

1 **Bowled over or over bowled? Age-related changes in the**
2 **performance of bowlers in Test match cricket**

3 *Running title: Age-related performance of Test match bowlers*

4 Jack Thorley¹

5 ¹ Department of Zoology, University of Cambridge, Downing Street, Cambridge CB2 3EJ,

6 UK

7 **Corresponding author:** Jack Thorley (jbt27@cam.ac.uk)

8 ORCID

9 Jack Thorley [0000-0002-8426-610X](https://orcid.org/0000-0002-8426-610X)

10 ABSTRACT

11 Data from elite professional sports players provide a valuable source of information on
12 human performance and ageing. Functional declines in performance have been investigated
13 across a wide range of sporting disciplines that vary in their need for physical strength,
14 endurance, cognitive ability and motor skills, but rarely have researchers considered other
15 sources of heterogeneity that can exist among individuals. Using information on all male
16 bowlers to have played Test match cricket since the early 1970s, I separated age-dependent
17 variation in bowling performance at the population-level into within-individual and between-
18 individual (cohort) changes. I found no evidence for senescence in bowling performance as
19 measured via economy rate or wicket-taking ability, irrespective of the style of the bowler
20 (fast or slow). Instead, analyses detected strong between-individual contributions to bowling
21 performance as higher quality bowlers were able to compete at the elite level for longer, and
22 were therefore over-represented in older age classes. Bowlers also experienced a deterioration
23 in the last year of their Test careers. These results highlight that the very best Test match
24 bowlers have been able to maintain and often improve their skill level well into their thirties,
25 but how they accomplish this alongside the physical demands of Test cricket remains
26 unresolved. Further multivariate models also identified a negative relationship among slow
27 bowlers between their economy rate and their wicket-taking ability, suggesting that in
28 general, the most economical slow bowlers in the modern era of Test match cricket have also
29 taken wickets at the fastest rate. The same is not true for fast bowlers, which is perhaps partly
30 because bowling at high speed compromises accuracy and thus increases scoring
31 opportunities for batsman.

32 **Keywords:** gerontology, ageing, selective disappearance, evolution, functional senescence,
33 cricket, trait compensation

34 INTRODUCTION

35 The vast majority of species experience declines in functional capacity in the later stages
36 of their lifespan (Monaghan et al., 2008; Nussey et al., 2013; Jones et al., 2014; Shefferson et al.,
37 2017). Contemporary human populations are no exception (Masoro and Austad, 2010), and the
38 physiological deterioration that comes with old age (*senescence* or *ageing*) is perhaps better
39 understood in humans than in any other species. Older humans have lower cognitive ability
40 (Murman, 2015), respiratory capacity (Sharma and Goodwin, 2006), immune function (Pawelec,
41 2012), and muscle mass (Doherty, 2003) than younger humans, and together, such factors
42 contribute to the increasing morbidity and mortality observed in the elder members of society
43 worldwide (Uhlenberg, 2009; Vaupel, 2010). Yet despite often being associated with old age,
44 declines in some physiological functions often begin much earlier in the life span than others
45 (Walker and Herndon, 2010; see also Hayward et al., 2015 for example in a non-human
46 population; Gaillard and Lemaître, 2017) and are not necessarily synonymous with debility. For
47 example, some aspects of cognitive decline already begin in healthy, educated adults as early as
48 their mid-to-late twenties (Salthouse, 2009), whereas the most pronounced declines in muscle
49 wasting (sarcopenia) do not begin until individuals are over 50 years of age (Doherty, 2003).
50 Understanding how and why the output of different physiological functions varies so markedly
51 across human life span, and the consequences for health outcomes, remains a major challenge for
52 modern gerontology (Christensen et al., 2009), but is complicated by the large variability
53 introduced by differing lifestyles and the methodological difficulties of separating genetic,
54 epigenetic, and environmental components of ageing (Christensen et al., 2006; Hjelmborg et al.,
55 2006; Steves et al., 2012; Passarino et al., 2016).

56 Since the start of the 20th century numerous studies have suggested that data from elite
57 sportsmen and sportswomen can be particularly useful for investigating human ageing (Hill,
58 1925; Moore, 1975; Stones and Kozma, 1984; Careau and Wilson, 2017), as well as for testing
59 predictions from evolutionary theory (Brooks et al., 2004; Pollet et al., 2013; Postma, 2014;

60 Lailvaux, 2018). Using sporting data for these purposes bears the distinct advantage that elite
61 sportsmen and women train rigorously throughout their sporting careers and show uniformly high
62 motivation to succeed in their chosen discipline. As a result, analyses of age-related changes in
63 performance in sportspeople reduce many of the biases surrounding differences in lifestyle and
64 behaviour that are present among the general population. Furthermore, data collected in sporting
65 competition is typically standardised; often provides large numbers of repeated records from
66 individuals; and because additional extraneous factors are measured and recorded, they can be
67 controlled for statistically.

68 The accumulated information from a large number of sports datasets converges upon the
69 finding that peak physiological function in humans occurs on or around thirty years of age, and
70 declines modestly thereafter, though the impact of age tends to depend upon the relative
71 requirement for athleticism versus skill in the sport in question (Schulz and Curnow, 1988;
72 Trappe, 2007; Bradbury, 2009; Baker and Tang, 2010). In general, sports involving greater speed
73 and stamina, as exemplified by track and field events in athletics, favour younger individuals
74 (Moore, 1975; Stones and Kozma, 1984; Young and Starkes, 2005), whereas those requiring
75 more fine-control motor skills and less intense physical exertion tend to exhibit more delayed
76 downturns (Baker et al., 2007; Schorer and Baker, 2009). This pattern is probably not surprising
77 to any sports fan. The oldest ever male and female winners of 100m Olympic gold, Linford
78 Christie and Fanny Blinkers-Koen, were 32 and 30 years of age when they won their medals in
79 1992 and 1948, respectively, and most winners have been considerably younger than this. If we
80 contrast this to golf, a sport where success has historically been more dependent on motor skills
81 than athletic ability, then we see that players have regularly competed on the world tour well into
82 their fifties, and a number of male players have won the Masters beyond 40 years of age.

83 In the context of human performance, it is perhaps more illuminating to examine
84 performance traits in sports demanding a more even contribution of skill and athleticism for
85 success. Where this is the case, it is apparent that individuals can sometimes compensate for

86 relative losses of function in physical attributes by increasing aspects of skill-based performance.
87 Tennis and basketball provide two illustrative cases. Sutter et al. (2018) analysed first-serve
88 performance in a large sample of modern professional tennis players and found that in both sexes,
89 players experiencing more pronounced declines in average serve speed with increasing age
90 displayed relative improvements in first serve accuracy. High average serve speed and high
91 average accuracy were both associated with an increased probability of winning the match, but
92 because both aspects of serving senesced, the compensatory increase in accuracy could only
93 partly offset the overall performance declines in the later stages of player's careers. In a separate
94 study, Lailvaux et al. (2014) examined points-scoring ability in professional basketball players
95 playing in the National Basketball Association (NBA). In male basketball players, but not
96 females, the decline in points arising from 'close-range' two-point field throws began three to
97 four years before that detected for 'longer-range' three-point field throws, which the authors
98 argued is indicative of compensation: as declines in speed and power reduce the ability to score
99 two-point field goals closer to the basket, players having the accuracy to continue scoring more
100 distant three-point field goals can maintain points-scoring ability. Although further examples of
101 such dynamic compensation in sports players are relatively few and far between (Schorer and
102 Baker, 2009), we should not necessarily be surprised by their presence in humans as trait
103 compensation is widespread across the animal kingdom (Husak et al., 2011; Cameron et al.,
104 2013; Dennenmoser and Christy, 2013) and is underpinned by evolutionary theory grounded in
105 trade-offs (Roff, 1992; Stearns, 1992).

106 Though sports datasets are often longitudinal in design, containing large numbers of
107 repeated records from the same individuals, very few studies of sporting performance have
108 explicitly sought to separate within-individual changes in performance from compositional
109 differences between different age classes, or what are sometimes referred to as cohort effects. It is
110 not that researchers in sports performance have failed to recognise cohort effects, for they have
111 been discussed and applied in several places (Young and Starkes, 2005; Stones, 2019), but rather

112 that they are rarely incorporated into analytical frameworks explicitly. There are two principal
113 reasons why the inclusion of between-individual ‘cohort’ effects is warranted. Firstly, by failing
114 to consider cohort effects, one risks under or overestimating age-related changes occurring within
115 individuals and therefore fail to correctly quantify the ageing process. Secondly, by incorporating
116 cohort effects one can gain important additional information about changes in human
117 performance that would otherwise go undetected. For instance, if only the highest quality sports
118 players enjoy long careers and compete professionally into the older age classes- because less
119 competent performers have already stopped or are no longer up to the required standard- then this
120 raises questions about how they are able to do so. Is their superiority gained earlier in their career
121 and maintained? What aspects of their performance allow them to continue competing later than
122 others? Do these long-lived professionals follow a different training regime? Equally, one might
123 wonder whether professional sports players that start competing at the highest level at a very
124 young age are relatively better or worse than individuals who started doing so later in life.

125 In this study, I examine age-related variation in the performance of bowlers in Test match
126 cricket and dissect changes occurring within individuals from changes occurring between
127 individuals. In so doing, I borrow methods from animal ecology where researchers routinely
128 analyse long-term data taken from animals tracked across their life span to understand how
129 individual variation in performance changes with age (van de Pol and Verhulst, 2006; Rebke et
130 al., 2010; Nussey et al., 2011). Like animals in natural populations, cricketers at the elite
131 international level are selected to perform to the best of their ability and their performance is
132 measured relative to other individuals seeking to do so the same. They ‘appear’ in the population
133 when they are deemed good enough to compete, have some scope to improve with experience,
134 but should they fail to compete effectively, then they will be replaced and ‘disappear’ from the
135 population. I focus on Test cricket as this provides the longest-running and most standardised
136 form of the sport, often being considered the game’s highest standard. An abridged outline of
137 cricket is provided in the methods, but in general, batsmen are specialised in the accruing of runs,

138 while bowlers are concerned with dismissing (“getting out”) batters and reducing the rate at
139 which they score runs (points). Bowlers can be broadly separated into fast bowlers, who bowl the
140 ball quickly (110-150kph), and slow bowlers (70-110kph), who more often rely on guile and
141 subtle variations in spin and trajectory to succeed. Both types of bowling require considerable
142 motor skill and stamina (Noakes and Durandt, 2000; Petersen et al., 2010), though fast bowlers
143 also tend to require a greater degree of athleticism in order to deliver the ball at speed from one
144 end of the wicket to the other.

145 By analysing the complete dataset of modern era (here defined as post-1973) Test match
146 bowlers, I find that two measures of bowling performance show no sign of senescent decline. I
147 identify other important within-individual and among-individual contributions to bowling
148 performance, and highlight a key difference in the relationship between wicket-taking ability and
149 economy rate in fast and slow bowlers.

150 MATERIALS AND METHODS

151 a) “Test Cricket”

152 It would take too much space to detail all the nuances of cricket. For this, I recommend
153 Woolmer’s *Art and Science of Cricket* (Woolmer, 2008). Instead, I provide enough information
154 for readers to understand the basic principles by which each match proceeds, and the
155 contributions that individuals make to team performance.

156 Test cricket is the longest format of cricket and is often considered the game’s highest
157 standard. Since the first official ‘Test match’ was contested between England and Australia in
158 1877, 12 international teams have been granted Test status by the International Cricket Council
159 and regularly compete against one another. As in all forms of cricket, either side fields eleven
160 players composed of batters and bowlers.

161 Cricket matches are played in innings. In a single team innings, one team bats while the
162 other fields. Test matches ordinarily comprise four innings with each team batting and bowling

163 twice in alternation. The most basic aspect of play in a game of cricket is a “ball”, where a
164 bowler, from the fielding team, propels a hard leather ball towards the batter attempting to get the
165 batter “out”, while the batter attempts to hit the ball to score “runs” (points). A bowler can
166 dismiss a batter by various means and thereby take their wicket at which point the batter leaves
167 the field of play and is replaced by another member of the batting team. Batters may also be
168 dismissed by the actions of other members of the fielding team independently of the bowler’s
169 actions. Bowlers bowl to batsmen in six-ball periods known as an “over”. While a single bowler
170 cannot bowl successive overs, there is no limit in Test cricket on the total number of overs a
171 bowler can bowl within an innings. i.e. a bowler could bowl 25 overs in an innings should their
172 captain wish them to do so, which would equate to 150 balls. Once the batting team loses 10
173 wickets (their innings is completed) the combined scores of all the batters generates a team total
174 that the opposition team then aims to meet or surpass. Note that an individual batting
175 performance is also called an innings.

176 Over a completed match, a team wins when they score more runs across their two innings
177 than the opposition while also taking all of the opposition’s wickets. A draw occurs when one
178 team scores more runs than the opposition without taking all of their wickets within the
179 designated playing time. To try and force a win, the team that is batting may therefore decide to
180 forfeit their remaining wickets (“declare”) in order to provide enough time for them to bowl out
181 the opposition.

182 Because Test matches historically varied in length from three days to more than a week,
183 the data was standardised by focussing only on cricketers who debuted after 14th February 1973,
184 from which point Test matches were uniformly restricted to a maximum of five days in length
185 with a minimum of 6 hours of play a day, weather permitting. In so doing, the analyses were also
186 restricted to modern cricketers who can be considered as elite sportsmen playing in an era when
187 the sport was largely professional.

188 b) The dataset

189 The bowling data of all male Test cricketers who debuted after 14th February 1973 was
190 extracted from *ESPN Cricinfo* (<https://www.espncricinfo.com/>). Specifically, the *Octoparse*
191 software (<https://www.octoparse.com/>) was used to acquire the unique ESPN profile identifier of
192 all individuals, as well as their date of birth and their bowling style. With the profile identifiers
193 the complete bowling record of every individual could then be accessed from *Cricinfo* using the
194 *getPlayerData()* function in the *cricketr* package (Ganesh, 2019) in R v 3.6.1 (Team, 2019). All
195 data extraction was conducted on the 21st June 2019. Bowlers were defined as cricketers who
196 fielded at least 10 times in their Test career and bowled in at least 70 percent of all innings they
197 fielded in. In order to correctly partition within- and between-individual effects, only individuals
198 whose Test career was thought to have finished at the point of data extraction were considered,
199 producing a dataset of 354 individuals ($n = 16,279$ per-individual innings bowled in). Bowlers
200 were described as either fast bowlers ($n = 227$; including fast, fast-medium, and medium-fast
201 bowlers) or slow bowlers ($n = 128$; medium-slow, and spinners) according to information on
202 *Cricinfo* and *Wikipedia* so that any possible influence of bowling speed/style on age-related
203 changes in performance could be separated. Spin bowlers represented 95.3% of the individuals in
204 the dataset of slow bowlers.

205 c) Univariate modelling of performance

206 To examine age-related variation in the performance of Test match bowlers, I fitted a
207 series of univariate mixed-effects models using the within-group centering approach of Van de
208 Pol and Verhulst (2006). This method separates age-related changes that take place within
209 individuals (due to improvement or senescence) from changes that place between individuals at
210 the population-level, as arise when individuals of differing quality appear or disappear from the
211 population sample more or less often at different ages. Fast bowlers and slow bowlers were
212 modelled separately, and in each case three performance attributes in each innings bowled were

213 assessed, i- economy rate: the number of runs a bowler concedes per over, ii- wicket taking
214 ability: the number of wickets taken by a bowler in an innings, and iii- proportion of the total
215 overs of an team's innings bowled by an individual. Economy rate was fitted to a Gaussian error
216 distribution, wicket-taking ability to a negative binomial distribution with a zero-inflation
217 parameter applied across all observations (i.e. $z_i \sim 1$), and proportional overs bowled to a
218 binomial distribution (logit link) with the number of overs bowled by an individual set as the
219 numerator, and the total overs bowled in the innings set as the denominator. For all three
220 attributes I first fitted a baseline model that included fixed effects of match innings number (four-
221 level factor: 1,2,3,4), and whether the match was played at home or away (two-level factor). For
222 the wicket-taking models I also included a term for the number of overs bowled by an individual.
223 In controlling for the number of overs bowled, wicket-taking ability is thus largely synonymous
224 with 'strike rate'.

225 The baseline model was then compared to additional models incorporating different
226 combinations of age-dependent or age-independent variables (Table 1). In these models, age was
227 fitted as either a linear or quadratic function, a longevity term specifying the age of last Test
228 match accounted for possible selective disappearance of poorer quality bowlers, and a factor
229 denoting if it was the last year of a bowler's career controlled for possible terminal declines in
230 performance. Lastly, I specified further models that interacted the age terms with the innings
231 number and the age of last appearance. As random effects I included random intercepts for the
232 individual bowler, for the interaction between the country a bowler played for and the decade of
233 the match, and for the interaction between the opposition and the decade of the match. The latter
234 two effects controlled for differences in the quality of the Test-playing nations across time. In the
235 economy rate models and the proportion of overs bowled models a random intercept of match
236 was also included. Likelihood ratio testing found that the exclusion of the match effect in the
237 wicket-taking models was preferable to a model in which the effect was present, which is
238 probably because the number of wickets in a match (maximum 20 per team) is constrained in

239 such a way that individuals that take a lot of wickets prevent others from doing so. Models were
240 ranked on their Akaike Information Criterion (AIC) under maximum likelihood settings, and with
241 $\Delta\text{AIC} < 2$ were considered to show competing support (Burnham and Anderson, 2002). Where
242 two models fell within 2 AIC units, the results of the simpler model are presented. All
243 continuous variables were standardised to the mean and unit variance prior model fitting.
244 Univariate models were fitted in the *lme4* and the *glmmTMB* R packages (Bates et al., 2015;
245 Brooks et al., 2017).

246 d) Multivariate bowlers

247 To investigate how wicket taking ability and economy rate covaried among individuals across
248 their career, I fitted bivariate mixed models that included the performance metrics as a negative-
249 binomial and Gaussian distributed response, respectively. The advantage of the multivariate
250 approach is that it allows for the estimation of the posterior correlation between traits of interest
251 after controlling for the confounding effects of other covariates (Houslay et al., 2018). Here, I
252 was interested in the posterior among-individual correlation between the two performance traits.
253 Fast and slow bowlers were again modelled separately, first with a model including only group-
254 level ('random') effects, before a second model then included appropriate population-level
255 'fixed' effects, as informed by the best-fitting univariate models. The only exception to this was
256 the exclusion of the age of last appearance term so as not to devalue individuals who played for a
257 long time; so that for estimate of the posterior correlation any variance previously attributed to
258 the longevity term was instead credited to the individual bowler and reflected in his individual
259 intercept (see Tables S4 and S5 for full model table). Models were fitted in the *brms* package
260 (Bürkner, 2018), with three chains of 3,000 iterations, of which 1,000 were dedicated to the
261 warm-up. Posterior predictive checks highlighted adequate mixing of chains and appropriate use
262 of default priors.

263 Lastly, the latter two multivariate models were refitted to two data sets that included cricketers
264 that were still playing at the time of data gathering, or who only stopped playing Test cricket very
265 recently. The updated fast bowler data set contained 274 individuals (n = 14033 per-individual
266 innings), the slow bowler data set 160 individuals (n = 6413 total per-individual innings). This
267 analysis was partly to estimate the posterior correlations with more data, but it also enabled the
268 identification and ranking of players still playing Test cricket against the very best bowlers of the
269 modern-era. For these models I also removed the population-level terminal effect as at the time of
270 data extraction and analysis it was not possible to know whether current players were in the last
271 year of their Test match career.

272 RESULTS

273 a) Age-related changes in cricketing performance

274 Patterns of age-related change in the performance of Test match bowlers varied according
275 to bowling style, the innings of the match, and the performance metric that was considered
276 (Figure 1, Figure 2, Table 1). In no case did models suggest that individuals were senescing in
277 their economy rate, or in their wicket-taking ability. For fast bowlers, the best fitting model
278 indicated that the economy rate of individuals improved (declined) with age (Figure 1a, Table
279 S1). This decline in economy rate was evident in all innings (Table S1), but the slope tended
280 towards being more significantly negative in the fourth innings of matches compared to the first
281 three innings (p value for pairwise contrast between first, second, and thirds innings versus the
282 fourth innings: 0.021, 0.011, and 0.068 respectively, Figure 2a).

283 In general, the wicket-taking ability of fast bowlers also improved with age, though the
284 magnitude of the change was dependent upon the innings in question (Table 1, Figure 2, Table
285 S2). The overall wicket-taking ability of fast bowlers as indicated by the intercept term was
286 graded across innings such that their success decreased from innings one to innings four (Figure

287 2). However, bowlers became more efficient at taking wickets in innings two, three, and four as
288 they got older (Figure 2c). In contrast, the age effect in the first innings displayed a negative
289 slope, though this effect was not significant (GLMM, fast bowlers estimate on log-link scale = -
290 0.024 ± 0.017 , z-value = -1.46, $p = 0.145$). Taken together, these results imply that both the rate
291 at which fast bowlers take wickets (the number of balls bowled per wicket or ‘strike rate’) and the
292 number of they runs concede while taking those wickets improves across their career.

293 The economy rate and wicket-taking ability of slow bowlers followed a different
294 trajectory to that of fast bowlers. After controlling for the strong effects of the innings number
295 (LMM, $\chi^2_3 = 31.26$, $p < 0.001$) and the location of the match (LMM, estimate away versus home
296 = -0.169 ± 0.041 , $\chi^2_1 = 16.86$, $p < 0.001$) the economy rate of slow bowlers did not change with
297 age (Figure 1, Figure 2, Table 1). The most parsimonious model for wicket-taking ability also
298 suggested that wicket-taking ability was independent of age once the total number of overs
299 bowled was controlled for (GLMM, estimate on log-link scale = 0.414 ± 0.014 , z-value = 30.31,
300 $p < 0.001$).

301 Both fast bowlers and slow bowlers bowled proportionally less of the total overs in an
302 innings between 25 and 30 years of age (Table 1, Table S3). While this is indicative of reduced
303 workload and could be related to physiological senescence, the size of the effect is small and
304 equates to only minor reductions in the total workload of bowlers, at most 1-2%. At the mean
305 innings duration in our dataset of 94.4 overs (1SD = 40.33), a 1% reduction in the number of
306 overs bowled by a fast bowler represents roughly one over less of bowling per innings- 6 balls.

307 b) Individual quality and terminal declines

308 In the absence of clear senescence effects in the key performance criteria, model
309 comparisons instead highlighted strong age-independent contributions to performance in the form
310 of terminal declines in the last year of a career and a clear effect of longevity - the ‘age at last
311 match’. In general, the performance of Test match bowlers deteriorated in the last year of their

312 career, as reflected in the increase in economy rate (LMMs, fast bowler estimate = 0.126 ± 0.036 ,
313 $\chi^2_1 = 12.11$, $p < 0.001$; slow bowler estimate = 0.121 ± 0.052 , $\chi^2_1 = 5.32$, $p = 0.021$) and the
314 decline in wicket-taking ability (GLMMs, fast bowler estimate on log-link scale = -0.110 ± 0.025 ,
315 z-value = -4.32 , $p < 0.001$; slow bowler estimate on log-link scale = -0.188 ± 0.041 , z-value = -
316 4.60 , $p < 0.001$). The ‘age at last match’ covariate provided a signature of individual quality in
317 most models (Figure 1), achieving significance in 5 of 6 cases (Supplementary Tables). The only
318 exception to this pattern was in the wicket-taking ability of slow bowlers (GLMM, estimate on
319 logit-link scale = 0.036 ± 0.025 , z-value = 1.42 , $p = 0.157$). Where significant, the longevity term
320 indicated that individuals with longer careers were better than the average Test match bowler
321 across their career, or put differently, lower quality bowlers were more likely to leave Test match
322 cricket at a younger age.

323 The subsequent addition of an interaction between terminal decline term and the age at
324 last appearance to each of the best fitting models indicated that magnitude of this terminal decline
325 in performance was independent of the quality of bowlers, being non-significant in all cases (fast
326 bowlers economy estimate (LMM) = 0.024 ± 0.031 , $\chi^2_1 = 0.57$, $p = 0.45$, slow bowlers economy
327 estimate (LMM) = -0.023 ± 0.048 , $\chi^2_1 = 0.22$, $p = 0.64$; fast bowler wicket-taking estimate
328 (GLMM) = 0.008 ± 0.022 , z-value = 0.34 , $p = 0.73$; slow bowler wicket-taking estimate
329 (GLMM) = 0.001 ± 0.032 , z-value = 0.02 , $p = 0.99$).

330 c) Multivariate bowlers

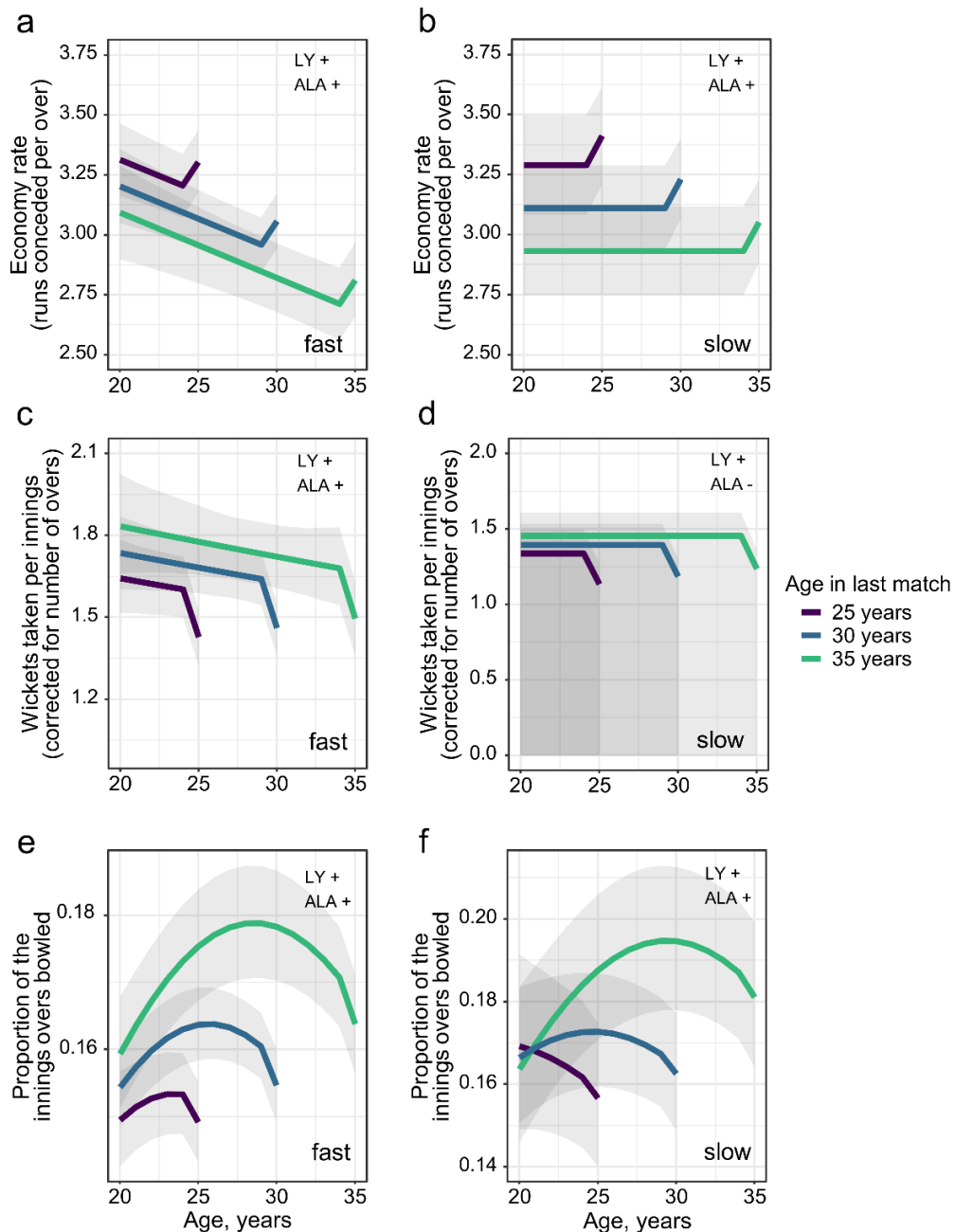
331 Multivariate models identified a significant, negative among-individual correlation
332 between economy rate and wicket-taking ability in both fast and slow bowlers in models where
333 only group-level effects were present (fast bowlers estimate = -0.27 , 95% credible interval = -
334 $0.45 - -0.08$; slow bowlers estimate = -0.45 , 95% credible interval = $-0.64 - -0.22$). After
335 controlling for various population-level effects, both posterior correlations were reduced, but
336 while there was little support for any correlation in fast bowlers thereafter (0.06 , 95% credible

337 interval = -0.18 –0.29), in slow bowlers there remained a significant negative correlation (-0.29,
338 95% credible interval = -0.55 – 0.00), suggesting that in general, the most economical slow
339 bowlers in the modern era of Test match cricket have also been the most productive at taking
340 wickets (see Table S4 for full model outputs). The incorporation of players that are still playing
341 Test match cricket - or those that retired only very recently - produced very similar posterior
342 correlations (fast bowlers estimate = 0.04, 95% credible interval = -0.17 – 0.25, slow bowlers
343 estimate = -0.30, 95% credible interval = -0.54 – 0.05) and identified a number of players in the
344 modern game who on their current trajectory could be considered amongst the best bowlers of the
345 modern era (Figure S1).

346 **Table 1: A comparison of models examining age-dependent and age-independent**
 347 **variation in the bowling performance of Test match cricketers across their careers.**
 348 Separate models were fitted to fast bowlers and slow bowlers, for three performance metrics,
 349 economy rate (number of runs conceded per over per innings), wicket-taking ability (the number
 350 of wickets taken per innings), and the proportion of the overs in the innings bowled. Baseline
 351 refers to the baseline model as outlined in the main text. ALA- Age at last appearance; LY- Last
 352 year of career. The most parsimonious model in each case is highlighted in bold.

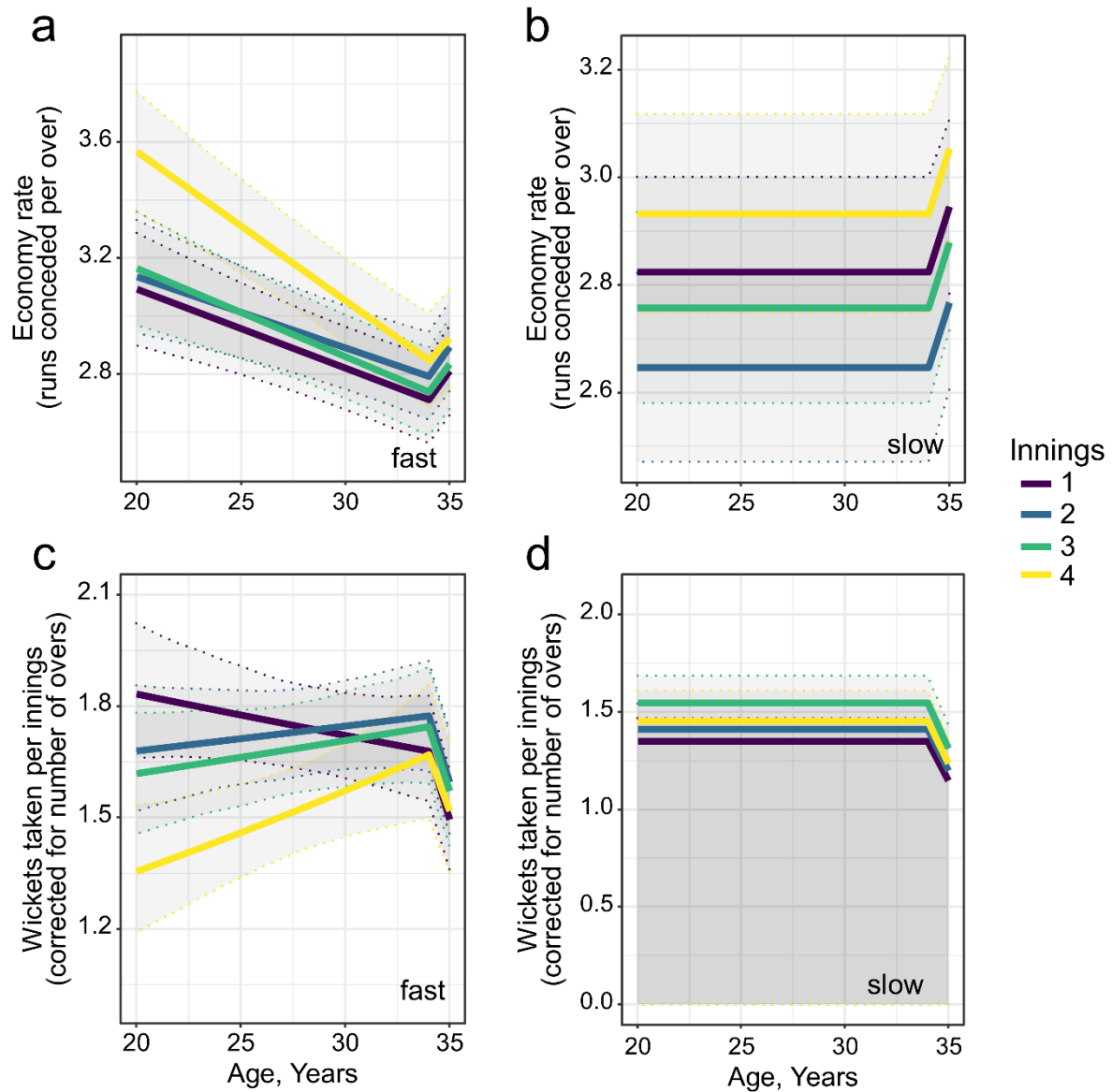
Fast bowling		Economy Rate		Wicket-taking ability		Prop. innings overs bowled	
		k	Δ AIC	k	Δ AIC	k	Δ AIC
	Model						
	Baseline	10	73.93	11	34.99	9	106.56
	Baseline + Age	11	29.34	12	36.97	10	108.56
	Baseline + Age + Age ²	12	31.18	13	37.95	11	73.83
	Baseline + ALA + LY	12	44.69	13	4.48	11	41.71
	Baseline + Age + ALA + LY	13	6.46	14	5.83	12	39.69
	Baseline + Age + Age ² + ALA + LY	14	8.41	15	7.67	13	17.47
	Baseline + Age*Inns + ALA + LY	16	0.00	17	0.00	15	37.85
	Baseline + Age*ALA + ALA + LY	14	7.93	15	7.66	13	41.19
	Baseline + Age*Inns + Age*ALA + ALA + LY	17	1.34	18	1.90	16	38.24
	Baseline + Age*Inns + Age ² *Inns + ALA + LY	20	6.67	21	1.99	19	19.52
	Baseline + Age*ALA + Age ² *ALA + ALA + LY	16	6.78	17	35.57	15	0.00
	Baseline + Age*Inns + Age ² *Inns + Age*ALA + Age ² *ALA + ALA + LY	22	4.68	23	4.72	21	2.17
Slow bowling		Economy Rate		Wicket-taking ability		Prop. innings overs bowled	
	Model	k	Δ AIC	k	Δ AIC	k	Δ AIC
	Baseline	10	18.22	11	20.70	9	57.14
	Baseline + Age	11	17.51	12	22.66	10	58.26
	Baseline + Age + Age ²	12	16.98	13	24.57	11	54.52
	Baseline + ALA + LY	12	0.00	13	1.15	11	36.74
	Baseline + Age + ALA + LY	13	1.57	14	0.74	12	33.72
	Baseline + Age + Age ² + ALA + LY	14	1.46	15	14.10	13	33.98
	Baseline + Age*Inns + ALA + LY	16	5.67	17	3.09	15	21.96
	Baseline + Age*ALA + ALA + LY	14	1.76	15	0.00	13	28.74
	Baseline + Age*Inns + Age*ALA + ALA + LY	17	5.90	18	2.33	16	17.02
	Baseline + Age*Inns + Age ² *Inns + ALA + LY	20	8.66	21	8.46	19	25.56
	Baseline + Age*ALA + Age ² *ALA + ALA + LY	16	4.26	17	2.62	15	8.48
	Baseline + Age*Inns + Age ² *Inns + Age*ALA + Age ² *ALA + ALA + LY	22	11.86	23	8.65	21	0.00

353



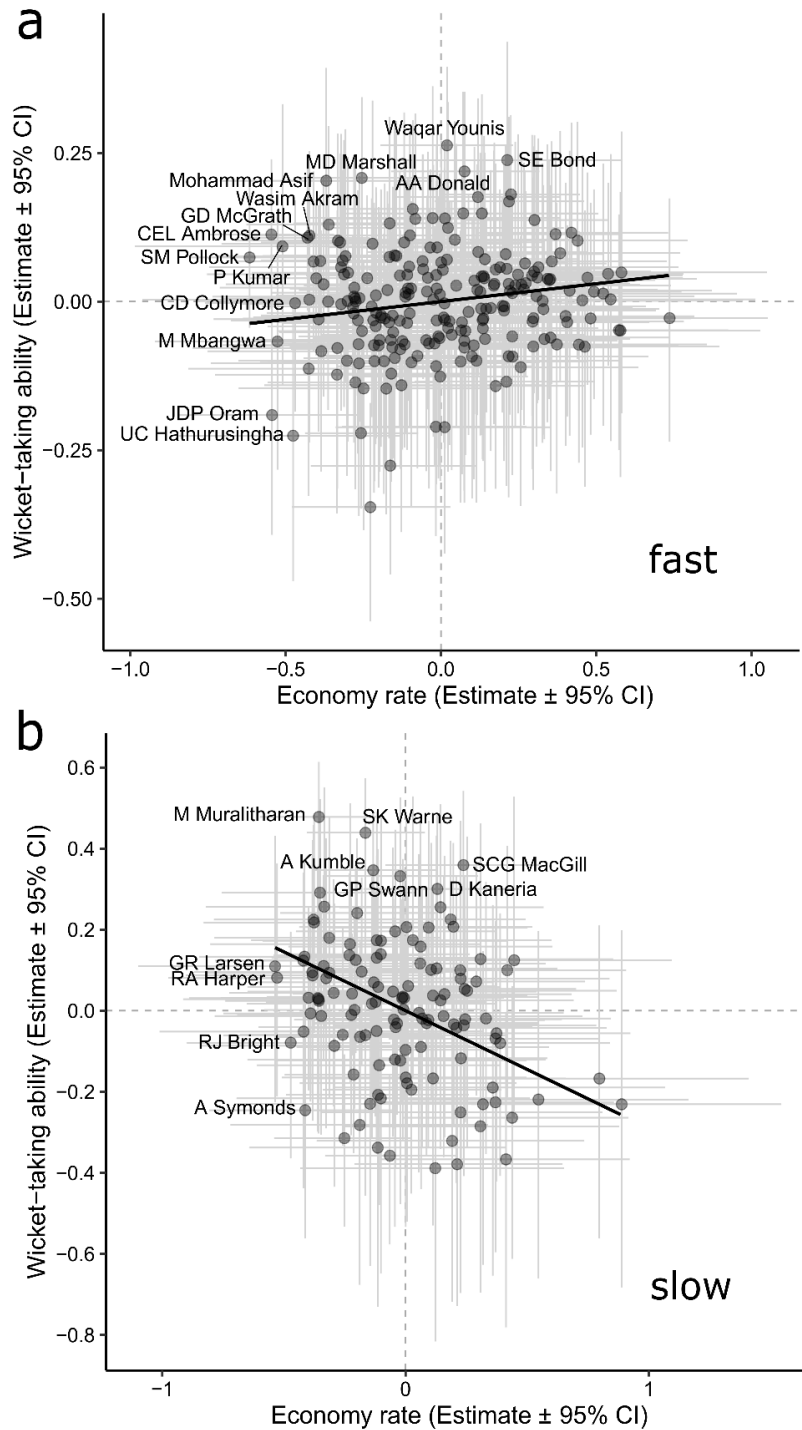
354

355 **Figure 1. Age-related changes in the performance of Test match bowlers, separated by**
 356 **bowling style.** Solid lines display the predicted performance from the best supported mixed effects
 357 models in each case for fast and slow bowlers; for economy rate (a, b), wicket-taking ability (c, d),
 358 and the proportion of the total overs in an innings bowled (e, f). Lines are coloured according to
 359 the age at which individuals stop playing Test match cricket, here estimated at the ages of 25,
 360 30 and 35 years. Shading displays the 95% confidence intervals conditional on the fixed effects. For
 361 the fast bowlers, predictions were made for innings 1 at home, while for the slow bowlers,
 362 predictions were made for innings 4 at home. Note that a lower economy rate indicates higher
 363 performance. The significance ($\alpha = 0.05$) of the presented terminal decline (LY- last year of career)
 364 or longevity effect (ALA- age at last appearance) for each model are noted with a +/- sign within
 365 the respective panels.



366

367 **Figure 2. Age-related changes in the performance of Test match bowlers according to the**
368 **innings of the match.** Solid lines display the predicted performance from the best supported
369 mixed effects models in each case for fast and slow bowlers, coloured according to the innings of
370 the match; for economy rate (a, b), and wicket-taking ability (c, d). Shading displays the 95%
371 confidence intervals conditional on the fixed effects. Predictions were made for individuals who
372 played their last match when they were 35 years old, with a terminal decline in the last year of life
373 included. Note that a lower economy rate indicates higher performance.



374

375 **Figure 3. Posterior correlation between economy rate and wicket-taking ability in a) fast and**
376 **b) slow bowlers, as estimated from multivariate models.** Points denote the player-specific
377 deviations in intercept for each performance metric with 95% CI (grey lines). The posterior among-
378 individual correlation is displayed by the solid line. Estimates are taken from models that controlled
379 for other confounding population-level effects. Individual players with particularly low economy rate
380 or particularly high wicket-taking ability have been highlighted. For aesthetic reasons Mohammed
381 Ashraful is not displayed in figure 3b as he represented an extreme outlier among slow bowlers.

382

383 DISCUSSION

384 Elite players in many sporting disciplines experience declines in performance at around
385 thirty years of age, but this has not been the case for bowlers playing Test match cricket in the
386 modern era. Irrespective of the style of the bowler – whether fast or slow – I find that neither
387 economy rate nor wicket-taking ability demonstrated significant age-related declines. On the
388 contrary, while the economy rate and wicket-taking ability of slow bowlers was maintained
389 across their career, for fast bowlers both performance metrics improved with increasing age.
390 Despite this, a long career is not reserved for all individuals. Test cricket, as its name implies, is a
391 testing arena in which to perform, and in most aspects of performance we find that it is only the
392 highest quality bowlers that continue to play into their mid-to-late thirties before being replaced.
393 Multivariate models also highlighted a clear separation between bowling styles on the basis of the
394 relationship between economy rate and wicket-taking ability. There was no correlation among
395 fast bowlers between the two performance metrics having controlled for various confounding
396 effects, whereas in slow bowlers – the majority of whom are spinners - individuals with lower
397 economy rates also tended to display higher wicket-taking ability. This finding lends credence to
398 oft-spoken adage that ‘pressure brings wickets’ and supports the notion of a general axis of
399 quality in international spin bowlers.

400 Clearly, Test match bowlers are not immune to the physiological downturns that affect
401 elite level sportsmen and women in other dynamic sports. In part, the ability to detect senescence
402 in performance is likely to be obscured by the strong cohort effect that manifests in only the
403 highest quality bowlers being retained in the older age classes. Specifically, late-playing fast
404 bowlers have above-average wicket-taking ability and bowl proportionally more overs compared
405 to players that leave Test cricket early, while late-playing slow bowlers have above-average
406 economy rates and likewise bowl proportionally more overs. Such cohort effects are largely
407 unappreciated in longitudinal studies of sporting performance but are likely to be widespread, and
408 where present, they have the potential to hinder the accurate quantification of age-related changes

409 occurring within individuals (van de Pol and Verhulst, 2006; van de Pol and Wright, 2009).
410 Furthermore, it is clear that any downturns in performance, whether senescent or otherwise, are
411 highly detrimental to a cricketer's ongoing international career. Across all but one model, bowlers
412 were seen to experience a significant terminal decline in the last year of their Test career, at
413 which point they were presumably dropped from the team and permanently replaced. The
414 magnitude of the terminal declines were unaffected by the age at which a bowler finished
415 playing, though it is possible that terminal declines are underestimated at older ages because a
416 sizeable fraction of international cricketers retire, and will often do so 'on a high'. As a result,
417 players disappearing from international cricket for dips in form beyond thirty years of age were
418 not differentiated from players who retired, which is likely to have reduced the effect size of
419 terminal declines in elder players. It would be interesting to know whether similar cohort effects
420 and terminal declines are prevalent in domestic cricket where selection criteria are likely to be
421 more forgiving and where individuals are likely to be retained in teams for longer in spite of
422 declining performance. This might allow one to pick up clearer age-related declines in
423 performance on the domestic circuit, but on the international scene, dips in form are heavily
424 penalised and careers are curtailed quickly thereafter.

425 The absence of senescence in overall performance does not preclude age-related declines
426 in other physiological attributes. In particular, it might be expected that the speed at which fast
427 bowlers deliver the ball declines with age. Serving speed peaks in professional tennis players at
428 around 28 years of age (Sutter et al., 2018) and the strikeout rate of pitchers in baseball – which is
429 thought to lean heavily on pitching speed – reaches its peak at just 23.5 years of age (Bradbury,
430 2009). Both of these activities bear biomechanical similarities to fast bowling which places heavy
431 demands on joints and on arm tendons and muscles (Orchard et al., 2015). Whether or not fast
432 bowlers do indeed bowl more slowly could not be discerned, for available speed data is not
433 publicly available, but it should exist in other databases (e.g. CricViz) and it remains an
434 intriguing possibility that as fast bowlers age they might compensate for declines in speed by

435 improving their accuracy or modifying other aspects of their bowling. The reductions in economy
436 rate with increasing age picked up by the models in this study could be indicative of improved
437 accuracy in fast bowlers as their bowling speed declines with age.

438 Why is it then that various aspects of bowling performance do not senesce but rather
439 improve with age? Bowling generally requires a high degree of motor control and so it seems
440 likely that domain-specific expertise, deliberate practice, and increased experience (in this case of
441 Test match cricket) are crucial to the ongoing success of bowlers. Such factors are frequently
442 invoked to explain maintenance or improvement of high-level sporting abilities more generally
443 (Helsen et al., 1998; Baker and Young, 2014; Careau and Wilson, 2017), and further information
444 on training regimes and more nuanced data on delivery trajectories under Test conditions could
445 shed light on each of these possibilities. Even so, distinguishing between the various alternatives
446 is likely to be difficult since practice, expertise, and experience are likely to be highly inter-
447 related. Nevertheless, a number of domain-specific characteristics that are not necessarily reliant
448 on physical ability could be hypothesized as being important for the continued improvement of
449 bowlers with increasing age: individuals could improve their ability to ‘work out’ individual
450 batters and target their weaknesses, could better adapt to the highly variable conditions they
451 experience across the world, or could develop a greater variety of deliveries that improve their
452 likelihood of taking wickets. Another possibility is that bowlers become more adept at bowling to
453 left-handed batters later in their career, or vice versa. Previously, Brooks et al. (2004) analysed
454 batting performance in the 2003 Cricket World Cup and demonstrated that left-handed batters
455 enjoyed a strategic advantage over their right handed counterparts, perhaps because of their
456 relative rarity on the domestic circuit, with the implication that bowlers were less experienced at
457 bowling to left handers on the international stage and thus suffered poorer returns. To my
458 knowledge, whether such a left-handed advantage is present in the longer format of cricket
459 remains untested, but if present, it is not inconceivable that bowlers could offset this advantage
460 with increased practice and training as their career progresses.

461 The application of a multivariate modelling framework revealed an important distinction
462 between fast and slow bowlers in the relationship between economy rate and wicket-taking
463 ability. While fast bowlers showed no apparent relationship between the two performance metrics
464 once other covariates are controlled for, the negative correlation in slow bowlers is suggestive of
465 a general axis of quality whereby those slow bowlers who are more economical also tend to take
466 more wickets. The reasons for this are intuitive- low economy rate is often thought to reflect
467 accuracy to some degree, such that slow bowlers with lower economy rate are more accurate and
468 thus ultimately derive greater success in the form of wickets. Conversely, the lack of equivalent
469 trend in fast bowlers might be partly explained by an indirect trade-off between speed and
470 accuracy at the higher velocities with which fast bowlers deliver the ball. Although any such
471 assessment in Test cricketers would require the explicit incorporation of speed information into
472 the multivariate framework, such a trade-off has been observed in tennis and football (van den
473 Tillaar and Fuglstad, 2017; Sutter et al., 2018; see also Fitts, 1954) and it may have contributed
474 towards the lack of negative association between economy-rate and wicket-taking ability here
475 (recall that low economy rate is favourable such that any significant trade-off would be noted by
476 a positive correlation). It is notable for example that some of the very best bowlers of the modern
477 era in terms of wicket-taking ability are some of the very fastest of all fast bowlers (Figure 3,
478 Figure S1), and that these individuals are rarely very economical. Even so, economy rate is not
479 directly substitutable for accuracy, and even if it were, accuracy or skill is hard to quantify in a
480 game where variety in terms of the trajectory and speed at which a ball is bowled can also bring
481 rewards. As a result, testing for a correlation between speed and economy rate at broad scales - or
482 accuracy by some measure (Feros et al., 2018) - is likely to remain elusive under match
483 conditions.

484 No consideration of individual performance in cricket is complete without a discussion of
485 rankings. Such discussions are often complicated by the need to draw comparisons across
486 different eras (Boys and Philipson, 2019), however, the multivariate methods used in this study

487 provide one such means of ranking Test match bowlers after having statistically controlled for
488 temporal changes in the quality of the team and the opposition, alongside other confounding
489 variables. If anything, the inclusion of a group-level effect of the Test playing nation in
490 interaction with the decade will slightly devalue players from the best-performing teams through
491 time. Nor do the models weight players according to their career longevity, which many would
492 perhaps like to be included in any consideration of overall ranking, but these caveats noted, the
493 approach provides a standardised means of ranking bowlers across the generations of the modern
494 era on the basis of their individual-level intercept (their deviation from the population mean in the
495 multivariate models; the full list of modern-era bowlers ranked by their individual-level intercepts
496 is provided in the supplementary tables 6-9). If we consider the slow bowlers first, then known
497 high performers are recovered at the top of the rankings: Muttiah Muralitharan (Sri Lanka) and
498 Shane Warne (Australia) sit first and second, respectively, in terms of their wicket-taking ability,
499 though other players retain high wicket-taking ability while also conceding very few runs per
500 over (the upper left of figure 3b). For fast bowlers, the best bowler in terms of their wicket-taking
501 ability is Waqar Younis (Pakistan), followed by Shane Bond (New Zealand) and Alan Donald
502 (South Africa), though with a less clear relationship between economy rate and wicket-taking
503 ability in fast bowlers, it could also be argued that other more economical bowlers have been
504 equally effective operators on the international stage. The inclusion of players that are still
505 playing Test match cricket or those that only recently stopped playing identified a number of
506 additional top performers who on current or recent merit would be placed amongst the very best
507 of the modern era (Fig S1). After their inclusion, for example, recently retired Dale Steyn (South
508 Africa) becomes the best-ranked fast bowler on the basis of wicket-taking ability, being closely
509 followed by Kagiso Rabada (South Africa), who at 24 years of age at the time of writing, is still
510 likely to play test match cricket for several years to come.

511 Overall, the results of this study reiterate the need for analyses of human sporting
512 performance to fully consider the variation occurring within and between individuals if they are

513 to accurately capture the shape and magnitude of age trajectories. Ecological and evolutionary
514 studies of animal populations provide a rich evidence-base to aid in this pursuit, which if
515 employed in a human setting (Careau and Wilson, 2017), have the potential to enrich our
516 understanding of changes in functional capacity across the human lifespan.

517 ACKNOWLEDGEMENTS

518 JT would like to thank Leejiah Dorward, and current and former members of the University of
519 Cambridge Zoology Department cricket team for comments that improved the manuscript.

520 FUNDING INFORMATION

521 There is no funding to declare for this manuscript.

522 DATA ACCESSIBILITY

523 There is no funding to declare for this manuscript

524 REFERENCES

- 525 Baker, A. B., and Tang, Y. Q. (2010). Aging performance for masters records in athletics, swimming, rowing,
526 cycling, triathlon, and weightlifting. *Exp. Aging Res.* 36, 453–477. doi:10.1080/0361073X.2010.507433.
- 527 Baker, J., Deakin, J., Horton, S., and Pearce, G. W. (2007). Maintenance of Skilled Performance with Age: A
528 Descriptive Examination of Professional Golfers. *J. Aging Phys. Act.* 15, 300–317.
529 doi:10.1123/japa.15.3.300.
- 530 Baker, J., and Young, B. (2014). 20 Years Later: Deliberate Practice and the Development of Expertise in Sport.
531 *Int. Rev. Sport Exerc. Psychol.* 7, 135–157. doi:10.1080/1750984X.2014.896024.
- 532 Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *J.*
533 *Stat. Softw.* 67, 1–48. doi:10.18637/jss.v067.i01.
- 534 Boys, R. J., and Philipson, P. M. (2019). On the ranking of test match batsmen. *J. R. Stat. Soc. Ser. C Appl. Stat.*
535 68, 161–179. doi:10.1111/rssc.12298.
- 536 Bradbury, J. C. (2009). Peak athletic performance and ageing: Evidence from baseball. *J. Sports Sci.* 27, 599–
537 610. doi:10.1080/02640410802691348.
- 538 Brooks, M., Kristensen, K., van Benthem, K., Magnusson, A., Berg, C., Nielsen, A., et al. (2017). glmmTMB
539 balances speed and flexibility among packages for zero-inflated generalised linear mixed modeling. *R J.* 9,
540 378–400.

- 541 Brooks, R., Bussière, L. F., Jennions, M. D., and Hunt, J. (2004). Sinister strategies succeed at the cricket World
542 Cup. *Proc. R. Soc. B Biol. Sci.* 271, 64–66. doi:10.1098/rsbl.2003.0100.
- 543 Bürkner, P.-C. (2018). brms: Advanced Bayesian multilevel modeling with the R package brms. *R J.* 10, 395–
544 411.
- 545 Burnham, K., and Anderson, D. (2002). *Model selection and multi-model inference: a practical information-*
546 *theoretic approach*. Berlin, Germany: Springer.
- 547 Cameron, S. F., Wynn, M. L., and Wilson, R. S. (2013). Sex-specific trade-offs and compensatory mechanisms:
548 Bite force and sprint speed pose conflicting demands on the design of geckos (*Hemidactylus frenatus*). *J.*
549 *Exp. Biol.* 216, 3781–3789. doi:10.1242/jeb.083063.
- 550 Careau, V., and Wilson, R. S. (2017). Performance trade-offs and ageing in the ‘world’s greatest athletes.’ *Proc.*
551 *R. Soc. B Biol. Sci.* 284, 1–9. doi:10.1098/rspb.2017.1048.
- 552 Christensen, K., Doblhammer, G., Rau, R., and W, J. V. (2009). Ageing populations: the challenges ahead.
553 *Lancet (London, England)* 374, 1196–1208. doi:10.1016/S0140-6736(09)61460-4.Ageing.
- 554 Christensen, K., Johnson, T. E., and Vaupel, J. W. (2006). The quest for genetic determinants of human
555 longevity: Challenges and insights. *Nat. Rev. Genet.* 7, 436–448. doi:10.1038/nrg1871.
- 556 Dennenmoser, S., and Christy, J. H. (2013). The design of a beautiful weapon: Compensation for opposing
557 sexual selection on a trait with two functions. *Evolution (N. Y.)* 67, 1181–1188. doi:10.1111/evo.12018.
- 558 Doherty, T. J. (2003). Invited review: Aging and sarcopenia. *J. Appl. Physiol.* 95, 1717–1727.
559 doi:10.1152/jappphysiol.00347.2003.
- 560 Feros, S. A., Young, W. B., and O’Brien, B. J. (2018). Quantifying Cricket Fast-Bowling Skill. *Int. J. Sports*
561 *Physiol. Perform.* 13, 830–838. doi:10.1123/ijsp.2017-0169.
- 562 Fitts, P. (1954). The information capacity of the human motor system in controlling the amplitude of movement.
563 *J. Exp. Psychol.* 47, 381–391. Available at:
564 http://www2.psychology.uiowa.edu/faculty/mordkoff/InfoProc/pdfs/Fitts_1954.pdf.
- 565 Gaillard, J. M., and Lemaître, J. F. (2017). The Williams’ legacy: A critical reappraisal of his nine predictions
566 about the evolution of senescence. *Evolution (N. Y.)* 71, 2768–2785. doi:10.1111/evo.13379.
- 567 Ganesh, T. V. (2019). cricketr: Analyze cricketers and cricket teams based on ESPN cricinfo. Available at:
568 <https://cran.r-project.org/package=cricketr>.
- 569 Hayward, A. D., Moorad, J., Regan, C. E., Berenos, C., Pilkington, J. G., Pemberton, J. M., et al. (2015).
570 Asynchrony of senescence among phenotypic traits in a wild mammal population. *Exp. Gerontol.*
571 doi:10.1016/j.exger.2015.08.003.
- 572 Helsen, W., Starkes, J., and Hodges, N. (1998). Team sports and the theory of deliberate practice. *J. Sport*
573 *Exerc. Psychol.* 20, 12–34.
- 574 Hill, A. V. (1925). The Physiological Basis of Athletic Records. *Sci. Mon.* 21, 409–428. doi:10.1016/S0140-
575 6736(01)15546-7.
- 576 Hjelmberg, J. B., Iachine, I., Skytthe, A., Vaupel, J. W., McGue, M., Koskenvuo, M., et al. (2006). Genetic
577 influence on human lifespan and longevity. *Hum. Genet.* 119, 312–321. doi:10.1007/s00439-006-0144-y.
- 578 Houslay, T. M., Vierbuchen, M., Grimmer, A. J., Young, A. J., and Wilson, A. J. (2018). Testing the stability of
579 behavioural coping style across stress contexts in the Trinidadian guppy. 424–438. doi:10.1111/1365-
580 2435.12981.
- 581 Husak, J. F., Ribak, G., Wilkinson, G. S., and Swallow, J. G. (2011). Compensation for exaggerated eye stalks
582 in stalk-eyed flies (Diopsidae). *Funct. Ecol.* 25, 608–616. doi:10.1111/j.1365-2435.2010.01827.x.
- 583 Jones, O. R., Scheuerlein, A., Salguero-Gómez, R., Camarda, C. G., Schaible, R., Casper, B. B., et al. (2014).
584 Diversity of ageing across the tree of life. *Nature* 505, 169–73. doi:10.1038/nature12789.
- 585 Lailvaux, S. P. (2018). “Mice and Men,” in *Feats of Strength: How Evolution Shapes Animal Athletic Abilities*
586 (New Haven, USA: Yale University Press), 228–246.

- 587 Lailvaux, S. P., Wilson, R., and Kasumovic, M. M. (2014). Trait compensation and sex-specific aging of
588 performance in male and female professional basketball players. *Evolution (N. Y.)*, 68, 1523–1532.
589 doi:10.1111/evo.12375.
- 590 Masoro, E., and Austad, S. (2010). *Handbook of the Biology of Aging*. 7th ed. Academic Press.
- 591 Monaghan, P., Charmantier, a., Nussey, D. H., and Ricklefs, R. E. (2008). The evolutionary ecology of
592 senescence. *Funct. Ecol.* 22, 371–378. doi:10.1111/j.1365-2435.2008.01418.x.
- 593 Moore, D. H. (1975). A study of age group track and field records to relate age and running speed. *Nature* 253,
594 264–265. doi:10.1038/253264a0.
- 595 Murman, D. L. (2015). The impact of age on cognition. *Semin. Hear.* 36, 111–121.
- 596 Noakes, T. D., and Durandt, J. J. (2000). Physiological requirements of cricket. *J. Sports Sci.* 18, 919–929.
597 doi:10.1080/026404100446739.
- 598 Nussey, D., Coulson, T., Delorme, D., Clutton-brock, T., Pemberton, J. M., Festa-bianchet, M., et al. (2011).
599 Patterns of body mass senescence and selective disappearance differ among three species of free-living
600 ungulates. *Ecology* 92, 1936–1947. doi:10.2307/23034827.
- 601 Nussey, D. H., Froy, H., Lemaitre, J.-F., Gaillard, J.-M., and Austad, S. N. (2013). Senescence in natural
602 populations of animals: widespread evidence and its implications for bio-gerontology. *Ageing Res. Rev.*
603 12, 214–25. doi:10.1016/j.arr.2012.07.004.
- 604 Orchard, J. W., Blanch, P., Paoloni, J., Kountouris, A., Sims, K., Orchard, J. J., et al. (2015). Cricket fast
605 bowling workload patterns as risk factors for tendon, muscle, bone and joint injuries. *Br. J. Sports Med.*
606 49, 1064–1068. doi:10.1136/bjsports-2014-093683.
- 607 Passarino, G., De Rango, F., and Montesanto, A. (2016). Human longevity: Genetics or Lifestyle? It takes two
608 to tango. *Immun. Ageing* 13, 1–6. doi:10.1186/s12979-016-0066-z.
- 609 Pawelec, G. (2012). Hallmarks of human “immunosenescence”: Adaptation or dysregulation? *Immun. Ageing* 9,
610 8–11. doi:10.1186/1742-4933-9-15.
- 611 Petersen, C. J., Pyne, D., Dawson, B., Portus, M., and Kellett, A. (2010). Movement patterns in cricket vary by
612 both position and game format. *J. Sports Sci.* 28, 45–52. doi:10.1080/02640410903348665.
- 613 Pollet, T. V., Stulp, G., and Groothuis, T. G. G. (2013). Born to win? Testing the fighting hypothesis in realistic
614 fights: left-handedness in the Ultimate Fighting Championship. *Anim. Behav.* 86, 839–843.
615 doi:10.1016/j.anbehav.2013.07.026.
- 616 Postma, E. (2014). A relationship between attractiveness and performance in professional cyclists. *Biol. Lett.* 10,
617 doi:10.1098/rsbl.2013.0966.
- 618 Rebke, M., Coulson, T., Becker, P. H., and Vaupel, J. W. (2010). Reproductive improvement and senescence in
619 a long-lived bird. *Proc. Natl. Acad. Sci.* 107, 7841–7846. doi:10.1073/pnas.1002645107.
- 620 Roff, D. A. (1992). *The Evolution of Life Histories: Theory and Analysis*. Chapman and Hall.
- 621 Salthouse, T. A. (2009). When does age-related cognitive decline begin? *Neurobiol. Aging* 30, 507–514.
622 doi:10.1016/j.neurobiolaging.2008.09.023.
- 623 Schorer, J., and Baker, J. (2009). An exploratory study of aging and perceptual-motor expertise in handball
624 goalkeepers. *Exp. Aging Res.* 35, 1–19. doi:10.1080/03610730802544641.
- 625 Schulz, R., and Curnow, C. (1988). Peak performance and age among superathletes: Track and field, swimming,
626 baseball, tennis, and golf. *Journals Gerontol.* 43, 13–20. doi:10.1093/geronj/43.5.P113.
- 627 Sharma, G., and Goodwin, J. (2006). Effect of aging on respiratory system physiology and immunology. *Clin.*
628 *Interv. Aging* 1, 253–260. doi:10.2147/ciia.2006.1.3.253.
- 629 Shefferson, R. P., Jones, O. R., and Salguero-Gómez, R. (2017). *Evolution of Senescence in the Tree of Life*.
630 Cambridge, UK: Cambridge University Press.
- 631 Stearns, S. (1992). *The Evolution of Life Histories*. Oxford, UK: Oxford University Press.

- 632 Steves, C. J., Spector, T. D., and Jackson, S. H. D. (2012). Ageing, genes, environment and epigenetics: What
633 twin studies tell us now, and in the future. *Age Ageing* 41, 581–586. doi:10.1093/ageing/afs097.
- 634 Stones, M. J. (2019). Age Differences, Age Changes, and Generalizability in Marathon Running by Master
635 Athletes. *Front. Psychol.* 10, 1–8. doi:10.3389/fpsyg.2019.02161.
- 636 Stones, M. J., and Kozma, A. (1984). Longitudinal trends in track and field performances. *Exp. Aging Res.* 10,
637 107–110. doi:10.1080/03610738408258552.
- 638 Sutter, A., Barton, S., Sharma, M. D., Basellini, U., Hosken, D. J., and Archer, C. R. (2018). Senescent declines
639 in elite tennis players are similar across the sexes. *Behav. Ecol.* 29, 1351–1358.
640 doi:10.1093/beheco/ary112.
- 641 Team, R. C. (2019). R: A language and environment for statistical computing.
- 642 Trappe, S. (2007). Marathon runners: how do they age? *Sport. Med.* 37, 302–305.
- 643 Uhlenberg, P. (2009). *International Handbook of Population Aging*. Springer Netherlands.
- 644 van de Pol, M., and Verhulst, S. (2006). Age-dependent traits: a new statistical model to separate within- and
645 between-individual effects. *Am. Nat.* 167, 766–773. doi:10.1086/503331.
- 646 van de Pol, M., and Wright, J. (2009). A simple method for distinguishing within- versus between-subject
647 effects using mixed models. *Anim. Behav.* 77, 753–758. doi:10.1016/j.anbehav.2008.11.006.
- 648 van den Tillaar, R., and Fuglstad, P. (2017). Effect of Instructions Prioritizing Speed or Accuracy on Kinematics
649 and Kicking Performance in Football Players. *J. Mot. Behav.* 49, 414–421.
650 doi:10.1080/00222895.2016.1219311.
- 651 Vaupel, J. W. (2010). Biodemography of human ageing. *Nature* 464, 536–542.
652 doi:10.1038/nature08984.Biodemography.
- 653 Walker, L. C., and Herndon, J. G. (2010). Mosaic Aging. *Med. Hypotheses* 74, 1048–1051.
654 doi:10.1016/j.mehy.2009.12.031.Mosaic.
- 655 Woolmer, B. (2008). *Bob Woolmer's art and science of cricket*. London: New Holland.
- 656 Young, B. W., and Starkes, J. L. (2005). Career-span analyses of track performance: Longitudinal data present a
657 more optimistic view of age-related performance decline. *Exp. Aging Res.* 31, 69–90.
658 doi:10.1080/03610730590882855.

659 SUPPORTING INFORMATION

660 Supporting Information 1 (PDF): Supplementary tables and figures

661 **Figure S1:** Posterior correlation between economy rate and wicket-taking ability in a) fast and b)
662 slow bowlers, as estimated from multivariate models including Test cricketers that are still
663 playing, or have only recently stopped playing. **Table S1:** Best fitting linear mixed effects model
664 for the economy rate of fast bowlers and slow bowlers. **Table S2:** Best fitting generalised linear
665 mixed effects model for the wicket-taking ability of fast bowlers and slow bowlers. **Table S3:**
666 Best fitting generalised linear mixed effects model for the proportion of the overs bowled in the
667 innings. **Table S4:** Results from Bayesian multivariate response models investigating the
668 posterior correlation between economy rate and wicket-taking ability in fast bowlers. **Table S5:**
669 Results from Bayesian multivariate response models investigating the posterior correlation
670 between economy rate and wicket-taking ability in slow bowlers. **Table S6:** Rankings for the fast
671 bowlers of modern era (post-1973) Test cricket on the basis of their wicket-taking ability. **Table**
672 **S7:** Rankings for the fast bowlers of modern era (post-1973) Test cricket on the basis of their
673 economy rate. **Table S8:** Rankings for the slow bowlers of modern era (post-1973) Test cricket
674 on the basis of their wicket-taking ability. **Table S9:** Rankings for the slow bowlers of modern
675 era (post-1973) Test cricket on the basis of their economy rate.

676 Supporting Information 2 (XLS)

677 Data files used for analyses.