005	0.0003	−0.0001	0.0011

Table 7. Segmented-regression parameter estimates

Parameter	Estimate
Breakpoint, $\hat{c}$	20.3142
Slope before breakpoint, $\hat{\beta}_1$	0.0058
Slope after breakpoint, $\hat{\beta}_2$	0.0003
Slope difference, $\hat{\beta}_2 - \hat{\beta}_1$	−0.0055

Table 8. Bootstrap uncertainty for the segmented regression

Quantity	95% CI Lower	95% CI Upper
Breakpoint c	1.9597	34.4198
Difference in slopes	−0.0121	0.0116

Table 9. Comparison of linear, spline, and segmented specifications

Model	Parameters	AIC	BIC	Adjusted R^2
Linear	3	−10747.99	−10728.91	0.0048
Spline	6	−10747.47	−10709.32	0.0053
Segmented	5	−10750.88	−10719.09	0.0059