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IZA DP No. 16963

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ISSN: 2365-9793

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ABSTRACT

Can Awareness Reduce (and Reverse) Identity-Driven Bias in Judgement? Evidence from International Cricket*

Competitions often suffer from biased judgments by officials tied to their social identities. In international cricket, home nation umpires favoured home teams, but neutral umpires were introduced successfully to address this bias. However, the COVID-19 pandemic prompted the return of home umpires, creating a natural experiment amid heightened scrutiny, modern technology, and sometimes empty stadiums. Consistent with the predictions of our behavioural model, we find no evidence of in-group bias during the pandemic; instead, we observe evidence of over-compensation. The pre-pandemic home team advantage in 'leg before wicket' decisions vanished, with home umpires seemingly favouring the away opposition, compared with neutral umpires in the period before, especially in more marginal or difficult decisions. This suggests that awareness and scrutiny can not only eliminate identity-driven judgement bias but may even reverse it.

JEL Classification: D01, D91, L83, Z2

Keywords: natural experiment, identity, judgement bias, social pressure, home advantage, COVID-19

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* We are grateful to Sudipta Sarangi (editor), two anonymous referees, James Fenske, Ian Gregory-Smith, Joo Young Jeon, Alex Krumer, Friederike Mengel, Dominic Schreyer, the participants of the 8th Annual Contests: Theory and Evidence Conference, the 2022 Erasmus Centre for Applied Sports Economics Workshop, the 9th UEA Behavioural Game Theory Conference, the Brunel 2023 Economic Development and Institutions Annual Conference, the 7th Sport Economics Sport Management Conference, 2024 Scottish Economic Society Annual Conference, and the seminar participants of the Indian Statistical Institute, National Taiwan University, and the Reading Online Sports Economics Seminar, for valuable comments. Any remaining errors are our own.

1. Introduction

Competition is essential in various aspects of life and the winners are normally rewarded more than the losers. Examples include workplace promotion and bonuses, litigation, rent seeking, patent races, grant applications, and sporting contests, among others. Often the outcome of a competition is not obvious, and official decision makers, such as judges and juries, teachers, managers, grant panel members, and referees, observe and judge the contestants. Such judgements have important implications for the competing parties, and for broader society (e.g., audiences, consumers, organisations, universities, governments). While correct and fair judgements from the officials are expected, sometimes they turn out to be wrong; incorrect decisions may occur due to error or due to judgement bias.

While errors can affect all the engaged parties randomly, judgement bias – if systematic – helps some parties over others. This bias can be driven by stereotypes (Campbell, 2015) or statistical discrimination (Rubineau and Kang, 2012). However, the bias is frequently also driven by the identity (race, gender, religion, nationality, language etc.) of the officials and competitors.[1] For instance, Shayo and Zussman (2011) showed that there is significant judicial bias in Israel according to the identity (Jewish or Arab) of the judge and parties in legal battles. Biases based on gender (Horowitz and Pottieger, 1991), immigration status (Marouf, 2010) and race are also documented in the US judiciary system – especially in administrative law (Golin, 1995). In education, Alesina et al. (2018) documented that for the same performance, immigrant students are often given lower marks than native students. Also from the classroom, Boring and Philippe (2021) found that male students discriminate against female teachers in teaching evaluations. In an experiment, Mengel (2021) showed that committee deliberation contributes to gender biases.

Such identity-driven judgement bias can lead to various undesirable outcomes (Breig and Kubitz, 2021). It discourages effort by the negatively affected parties, as they do not expect fair judgement, and by the positively affected parties, since they expect favour. In turn, this reduces participation from the unfavoured parties, and creates long term inequality, discrimination, and welfare loss for third parties (e.g., disappointment and disillusionment for an audience in sports events). Hence, the designers of competitions try to alleviate such bias for business, ethical, and social reasons.

There are several ways to deter such judgment bias: by providing performance-based rewards or sanctions to the officials, by placing decisions under greater public scrutiny, and by giving feedback

[1] The salience of in-group versus out-group identity is crucial in determining effort provision in group competitions (Chowdhury et al., 2016). However, such salience for an official decision maker is still under-researched.

or raising awareness that such bias (even implicitly) exists. Since the former methods may not be implemented easily or cheaply, there is growing interest in understanding whether raising awareness of judgement bias can reduce it and lead to corrective behaviour. Recent studies of bias according to gender (Della Giusta and Bosworth, 2020; Boring and Philippe, 2021; Mengel, 2021), immigration status (Alesina et al., 2018) and race (Haaland and Roth, 2023; Pope et al., 2018; Shayo and Zussman, 2017) all contribute to this area. Specifically, Alesina et al. (2018), Boring and Philippe (2021) and Mengel (2021) showed experimentally that raising awareness about judgement bias, or giving feedback about somebody's implicit bias, reduces and often eliminates the problem.

It is difficult to test these issues with field data, where the biases are not clearly documented. Experimental data has its own limitations for external validity and identifying any longer-run effects. After awareness is raised about a source of systematic judgement bias, the existing studies from the field have found either no efficient effects (Shayo and Zussman, 2017; Haaland and Roth, 2023; Krumer et al., 2022) or a reduction in the bias (Pope et al., 2018). To the best of our knowledge, however, no studies exist for a natural experiment where a policy that was meant to reduce well-known identity-driven judgment bias was subsequently reversed along with greater scrutiny, potentially prompting overcompensating behaviour by the decision makers once they return to judging competitors who share their identity.[2] We contribute to this area by employing field data from sports, using a sudden and distinctive change of rules due to the COVID-19 pandemic.

We study the game of cricket, where it was suspected historically that the umpires (match referees or officials) were biased towards their own countries in international competition. One (in)famous example involves the England's 1958-59 to Australia, in which the Australian umpires allegedly allowed illegal bowling by Australia but judged normal bowling by England as illegal. This incidence was pivotal in fundamentally changing the Laws of Cricket (Trueman, 2004). Another example comes from India's tour of Pakistan in 1978, when India decided to concede a match due to their view that the umpiring was biased, the first such incidence in international cricket (Mukherjee, 2016). There was a similar affair during England's tour of Pakistan in 1987-88, when a heated debate between England captain Mike Gatting and Pakistani umpire Shakur Rana, about the latter's alleged bias, led to a diplomatic dispute between the two countries (Mustafi, 2015). Specifically, regarding the subjective Leg Before Wicket (LBW) dismissal rule, Date (2015) hinted at home bias in umpiring that both helped (at home) and negatively affected (away from home) the Pakistani cricket legend

[2] There are studies in which a 'reverse bias' by officials against their own type are documented. For example, judges in US juvenile courts were seen to be harsher to the juvenile convicts of their own race (Depew et al., 2017). Also, Male music professors tended to favour female classical music composers – a male dominated field – in evaluation (Ting et al., 2022). However, those studies did not discuss whether such effects were the result of awareness of bias towards the decision maker's own type.

Javed Miandad: "In Pakistan, Miandad was LBW eight times in 73 dismissals. Outside Pakistan, 25 times in 95. Outside India and Pakistan, 17 times in 76. Miandad seems to have fallen LBW very often in India - eight out of 19 dismissals." While judged by Pakistani umpires, Miandad was given the subjective decision LBW for about 11% of his dismissals, while he was given out LBW twice as often per innings anywhere else in the world, except in India by Indian umpires, where it was 42%.

Incidences such as the above led to cricket's governing body, the International Cricket Council (ICC), partially using neutral umpires in international Test matches since 1994 and only using neutral umpires since 2002. Sacheti et al. (2015) have empirically shown the existence of judgment bias by cricket umpires that benefitted their home country team, demonstrating that the sport's policy makers were justified in turning to neutral country umpires. Fernando and George (2023) added evidence that the partial presence of neutral umpires before 2002 put peer pressure on home umpires, which led to more unbiased decisions among the latter. Such revelations earned media visibility and raised awareness about the value of neutral umpires.[3] However, due to the COVID-19 pandemic, the ICC temporarily brought back home umpires. This provides the basis of a natural experiment that allows us to examine whether (i) awareness of past bias leads to corrective behaviour, and (ii) whether the pressure of awareness and scrutiny can lead to overcompensating behaviour, i.e., reverse bias against home teams, potentially undoing the general advantage that teams tend to have in international professional sports when playing at home even with neutral adjudicators. We find no evidence that the temporary reintroduction of home umpires, along with greater scrutiny of their decisions, resulted in the return of biased adjudication favouring the home teams. Instead, we find indications of judgement error or bias by home umpires that tended to go against the home team, since decisions on average tended to favour the away team significantly more than during the preceding period that had neutral umpires. This suggests that, even in the field, the awareness and scrutiny of judgement bias can not only eliminate such bias but also reverse its direction. Overall, with home umpires, we find that the home advantage that existed under neutral umpires was reduced, representing a reversal compared with what happened historically with home umpires. In the case of one set of important decisions, the previous home advantage in outcomes became insignificant from zero with home umpires during the pandemic period. These results are inconsistent with standard expected utility theory, whereby awareness and scrutiny would only tend to eliminate incentives to make biased judgements. Instead, our findings are in line with a behavioural model which indicates that umpire identity-driven preferences can even reverse due to awareness and scrutiny.

[3] The results from Sacheti et al. (2015) were shared and discussed on the Guardian news website on 27 December 2014 by Selvey (2014): bit.ly/3PpucVl

Our findings contribute to the literature on identity and bias (e.g., Shayo and Zussman, 2011, 2017 among others). They also contribute to the literature on contests (Konrad, 2009), where the contests are biased (Chowdhury et al., 2023) or an official is present (Breig and Kubitz, 2021), and on behavioural biases in policy issues around contests (e.g., Baharad and Nitzan, 2008). In the area of sports economics, our findings specifically contribute to the literature that focuses on the role of nationality and group identity in the bias of officials in sport (e.g., for football see Dawson and Dobson, 2010; Dagaev et al., 2024; Faltings et al., 2023; Pope and Pope, 2015; Principe and van Ours, 2022; and for sports involving panels of judges, such as Ski Jumping and Dressage, see Coupe et al., 2018; Krumer et al., 2022; Sandberg, 2018; Zitzewitz, 2006).

We organise the rest of the paper as follows. Section 2 introduces a behavioural model that provides a micro-foundation for our research aim and hypotheses. In Section 3, we introduce the game of cricket, the specifics of the temporary rule change that led to the natural experiment, and the corresponding testable hypotheses. Section 4 describes the data and empirical strategy. We report the estimation results in Section 5, and Section 6 concludes.

2. Theoretical Micro-foundation

A standard model involving expected utility theory would evaluate an umpire's decision in a cost-benefit framework. However, we deviate from this and instead follow the behavioural models of Bordalo et al. (2013) and Kőszegi and Szeidl (2013), to explain and provide a micro-foundation for how awareness and scrutiny not only eliminate own-group bias but may also enable preference reversal among officials, resulting in reverse bias. Moreover, although we will frame the model in terms of cricket umpires, similar logic can be followed for other official decision makers, such as judges, juries, teachers, etc.

Let us consider an umpire with identity 'Home' (H), who is aligned with the home team. The only other relevant identity that he or she officiates in is the 'Away' team (A), which is mutually exclusive from Home. The umpire makes a choice i between two subjective, difficult, and controversial decisions that can favour either the home or the away team, $i = H, A$. Each decision is characterised by the utility the umpire gains from the decision (u_i) and the associated reputation or 'backlash' cost (c_i), due to subjectivity and any controversy that is caused.

Decision H, that favours the home team aligned with the umpire, is the high-utility decision, potentially due to nationality-driven bias in our focus of international Test cricket. Conversely, decision A is of low utility. However, when a subjective decision goes in favour of the home team, it also incurs more of a reputation cost for the umpire (as described in the previous section) compared with when it goes in favour of the away team. These features can be written as:

$$u_H > u_A > 0 \text{ and } c_H > c_A > 0 \tag{1}$$

Without any distortions due to awareness and scrutiny, an umpire makes their decision according to a linear payoff function that attaches equal weight to utility and cost: $\pi_i = u_i - c_i$. In such a case, the home-aligned umpire will favour the home team as long as $\pi_H > \pi_A$. Even when the reputation cost of a decision goes up due to awareness and scrutiny, the result does not change. If the costs adjust in such a way that $\pi_H = \pi_A$, then the bias disappears.

However, as in Kőszegi and Szeidl (2013), we posit that when decisions are affected by salience, due to awareness and scrutiny, it brings about behavioural distortions. Then an umpire evaluates decision i according to the following revised payoff function, where the utility and cost are weighted:

$$\pi_i = w_u u_i - w_c c_i \tag{2}$$

The decision weights, w_u and w_c, measure the importance of the utility and cost dimensions in the decision process. The weights are the same for both decisions. While we consider the symmetric case, it will be easy to allow asymmetry while retaining the qualitative results.

Kőszegi and Szeidl (2013), in a market set up, assume that the decision weight function reflects diminishing sensitivity to the cost. However, in our framework, we instead argue that the sensitivity of the cost is increasing with awareness and scrutiny. Hence, we consider the decision weight function on attribute x to be its average divided by its possible range. For two values x_1 and x_2 in the consideration set, the decision weight on attribute x is:

$$w_x = [(x_1 + x_2)/2] \ / \ [Max(x) \ - Min(x)] \tag{3}$$

Note that the sensitivity of an umpire's reputation cost depends on the cost level: they are more cost sensitive when choosing among more costly decisions, and when decisions are marginal. Now, consider the following two situations:

- Pre-awareness: decisions H and A have costs c_H and c_A, respectively (e.g., in our focus, before the year 1994 when all Test matches were officiated by home umpires).
- Post-awareness: the cost of any subjective decision is marked up by $\Delta > 0$. Hence, costs are $(c_H + \Delta)$ and $(c_A + \Delta)$, respectively (e.g., in our focus, in the time of the pandemic when home umpires returned after a long gap and the earlier home bias was well documented).

Since awareness does not affect the utility component in decisions, the weight for utility, w_u, remains the same in the pre-awareness and post-awareness situations. Let us denote the post-awareness weight for the cost as w_c^{Δ}, then following (3):

$$w_c = \frac{[(c_H+c_A)/2]}{[c_H-c_A]} \tag{4}$$

$$w_c^{\Delta} = \frac{[(c_H+\Delta)+(c_A+\Delta)]/2}{[(c_H+\Delta)-(c_A+\Delta)]} = \frac{[(c_H+c_A)/2]+\Delta}{[c_H-c_A]} \tag{5}$$

Comparing (4) and (5), observe that $w_c^{\Delta} > w_c$, since $\Delta > 0$.

Now, consider the pre-awareness situation. The presumably identity-driven biased choice of decision H by a home-aligned umpire, again, requires the condition: $\pi_H > \pi_A$, or $(w_u u_H - w_c c_H) > (w_u u_A - w_c c_A)$. This can be rearranged and expressed as:

$$[w_u(u_H - u_A) \,/\, (c_H - c_A)] > w_c \tag{6}$$

Similarly, in the post-awareness situation, due to preference reversal, a home-aligned umpire chooses decision A only if $\pi_A^{\Delta} > \pi_H^{\Delta}$, or $[w_u u_A - w_c^{\Delta}(c_A + \Delta)] > [w_u u_H - w_c^{\Delta}(c_H + \Delta)]$. This can be rearranged and be expressed as:

$$[w_u(u_H - u_A) \,/\, (c_H - c_A)] < w_c^{\Delta} \tag{7}$$

Ceteris paribus, the left-hand side of (6) and (7) are the same and constant. Moreover, from (4) and (5), $w_c^{\Delta} = w_c + \frac{\Delta}{[c_H-c_A]}$. Hence, for a low value of w_c, condition (6) can be satisfied. For a very small value of the cost markup Δ, due to awareness and scrutiny, condition (6) will still be valid. As the cost markup goes up, and eventually $\Delta = [\{w_u(u_H - u_A) \,/\, (c_H - c_A) - w_c\}](c_H - c_A)$, then the identity-driven bias completely vanishes. However, for a higher value of Δ, condition (7) can also be satisfied. Hence, the increasing sensitivity of cost due to awareness and scrutiny can eliminate or even reverse the identity-driven judgement bias, showing a behaviour of overcompensation. In the case of professional sports, where there is normally home advantage even with neutral adjudicators, our theory predicts that home advantage could be reduced, eliminated, or even reversed, if home umpires replace neutral umpires along with the former perceiving sufficient costliness of being seen to favour their own-country team.

As mentioned earlier, 'reverse bias' by officials in other contexts (e.g., the US juvenile court judges who are harsher to their own race (Depew et al., 2017) or Male music Professors who favour female composers (Ting et al., 2022)) could be explained through our behavioural model. However, there are further important corollaries that come from the model, matching real-life observations in international Test cricket itself. First, consider the situation with no change in umpires but variation in whether it is a home or an away match for a team. This would only have the effect of home conditions and audience pressure. For instance, if we assume that a home match provides a higher utility of giving decisions favouring the home team due to home-audience pressure, then the theoretical model suggests that the COVID-19 pandemic and resulting reduction in crowd support would reduce home advantage. Second, from the conditions in (6) and (7), if the marginal sensitivity of reputation cost goes up, then crucial or more marginal decisions should be observed more frequently as being given against the home team.

3. The Game of Cricket and Behavioural Hypotheses

In this section, we first provide a brief description of international Test match cricket, the importance of subjective judgements by officials in this sport, and a history of their bias. We then discuss the possible effects of the COVID-19 pandemic on the performance and outcome of different sports, before extrapolating behavioural hypotheses on home advantage and judgement bias in cricket, which align with the behavioural model in the previous section.

Sports contests provide excellent settings and natural experiments to study human behaviour in competitive and pressured situations with high stakes (Balafoutas et al., 2019; Bar-Eli et al., 2020). Cricket is a bat-and-ball game originating in England at least as far back as the 16th century. Several features can make cricket attractive to economists: it is a popular sport with over one billion global fans;[4] prize money and revenue are high;[5] it includes influential degrees of randomness, such as the weather conditions and the toss of a coin (Bhaskar, 2009); and the discrete nature of the game allows easy measurement of individual performance, productivity, and decision making. Decisions made by an official (umpire) in cricket are often under pressure, with some requiring a level of judgement and subjectivity. Cricket offers a wealth of data, and we can test our hypotheses on judgement bias due to a sudden and temporary change to the rules of the game.

Test match cricket is played between two international teams of eleven players, consisting of up to four innings played over a period of up to five days. It is the pinnacle of the sport. Tests take place in stadiums and on fields, containing a pitch (twenty-two yards in length) with a wicket (stumps) at both ends. The game is overseen by two on-field umpires, a third umpire (television match official), and a match referee. In an innings, one team bats and one team bowls (fields), and these roles are reversed in the next innings. Whoever bats first is determined by whichever team captain wins a pre-match coin toss. An innings consists of a series of overs (six legal balls bowled to the batting team). It

[4] "ICC survey reveals over a billion fans - 90% in subcontinent" (27 June 2018), Samiuddin (2018): bit.ly/3Pqbi0g

[5] The Indian Premier League, for example, is estimated as the 2nd richest sports league in the world ("Top 10 Richest Sports Leagues In The World Right Now (Updated 2022)"): bit.ly/3L9UZlN

normally ends when ten wickets have fallen (ten of a team's eleven batters are given out by the umpire) or when one team has won the match by scoring more runs than their opponent did in their combined completed innings. A team wins (loses) if it scores more (less) runs than the other team over its two completed innings, and a draw is called if no result has occurred within the five days.[6]

Whether to give a player out or not after each ball is bowled is one of the key decisions made by the on-field umpires, with some of these decisions requiring a degree of judgement under time pressure. There are currently nine ways of getting out and we focus mostly on 'leg before wicket' (LBW) decisions, which require umpires to make rapid and often subjective judgments, when the ball hits the batter at the other end of the pitch as little as half a second after being released by the bowler from alongside the umpire. If a batter is hit by the ball on the leg (or anywhere besides the bat or gloves), and the ball is judged by the on-field umpire to be going on to hit the stumps, then they are given out LBW subject to certain conditions.[7,8]

Employing two home umpires (i.e., umpires of the same nationality as the host country) was the norm in Tests until 1994, after which one neutral umpire (who is not from the country of the home or the away team) was employed following a trial in the 1992-93 seasons. By 2002, there was a further move to officiate with two neutral umpires. Any bias in favour of the home team, however, could be attributed to either own-identity bias of the home umpires or misjudgement due to the pressure from the home crowd. Sacheti et al. (2015) exploited these changes in umpire employment and focused on LBW decisions, to separate out umpire identity bias from the influence of any pressure imparted by home crowds. They found that the home team received fewer LBWs with two home umpires (see also Crowe and Middeldorp, 1996; Ringrose, 2006). This favouritism was reduced with one neutral umpire and was insignificant with two neutral umpires.

After a brief hiatus due to the COVID-19 pandemic, in June 2020, with the return of cricket imminent, some interim regulation changes were announced by the ICC – the governing body of the sport.[9] Perhaps the biggest change was relaxing the neutral-umpires rule, leading in most cases to two home umpires, justified by reducing overseas travel. Umpires are appointed by the ICC from an Elite Panel, so using only officials from the home country meant a smaller pool to choose from for any given

[6] There is a rare outcome of a tie when teams score the same number of aggregate runs across their completed innings, but this has only happened twice in Test match cricket's history.
[7] Other common ways of getting out include: bowled (the stumps are hit by the ball from the bowler's delivery), caught (the ball is caught directly after hitting the batter's bat or gloves), run out (the stumps are broken with the ball when a batter attempts a run but is out of their ground), and stumped (a batter is out of their ground following the delivery of the ball and the wicketkeeper breaks the stumps with the ball).
[8] The ball must pitch in line or outside of off stump and it should hit the player in line. However, if they are adjudged by the umpire not to have offered a shot then they can also be given out LBW if they are hit outside of the line of off stump.
[9] "Interim regulation changes approved" (9 June 2020): icc-cricket.com/media-releases/1679360

match compared to prior to the pandemic. The combined experience of the two umpires was expected to be less than prior to the pandemic, so the ICC increased the maximum number of technology-assisted decision review system (DRS) referrals that teams could make per innings, from two to three for Tests. We control for this change later, but in our theory, this would act against the effects of heightened scrutiny on the home umpires. All international Test matches are televised in our sample period, and every single event is recorded and scrutinised not only by TV and radio commentators and experts but also by online ball-by-ball text commentary on major news websites. Umpires are also evaluated constantly by the ICC and can be relegated from the Elite Panel for poor performance. As such, the increase in DRS referrals does not directly increase scrutiny on umpires. Instead, it increases the possibility that their mistakes are corrected after review. This is equivalent to a decrease in the costliness of making mistakes or biased decisions in our theoretical framework, which would work opposite to the added scrutiny placed on umpires because of their home identity.

Other changes due to the pandemic included a ban on applying saliva to the ball; a means to shine the ball to aid "swing" and improve the chances of taking wickets. Swing bowling is especially effective in England, due to the use of the Dukes ball and other playing conditions there.[10] Therefore, if this rule change reduced home advantage, we would expect this to be most obvious within England, where the home bowlers may have otherwise benefited from their greater ability to take care of and swing the ball. COVID-19 replacements were also permitted for players displaying COVID-19 symptoms in accordance with the rules for concussion replacements, i.e., a (close to) like for like replacement would be approved by the match referee. This rule change might have favoured the home teams, who had better access to pools of replacement players, but it was used very rarely.[11] Like other sports, some of the cricket matches during the pandemic were also played behind closed doors, without fans in attendance at the stadiums.

Judgement bias by an umpire may be intertwined with home advantage in cricket. The existence of a home advantage in sport - the higher likelihood of a win for a team or individual when competing in their home venue of country - has been well documented and studied across sports (e.g., Schwartz and Barsky, 1977; Nevill and Holder, 1999; Pollard and Pollard, 2005). Potential reasons for home advantage include the presence of supportive home fans, the bias of officials due to the social pressure of a crowd or favouritism, familiarity with the conditions and venue, and away teams suffering from

[10] See, for example, "The cricket ball comparison: SG vs Kookaburra vs Dukes explained" (11 February 2021) : https://timesofindia.indiatimes.com/sports/cricket/england-in-india/the-cricket-ball-comparison-sg-vs-kookaburra-vs-dukes-explained/articleshow/80848209.cms

[11] There are four cases of COVID-19 induced replacement players over three Test matches in 2022 mentioned on the current Wikipedia entry about substitutions in cricket: https://en.wikipedia.org/wiki/Substitute_(cricket) (accessed 17 March 2024).

travel fatigue. The sports economics literature has largely focused on the (conscious and unconscious) bias of officials toward the home team (for reviews see: Dohmen and Sauermann, 2016; Reade, 2019). In cricket, home teams usually have a sizable advantage due to familiarity with the playing conditions, since there is considerable variation in the weather, pitch, and audiences across venues, especially at the international level of the game. Hence, it would normally be difficult to separate out the social pressure of a crowd and favouritism as explanations for judgement bias. Despite cricket having several useful features, there is limited research on the economics of cricket and only a handful have looked at home advantage (for reviews see Jewell et al., 2021; Szymanski and Wigmore, 2022).[12] It is also plausible that the social pressure of home crowds may be felt less by cricket umpires compared to referees in other sports, since there is substantial variation in crowd sizes and density within international cricket. The loudness or hostility of the crowd may play a role too. In a rare experimental study with officially qualified English football referees, Nevill et al. (2002) found that background noise significantly affected judgements of what constituted foul play, with decisions becoming less certain and increased bias toward the home team. Cricket is less known than football for its vocally partisan crowds.

The absence of crowds at sporting events during the pandemic has been regarded as a natural experiment. It has led to a spate of papers interested in exploring the impact of (the absence of) crowds on home advantage and the bias of officials. These studies relate especially to football (Bryson et al., 2021; Fischer and Haucap, 2021; Leitner et al., 2023; Reade et al., 2022; Scoppa, 2021), and a number of North American sports (Guérette et al., 2021; Losak and Sabel, 2021; Szabó, 2022), all using the pandemic to isolate the impact of crowds from other sources of home advantage. This natural experiment of no crowds also allowed researchers to find other effects on player performances, due to the absence of racial harassment (Caselli et al., 2023; Colella, 2021) or general pressure (Ferraresi and Gucciardi, 2021). Only limited research on small samples of football matches has examined the impact of playing professional sport completely behind closed doors prior to COVID-19 (Pettersson-Lidbom and Priks, 2010; Reade et al., 2022; Singleton et al., 2023) or with away supporters banned (Colella et al., 2023). The evidence exploiting the pandemic on judgment bias is mixed: while most studies found a reduction in judgement bias by officials toward home teams, Benz and Lopez (2023) and Bryson et al. (2021) observe that the differences in match outcome home advantage with and without crowds varied substantially across competitions, leagues, and countries. Notably, a few

[12] De Silva and Swartz (1998), Allsopp and Clarke (2004), Morley and Thomas (2005), and Dawson et al. (2009) explored home advantage in the context of the shorter form of the game. They found evidence of home advantage, especially in day/night matches, with some evidence in the context of Test matches (Allsopp and Clarke 2004). However, studying a later recent sample period, Cannonier et al. (2015) found no significant evidence of home advantage in international limited overs cricket, but some evidence within the Indian Premier League.

studies have also shown that it appears to have been the complete absence of crowds that affected outcomes, with no or smaller effects of restricted crowds, and no clear and consistent patterns of effects according to the size of the regular attendance at the events (e.g., Benz and Lopez, 2023; Bryson et al., 2021; Ehrlich and Potter, 2023; van Ours, 2024). Accordingly, based on this evidence and the corollary predictions of the theoretical model in the previous section, we state our first testable hypothesis on the effects of closed-door competition (due to the pandemic) on home advantage:

HYPOTHESIS 1. Home advantage in international Test cricket decreased during the pandemic due to a lack of social pressure from crowds in the stadiums**.**

We further argue that home umpires were under greater scrutiny after the pandemic, and that there was consciousness of the perceived historical bias of home umpires.[13] This could lead to an elimination of the official home bias, or, as predicted in our theoretical model in a more extreme case, to overcompensation and penalising home teams relatively more compared to pre-pandemic. Following the existing research, and to maintain parsimony in our analyses, we focus on the subjective LBW decisions. In a closely related study, Pope et al. (2018) analysed the impacts of an earlier study by Price and Wolfers (2010) that highlighted the racial bias of referees in the National Basketball Association in North America. Pope et al. (2018) found that the racial bias of the referees disappeared after media coverage of the earlier study. Along similar lines, we state our next hypothesis on public scrutiny and subjective judgement decision bias. The crowd pressure may result in unconscious bias in both home and neutral umpires to make favourable decisions towards the home team. However, since the home umpires were aware of possible conscious judgement bias while adjudicating during the pandemic period, they will consciously try to overcome such bias, as per Equations (6) and (7) of our behavioural model.

HYPOTHESIS 2.1 LBW decisions were relatively less favourable toward the home team during the pandemic than pre-pandemic, independent of whether there was a crowd.

Furthermore, since 2008, cricket has used a Decision Review System (DRS), whereby players can refer some of the on-field decisions of the two main umpires to a third umpire, who is aided by technology. The rationale for DRS is to reduce any obvious mistakes by the on-field umpires, which

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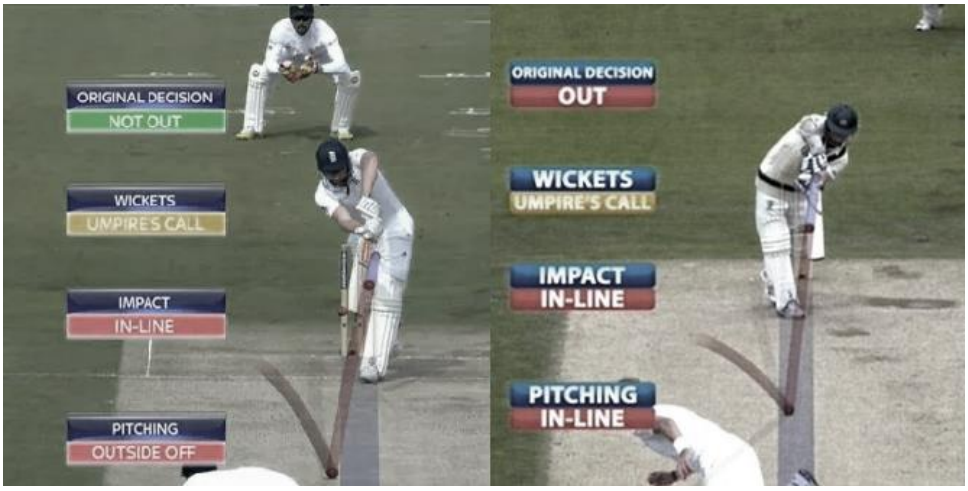
[13] The period covered in Sacheti et al. (2015) was Jan 1986-July 2012. It received mainstream media attention in December 2014 with the paper published in June 2015. As an example of awareness and commentary on the potential for home umpire bias during the pandemic cricket analyst and commentator Aakash Chopra, who has four million Twitter followers, wrote on that platform the following on 10th January 2021: "That's two LBW decisions given when the ball was shown comfortably going over the stumps. Not exactly what you want to see from the on-field umpires. That's when you start feeling that marginal calls are going against you… I'm not suggesting that 'home' umpires are biased but it's a question of credibility...and that's earned overtime. About time neutral umpires start traveling with teams and stay in bubbles. There was a reason why neutral umpires were made mandatory." bit.ly/3r0YS5W

in turn may reduce the impacts of any (conscious or unconscious) umpire bias. The most common decisions reviewed relate to LBW. Gregory-Smith et al. (2019) showed that DRS can reduce the potential bias of LBW decisions in favour of the home team. Shivakumar (2018) also found that decisions are more likely to be overturned if they were originally given out, and there is no evidence of a difference between the home and away teams in the likelihood of an LBW or caught decision being overturned. Since the technology has a natural margin of error, an important aspect of the DRS system, specifically relating to LBW decisions, is known as "umpire's call". If any of the parameters for an LBW decision are within a pre-defined margin of error, then they are classed as umpire's call and the outcome of a review is to stay with the original on-field decision. Therefore, whether a very close decision is given out after review can depend on the on-field umpire's original judgment. This concept of umpire's call is demonstrated by two real examples from Test cricket in Figure 1. In both cases, the ball tracking system suggested the ball would have gone on to hit the stumps had it not struck the batter. But this was within a margin of error, such that the umpire's original decision of not out, in the LHS image, and out, in the RHS image, were upheld.

If home umpires are overcompensating for their judgement bias, then we expect to find that the home team receives more umpire's call outcomes of reviews than the away team. We therefore investigate LBW decisions in more depth by examining the numbers of reviews and umpire's call outcomes before and during the pandemic. This leads to our last hypothesis, which is closely related to our previous one and to the predictions of our behavioural model.

HYPOTHESIS 2.2 The home team receives relatively more umpire's call outcomes of reviews than the away team during the pandemic than pre-pandemic.

Figure 1. Illustration of Umpire's Call affecting review outcomes

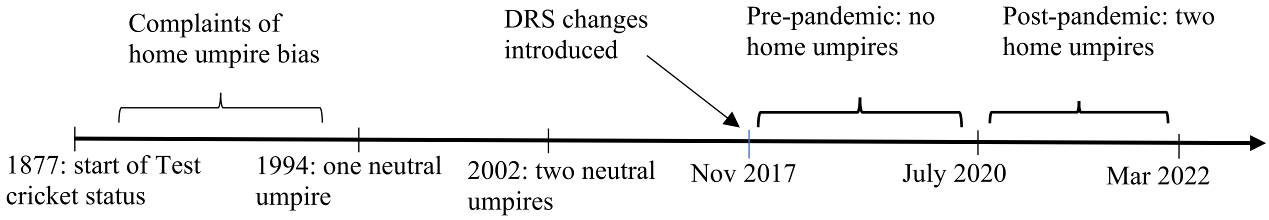


Source: Sky Sports

4. Data and Empirical Strategy

Our interest centres on understanding the impacts of temporarily reverting to employing two home umpires for some recent Test cricket matches. We compare this with similar matches in an earlier period, between November 2017 and up to the beginning of the temporary rule change, where every match had two neutral umpires. In November 2017, the ICC made major changes to the DRS system, with teams thereafter having two reviews per innings but not losing a review if the outcome was umpire's call.[14] We argue that other factors, such as the pool of elite professional Test umpires, regulations, and the use of technology (beyond the extra review), should have been similar since November 2017, with the only substantive differences in the general conditions of play being induced by the COVID-19 pandemic rules, as discussed above. Our pandemic period starts from July 2020, when Test matches were restarted behind closed doors, after the announcement of the temporary rule changes the month before (see Figure 2 for a summary timeline).

Figure 2. Timeline of important cricket umpiring changes and our data (not to scale)



Our dataset covers men's international Test matches played between November 2017 and March 2022, and we collected scorecard information from the CricketArchive database.[15] A total of 179 Tests were played over our study period: 72 during the pandemic period (start date 8th July 2020-24th March 2022) and 107 during the pre-pandemic period (start date 16th November 2017-29th February 2020). We exclude five Test matches played at a non-home venue.[16] Matches played at venues appearing only once in the dataset are also excluded (21 matches: 15 pre-pandemic and 6 pandemic), since we will include venue-specific effects in our models. Hence, we use a final sample of 153 Test matches (90 pre-pandemic and 63 during the pandemic). The distribution of these over the host countries (Australia, Bangladesh, England, India, New Zealand, Pakistan, South Africa, Sri Lanka,

[14] There are several parameters that are required for a player to be adjudged to be LBW. For an LBW decision to be overturned there must be evidence of a clear mistake. Hence, if any of the parameters are shown to be marginal, then the original decisions stand as umpire's call. Some minor changes were made to umpire's call from April 2021 (see icc-cricket.com/media-releases/2081342). As a robustness check we considered a dummy variable to control for this period in our regression models, but our results remain qualitatively unchanged.
[15] Available from cricketarchive.com with a subscription.
[16] These include the inaugural Test championship final (during the pandemic) and "home" Afghanistan matches which were played in the UAE or India (two pre-pandemic and two during the pandemic). Pakistan played their home games in the United Arab Emirates for around a decade until December 2019, so we have classed these as home games rather than being on a non-home ground and excluding these from the analysis does not change our main results and conclusions.

West Indies, and Zimbabwe) before and during the pandemic are shown in Appendix Figure A1. Appendix Table A1 also shows the distributions of bilateral fixtures in the sample. There were seven occasions in Tests during the pandemic period where one neutral umpire alongside one home umpire was used, and we exclude these from the estimation sample later as a robustness check.

As stated in our research question and hypotheses, we focus mainly on two outcomes: the probability of a home win (Hypothesis 1) and the number of LBWs (Hypothesis 2.1). We then further investigate the decision review system and umpire's call (Hypothesis 2.2).

Unlike Sacheti et al. (2015), we control for venue fixed effects, rather than host country fixed effects since playing conditions can vary substantially across venues within Test-playing nations. Further, the pandemic affected the choice of venues. For example, when tours were scheduled or re-arranged during the pandemic, stadiums were favoured that had hotels attached, so the teams, officials, media, and other involved parties could be more easily placed in a "bio-secure bubble". For robustness, we later consider estimates of our models that also allow for fixture fixed effects, controlling for heterogeneity specific to a given home and away team pair, e.g., England playing India in England. This is quite restrictive for our data, as 11 of the 153 Tests in our main estimation sample were fixtures that only took place once either before or after the pandemic began, thereby reducing the number of matches to 142 Tests.

We collected the home country of the umpires using the ESPNcricinfo and CricketArchive websites, and collated information on whether matches were played behind closed doors or with crowds using various media sources. We construct time-varying measures of the teams' relative strengths using the entire history of Test match cricket back to 1877. We generate dynamic Elo (1978) ratings, updated using a recursive algorithm after every match result – the ICC use a version of the ELO ratings as a basis for Test match team rankings.[17] We calculate the predicted probability of a home win based on the ELO ratings. Unlike Sacheti et al. (2015), we use teams' dynamic relative strengths and ELO predictions rather than innings' batting/bowling team fixed effects. Like Sacheti et al. (2015), we

[17] The original application of this rating system was applied to chess players and leagues, but it has since been used widely in the sports economics literature to capture dynamically the relative abilities of teams, depending on the relative strengths of the opponents they have played up to that point in time (e.g., Hvattum and Arntzen, 2010). To apply the rating system to cricket, we score a win as 1, a draw as 0.5, and a loss as 0. We choose an updating (weighting) factor of 40. There could be a criticism that using dynamic team strengths as covariates in the models could partly confound the effects of interest during the pandemic period. To check this, we also estimated models that only used Elo ratings fixed at their March 2020 levels, finding our results are robust to doing so.

include combined on-field umpire experience and the innings number as control variables.[18] Table 1 provides a list of the variables used in our analysis, with definitions and descriptive statistics.

We test Hypothesis 1 using the following match-level equations:

$$E[\mathrm{HW}_m] = \gamma_0 + \gamma_1 \mathrm{Pandemic}_m + \mathbf{X}_m' \boldsymbol{\gamma}_2 , \tag{8}$$

$$E[\mathrm{HW}_m] = \beta_0 + \beta_1 \mathrm{Closed}_m + \beta_2 \mathrm{Crowds}_m + \mathbf{X}_m' \boldsymbol{\beta}_3 , \tag{9}$$

where $E[\mathrm{HW}_m]$ is the expected probability of a home team win in match m. Equation (8) includes a dummy for whether the match was played during the pandemic period or not ($\mathrm{Pandemic}_m$), plus a vector of match-level controls ($\mathbf{X}_m$). Equation (9) instead separates matches in the pandemic period, using two dummy variables, into those played behind closed doors (Closed_m) and those in front of crowds (Crowds_m). We would expect γ_1 in Equation (8) to be negative in line with the research in other sports, i.e., home advantage was diminished during the pandemic. If this is due to the 'social pressure of crowds' mechanism, then we would expect, from Equation (9), $\beta_1 < 0$ and $\beta_2 = 0$. If $\gamma_1 < 0$ and $\beta_1 = \beta_2$ or $\beta_2 \neq 0$, then it suggests that something else was on average affecting home advantage differently in the pandemic period, such as the return to two home umpires. We estimate Equations (8) and (9) as linear probability models, with the dependent variable being a dummy variable equal to one if the home team wins and zero otherwise.[19] Initially we include drawn matches in the estimation samples and exclude them later in a robustness check. We include in $\mathbf{X}_m$ a prediction for the home team winning based on ELO ratings and venue fixed effects.

[18] We do not prefer including a time trend owing to the short period of our data, and the collinearity with our pre- and post-pandemic periods. Regardless, including a linear time trend does not change our main findings and is statistically insignificant in the models.

[19] A linear probability model is preferred due to the incidental parameter issue that would arise with a logit or probit model, given the small number of matches per venue. We also checked Poisson regression model estimates, which are more forgiving as a non-linear alternative, and our main findings are robust to doing so, though the estimation sample then has to drop 13 matches from venues where the home team never won in our sample period.

Table 1. Variable definitions and descriptive statistics

Variable	Description	Mean	St. dev.	Min.	Max.
Match level: (N = 153)					
Dependent variable					
Home win	= 1 if home team wins the match, 0 otherwise	0.53	0.50	0	1
Explanatory variables					
Pandemic	=1 if match played 8 July 2020-24 March 2022; 0 if played 16 November 2017-29 February 2020	0.41	0.49	0	1
Behind Closed Doors	=1 if during pandemic period and match played behind closed doors, 0 otherwise	0.16	0.36	0	1
Crowds	=1 if during pandemic period and match played in front of crowds, 0 otherwise	0.25	0.44	0	1
ELO Predict	Probability forecast of a home team win based on ELO ratings; 1= a certain home win	0.49	0.18	0.11	0.93
Innings Level: (N=568; N=528 for decision review system (DRS) variables)					
Dependent variables					
Number of LBWs	Number of batters out to leg before wicket (LBW) in innings	1.44	1.28	0	6
Overturned – batting	Number of decisions overturned – batting team	0.57	0.74	0	3
Overturned – bowling	Number of decisions overturned – bowling team	0.37	0.58	0	3
Umpire's call - batting	Number of umpire's call - batting team	0.29	0.57	0	3
Umpire's call - bowling	Number of umpire's call - bowling team	0.33	0.54	0	3
Explanatory variables					
Home team batting	=1 if home team is batting in innings	0.48	0.50	0	1
Umpire experience	Combined number of previous matches officiated by umpires	86.96	42.56	5	199
Log overs	Log of number of overs bowled in the innings	4.29	0.59	0.34	5.30
Second innings	=1 if second innings, 0 otherwise	0.27	0.44	0	1
Third innings	=1 if third innings, 0 otherwise	0.27	0.44	0	1
Fourth innings	=1 if fourth innings, 0 otherwise	0.20	0.40	0	1
Reviews by batting team	Number of decision review system (DRS) reviews made by batting team in innings	1.77	1.19	0	6
Reviews by bowling team	Number of decision review system (DRS) reviews made by bowling team in innings	1.47	1.21	0	8

We test Hypothesis 2.1 using the following innings-level equations:

$$Log(E[\text{NLBW}_i]) = \gamma_0 + \gamma_1\text{Hometeam}_i + \gamma_2\text{Pandemic}_i + \gamma_3\text{Hometeam}_i \times \text{Pandemic}_i + \mathbf{X}_i'\boldsymbol{\gamma}_4\,, \quad (10)$$

$$\begin{aligned} Log(E[\text{NLBW}_i]) = \beta_0 &+ \beta_1\text{Hometeam}_i + \beta_2\text{Closed doors}_i + \beta_3\text{Crowds}_i \\ &+\beta_4\text{Hometeam}_i \times \text{Closed doors}_i + \beta_5\text{Hometeam}_i \times \text{Crowds}_i + \mathbf{X}_i'\boldsymbol{\beta}_6\,, \quad (11) \end{aligned}$$

where NLBW_i is the number of batters given out LBW in innings i and Hometeam_i is a dummy variable for whether the home team is batting. In Equation (10), we control for whether the match was played during the pandemic (Pandemic_i) and interact this with whether the home team was batting. In Equation (11), as in Equation (9), we split the innings during the pandemic into those played behind closed doors (Closed doors_i) and those in front of crowds (Crowds_i), and interact these with whether the home team was batting. In both Equations (10) and (11), we control for a set of innings controls ($\mathbf{X}_i$), which include combined umpire experience (number of Test matches officiated), the log of overs in the completed innings, a probability prediction of the home team winning based on ELO ratings, and the innings number within the match.

Prior to the pandemic, we predict γ_1 in Equation (10) to be non-positive due to home advantage. If $\gamma_3 < 0$, then it suggests that there is a return to home umpires favouring the home team, and $\gamma_3 > 0$ provides evidence that the umpires are overcompensating, and their decisions now favour the away team relative to the home team. We can also test from Equation (10) whether $\gamma_1 + \gamma_3 = 0$; did any home team advantage on average disappear? Using Equation (11), we also test the overall home advantage effects separately for matches behind closed doors and in front of crowds, i.e., we test whether $\beta_1 + \beta_4 = 0$ and $\beta_1 + \beta_5 = 0$, respectively. Since the number of LBWs in an innings is a count variable, we estimate Equations (10) and (11) using Poisson regression.[21]

To test Hypothesis 2.2, we estimate versions of Equations (10) and (11) using the same model specifications, estimators, and those innings that used DRS, but instead with dependent variables being the numbers of reviewed decisions in an innings overturned (NOVERTURN_i) and umpire's call (NUMPCALL_i).

[21] We prefer Poisson (Quasi Maximum Likelihood Estimator; QMLE) to the negative binomial regression because the former is efficient in the class of consistent estimators with under or overdispersion (variance/mean ratio is constant) for effects on the conditional mean, provided it is correctly specified (Santos Silva and Tenreyo, 2006; Wooldridge, 2010). In other words, the Poisson QMLE estimator does not require the dependent variables to have a Poisson distribution. It is also robust to different forms of heteroskedasticity and measurement error, as well as being well-behaved for large fractions of zeros in the estimation sample (Santos Silva and Tenreyo, 2011).

5. Results

5.1 Home Wins

As Table 2 shows, 59% of Test matches in our pre-pandemic sample were won by the home team, but this was significantly lower (using a one-sided *t*-test) at 44% during the pandemic. Specifically, there was a significant drop in the likelihood of the home team winning behind closed doors. Table 3 presents estimates of the probability of a home win, using Equations (8) and (9). During the pandemic (moving from two neutral to two home umpires), as shown in Column (I), the probability of a home win was reduced by 18 percentage points, controlling for the composition of matches with the Elo prediction and fixed effects for the 39 different venues in the sample. The measured reduction in home advantage is bigger for matches played behind closed doors, although not statistically significantly so (see Column II). Whilst a statistically significant reduction in the probability of a home win in cricket during the pandemic is consistent with other professional sports (see Section 2), we find no statistically significant difference in that effect depending on whether there was a crowd, though these match-level tests are relatively under-powered. These results are robust to removing draws and the seven matches that had one neutral umpire from our estimation samples;[22] the pandemic effect is of a similar magnitude (only slightly weaker) but is less statistically significant, reflecting the drop in observations (Columns III-VI of Table 3).

The final two columns of Table 3 show results when we interact the main variables of interest with a dummy variable for whether the Test was played in England. This provides a check of whether the significant drop in overall Test match home advantage during the pandemic was explained by matches in England, where we would expect the ban on applying saliva to the ball to have disadvantaged England more than visiting teams. Accordingly, the estimated coefficients on the interaction terms are negative though insignificant from zero. The overall negative pandemic effect on home wins in column (VII) is thus attenuated but remains statistically significant at the 10% level.

[22] 3 matches in Zimbabwe and 4 in Bangladesh.

Table 2. Descriptive statistics at match and innings levels, estimation samples, November 2017 – March 2022

	Match Level				Innings Level					
	Home win	Home win excl. draws	Umpires exp.	ELO predict	Number of LBWs			Log overs		
					Home	Away		Home	Away	
Pre-pandemic:										
Mean	0.59	0.68	101.94	0.49	1.28	1.60	**	4.35	4.22	*
St. Dev.	0.49	0.47	38.66	0.18	1.15	1.38		0.68	0.52	
Min.	0	0	41	0.11	0.00	0.00		0.34	1.10	
p50	1	1	96	0.45	1.00	1.00		4.46	4.30	
Max.	1	1	199	0.93	6.00	6.00		5.30	5.29	
N	90	78	90	90	160	174		160	174	
Pandemic										
Mean	**0.44**	***0.56***	**64.02**	0.50	1.42	1.46		4.34	4.28	
St. Dev.	0.50	0.50	36.70	0.19	1.23	1.31		0.59	0.56	
Min.	0	0	5	0.12	0.00	0.00		1.63	2.35	
p50	0	1	66	0.51	1.00	1.00		4.39	4.39	
Max.	1	1	142	0.91	5.00	5.00		5.23	5.25	
N	63	50	63	63	114	120		114	120	
Diff-in-Diff						0.285			-0.07	
Pandemic - closed doors:										
Mean	**0.38**	**0.47**	**68.46**	0.49	1.41	1.71		4.33	4.36	
St. Dev.	0.49	0.51	33.32	0.19	1.21	1.39		0.57	0.48	
Min.	0	0	5	0.12	0.00	0.00		2.58	3.19	
p50	0	0	68.5	0.50	1.00	2.00		4.41	4.42	
Max.	1	1	136	0.76	5	5		5.19	5.25	
N	24	19	24	24	44.00	45.00		44.00	45.00	
Diff-in-Diff						0.02			-0.15	
Pandemic - crowds:										
Mean	0.49	0.61	**61.28**	0.51	1.43	1.31		4.34	4.24	
St. Dev.	0.51	0.50	38.79	0.19	1.25	1.24		0.61	0.60	
Min.	0	0	6	0.20	0.00	0.00		1.63	2.35	
p50	0	1	59	0.52	1	1		4.38	4.37	
Max.	1	1	142	0.91	5.00	5.00		5.23	5.24	
N	39	31	39	39	70.00	75.00		70.00	75.00	
Diff-in-Diff						0.45	*		-0.02	

Notes: author calculations using data from cricketarchive.com/, accessed 28/03/2022. All matches played in the sample period, with the pre-pandemic period covering matches played between 16 November 2017 and 29 February 2020 and the pandemic period covering matches played 8 July 2020 and 24 March 2022. Values in bold (bold italic) are statistically significantly different from pre-pandemic values at the 5% (10%) level, unpaired one-sided *t*-tests for match level and two-sided tests for innings level (with no prior expectation of direction in any difference for innings level variables). Diff-in-Diff refers to: (HomePan - HomePre) - (AwayPan - AwayPre); ***,**,* indicate significance at 1%, 5% and 10% levels, respectively, two-sided *t*-tests.

Table 3. Estimated effects of the COVID-19 pandemic and playing behind closed doors on Test international home advantage: linear probability models

	All Tests		Excl. draws		Excl. one neutral umpire		England Effects	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Pandemic (γ_1)	-0.181**		-0.146		-0.158*		-0.145*	
	(0.082)		(0.092)		(0.090)		(0.085)	
Pandemic (ref: pre-pandemic):								
Behind Closed Doors (β_1)		-0.202		-0.162		-0.167		-0.185
		(0.156)		(0.169)		(0.199)		(0.143)
Crowds (β_2)		-0.171*		-0.138		-0.155		-0.125
		(0.091)		(0.106)		(0.096)		(0.101)
ELO predict	0.831***	0.841***	0.677**	0.680**	0.781**	0.784**	0.842***	0.825***
	(0.303)	(0.299)	(0.330)	(0.330)	(0.304)	(0.296)	(0.296)	(0.290)
England × Pandemic							-0.201	
							(0.259)	
England × B.C.D								-0.048
								(0.803)
England × Crowds								-0.265
								(0.183)
Constant	0.195	0.191	0.355**	0.354**	0.222	0.221	0.190	0.197
	(0.158)	(0.155)	(0.171)	(0.172)	(0.164)	(0.159)	(0.153)	(0.145)
p-value: $\beta_1 = \beta_2$		0.859		0.902		0.957		0.7259
Venue Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N of matches	153	153	125	125	146	146	153	153
R^2	0.333	0.333	0.360	0.360	0.302	0.302	0.337	0.339

Notes: author calculations using data from cricketarchive.com/, accessed 28/03/2022. All matches played in the sample period, with the pre-pandemic period covering matches played between 16 November 2017 and 29 February 2020 and the pandemic period covering matches played 8 July 2020 and 24 March 2022. Since the regression models include venue fixed effects, those venues appearing only once in the respective samples were dropped (21 matches). Least squares estimates of Equations (8) and (9). ***,**,* indicate significance at 1%, 5% and 10% levels, respectively, two-sided tests, standard errors in parentheses are robust to venue clusters.

Some of the studies discussed in Section 3 have argued that the reduction in home win probabilities, after COVID-19 affected sports, was driven by removing the social pressure from crowds and the impact this tended to have on officials. However, we do not find any compelling evidence here to support Hypothesis 1, that home advantage in international Test cricket decreased during the pandemic due to a lack of social pressure from crowds. The rejection of Hypothesis 1 suggests that something else may be affecting the pattern of outcomes in Test match cricket over this period, so we next focus on the re-introduction of home umpires and their decision making.

The results from Table 3 also contrast with what we might expect based on Sacheti et al. (2015) and Fernando and George (2023), who found a reduction in home advantage in Test cricket following the introductions of neutral umpires in 1994 and 2002. An explanation for our findings could be that home umpires are now more conscious that they are being monitored, not least because of modern high-definition live footage of every ball bowled, with the availability of the DRS technology for commentators, fans and the teams involved to evaluate every decision. More generally, and as mentioned earlier, umpires and other officials (such as judges, board members, reviewers) may be more aware of well-known historical biases, and so they overcompensate, particularly in relation to marginal decisions, which could be stronger in the presence of social pressure where the biases are expected to be greater.[23] Our findings relating to Hypothesis 1 can be summarised as follows.

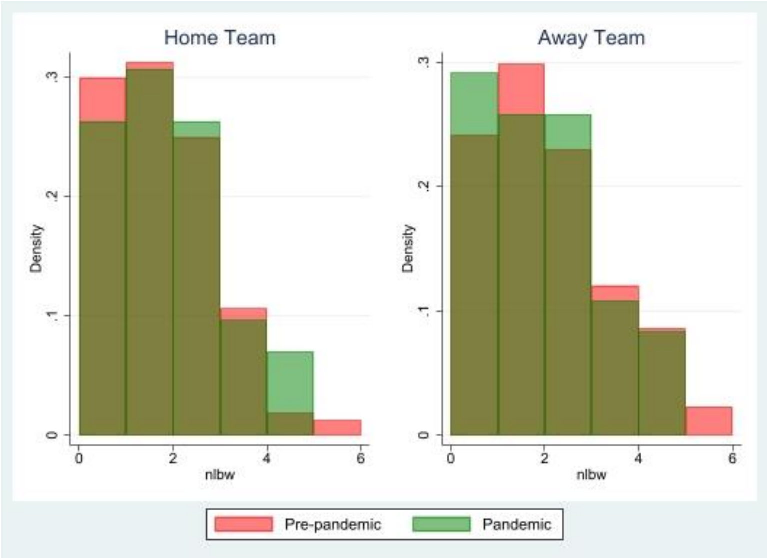
RESULT 1. There is no evidence that home advantage in international Test cricket reduced during the COVID-19 pandemic because stadium crowds were absent.

5.2 LBW Decisions

As reported in Table 2, significantly more LBWs per innings were given to the away batters (1.6) compared to the home batters (1.28) during the pre-pandemic sample period (p-value = 0.022, two-sided t-test), when there were two neutral umpires in each Test. During the pandemic with two home umpires, this average difference between the home and away batters was smaller (0.04) and insignificant. Giving an LBW decision to a batter is a negative outcome for them and their team. Hence, these descriptive results suggest that the home advantage in these decisions disappeared during the pandemic. There was an increase (fall) in LBWs for the home (away) teams during the pandemic and hence a relative increase in LBWs for the home teams (difference-in-difference=0.45, p-value=0.079) during the pandemic in front of crowds. However, none of the differences between matches played behind closed doors and in front of crowds, in terms of the average LBWs per innings, are significantly different. Illustrating these patterns, Figure 3 displays the sample distributions of LBWs at the innings level for the home and away teams, before and during the pandemic.

[23] Table 2 shows that the combined experience (number of previous matches umpiring) of umpires is significantly lower for matches during the pandemic, i.e., picking two home umpires result in less combined. This was the stated reason for the ICC increasing the number of DRS reviews per innings by one during the pandemic.

Figure 3. Number of LBWs for home and away teams in a Test match innings, before and during the COVID-19 Pandemic



Source: author own calculations using data from cricketarchive.com/, accessed 28/03/2022.

In Table 4, we test Hypothesis 2.1 by estimating Equations (10) and (11). The results in Column (I) show that 26% fewer LBWs (γ_1) were given against the home batters in the pre-pandemic sample (two neutral umpires), controlling for the length of the innings, relative strengths of teams, venue-specific effects, etc. However, this gap was diminished significantly, in favour of away batters during the pandemic (γ_3), especially in front of crowds (see Column II, β_3). We formally test in Column (I) whether $\gamma_1 + \gamma_3 = 0$, and we can't reject the notion that two home umpires reduced the LBW pre-pandemic home advantage with neutral umpires to zero (*p*-value=0.661). As shown in Column (II), this reduction in LBWs home advantage was present both for matches played behind closed doors and in front of crowds (see Column II, *p*-value=0.423 and *p*-value=0.749, respectively) and there was no statistically significant difference between these two situations (*p*-value=0.409). As such, the overall home advantage in LBWs was insignificant from zero during the pandemic, both overall and with or without crowds.[24] Columns (III) and (IV) show that these findings are robust to estimating variants of the model that admit fixture fixed effects (e.g., England playing India in India), though this drops 11 matches from the sample that were singleton fixtures in our sample period.

[24] We undertook further robustness checks (see Table A2 in the Appendix), where we excluded the five Test matches with a non-home umpire, used the number of LBWs per 100 overs, and least squares estimation, which leave results unchanged. Moreover, in April 2021 there was a rule change relating to LBWs and the review system. When we include a dummy for this period (35 matches were played during this period: 7 behind closed doors and 28 in front of crowds) here and in the home win model in Table 3, our results remain unchanged. Further, our main findings here are robust to including interaction terms with a dummy variable for whether the match took place in England.

Table 4. Poisson regression effects (%) of the COVID-19 pandemic and playing behind closed doors on the number of LBWs in Test match international innings

	Without reviews		With Fixture FEs		With reviews	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Home team batting (γ_1 or β_1)	-0.264***	-0.265***	-0.293***	-0.293***	-0.190**	-0.191**
	(0.080)	(0.079)	[0.080]	[0.079]	(0.075)	(0.075)
Pandemic (γ_2)	-0.254***		-0.254***		-0.320***	
	(0.084)		[0.094]		(0.071)	
Home team × Pandemic (γ_3)	0.296*		0.318*		0.149	
	(0.189)		[0.209]		(0.157)	
Pandemic (ref: pre-pandemic):						
Closed doors (β_2)		-0.328**		-0.279**		-0.386***
		(0.105)		[0.105]		(0.102)
Crowds (β_3)		-0.198*		-0.267*		-0.264***
		(0.105)		[0.105]		(0.075)
Home team × Closed doors (β_4)		0.143		0.100		0.089
		(0.272)		[0.303]		(0.250)
Home team × Crowds (β_5)		0.414**		0.489***		0.165
		(0.221)		[0.227]		(0.159)
Umpire experience	-0.001	-0.001	0.001	0.001	-0.001	-0.001
	(0.001)	(0.001)	[0.001]	[0.002]	(0.001)	(0.001)
Log overs	0.253***	0.250***	0.329***	0.330***	-0.033	0.029
	(0.087)	(0.087)	[0.100]	[0.103]	(0.063)	(0.063)
ELO predict	-0.329*	-0.323*			-0.184	-0.173
	(0.156)	(0.160)			(0.183)	(0.184)
Innings number (ref: first):						
Second	0.201*	0.198*	0.22	0.216	-0.001	0.002
	(0.117)	(0.118)	[0.149]	[0.151]	(0.097)	(0.097)
Third	0.021	0.020	0.075	0.074	-0.085	-0.086
	(0.110)	(0.111)	[0.144]	[0.145]	(0.096)	(0.096)
Fourth	0.083	0.079	0.068	0.067	-0.068	-0.067
	(0.148)	(0.149)	[0.162]	[0.163]	(0.116)	(0.118)
Number of reviews:						
Reviews by bowling team					0.091***	0.089***
					(0.032)	(0.031)
Reviews by batting team					0.332***	0.327***
					(0.036)	(0.037)
Constant	-0.126	-0.127			0.418	0.384
	(0.315)	(0.310)			(0.493)	(0.475)
p-value: $\gamma_1 + \gamma_3 = 0$	0.661		0.610		0.501	
p-value: $\beta_2 = \beta_3$		0.409		0.9342		0.776
p-value: $\beta_1 + \beta_4 = 0$		0.423		0.310		0.559
p-value: $\beta_1 + \beta_5 = 0$		0.749		0.686		0.560
Venue fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixture fixed effects	No	No	Yes	Yes	No	No
N of innings	568	568	529	529	550	550

Notes: author calculations using data from cricketarchive.com/, accessed 28/03/2022. All matches played in the sample period, with the pre-pandemic period covering matches played between 16 November 2017 and 29 February 2020 and the pandemic period covering matches played 8 July 2020 and 24 March 2022. Since the regression models include venue fixed effects, those venues appearing only once in the respective samples were dropped (21 matches). The models with fixture fixed effects led to 11 matches being dropped due to the fixture only appearing once. Poisson regression estimates of Equations (10) and (11). ELO predict is from the perspective of the team batting. Effects shown are $\exp(\hat{\beta}) - 1$, so can be interpreted as percentage effects on the number of LBWs in an innings. ***,**,* indicate significance at 1%, 5% and 10% levels, respectively, two-sided tests, standard errors in parentheses are robust to clusters at the venue and match levels.

These findings support Hypothesis 2.1. They fit with the notion that home umpires were aware of the possible home bias and were overcompensating, neutralising the home advantage. This pattern was stronger in front of crowds, where the umpires may feel greater scrutiny. This could have been consistent with a social cue effect. It is known from the economics and psychology literature that people often behave more pro-social (Haley et al., 2005; Rigdon et al., 2009) or reduce anti-social behaviour (Nettle et al., 2012) while being watched. Since the own home country judgement bias in cricket was publicised and discussed among commentators, it had a negative connotation among the public. While officiating in front of a stadium crowd, as well as on television, a feeling of being watched may have affected the umpires as a social cue, resulting in them trying harder to avoid any perception by others of possible home team bias.

Given that there were more DRS reviews available at the time of the pandemic, incorrect LBW decisions could have been corrected through this system, resulting in undermeasurement of any potential home umpire bias. As a check in Columns (V) and (VI) of Table 4, we add the number of reviews made by the bowling and batting teams within an innings as regressors. These variables are positively related with the number of LBWs decisions, as they are the most likely ones to be referred by players – this relationship is stronger for reviews by the batting teams where the umpire's decision would have given the batter out. When we add the number of reviews to the regression models, the estimated effect of the home team batting in an innings on the number of LBWs is smaller but remains significant. The magnitude of the estimated increased number of LBWs for the home team batters during the pandemic is also smaller in these models. However, the *t*-tests show that we can't reject that the return to two home umpires reduced the pre-pandemic significant LBW home advantage to zero. These findings relating to Hypothesis 2.1 are summarised as follows.

RESULT 2.1 Home umpires show evidence of a 'reverse' or 'overcompensating' bias against the home team for crucial judgment decisions, in contrast with an earlier period when significant bias for the home team by home umpires was observed, widely known about, and corrected by the ICC.

5.3 Decision Reviews and Umpire Bias

To investigate Hypothesis 2.2, we next look more closely at the reviews of the on-field umpires' decisions before and during the pandemic. We first study all innings, including those with no reviews, and then focus on innings that had at least one review.[25] Table 5 gives sample descriptives for the reviews at the innings level, distinguishing between whether the home or away team were batting. In general, the proportion of reviews in an innings made by the home team did not significantly change because of the pandemic: 47% during compared to 46% before. As expected, the average number of reviews increased during the pandemic, particularly for the bowling teams, likely due to the simultaneous policy change allowing an additional unsuccessful review per innings per team. However, there was no significant increase in the average number of reviews for the away teams when they were batting at the time of the pandemic compared with the period before.

We find that, during the pandemic, significantly more decisions were overturned that were originally given out (reviewed by the batting team) than not given out (reviewed by the bowling team). Further, there was no difference in the numbers of overturned decisions between the home and away team in the pre-pandemic period. Both these results are consistent with Shivakumar (2018), who examined Test match review decisions during the 2009-2014 period. However, there was an increase in the number of overturned decisions for the away teams relative to the home teams during the pandemic. The proportion of decisions that were overturned decreased during the pandemic for the home teams (driven by batting reviews), but this was not the case for the away teams. At first look, this suggests that more mistakes were made by umpires that went against the away team. However, it is important to consider the most marginal decisions when investigating why there may have been a change in the relative proportion of decisions overturned for home and away teams. We address this by studying the DRS feature of umpire's call.

[25] Not all Test innings have controversial decisions or reviews, and some did not feature the use of the DRS system at all during our sample period. Five Test matches where Zimbabwe were the hosts (two pre-pandemic and three during the pandemic) did not use the DRS system. With DRS, 64 innings did not have any reviews, with 77% of those being the 4th innings of a match.

Table 5. Sample descriptives (averages and percentages) for on-field technology assisted reviews of umpire decisions (DRS) in Test match innings, before and during the pandemic, November 2017 – March 2022

	Home Team Batting			Away Team Batting			Home-Away				Diff-in-Diff	
	Pre-pandemic	Pandemic		Pre-pandemic	Pandemic		Pre-pandemic		Pandemic			
All matches with DRS:												
N of reviews	2.79	3.82	***	2.53	3.33	***	0.26		0.50	**	0.23	
N of reviews – batting	1.24	1.55	**	1.29	1.48		-0.05		0.06		0.11	
N of reviews – bowling	1.56	2.28	***	1.24	1.84	***	-0.31	**	-0.44	***	-0.12	
N of innings	156	108		196	132							
All innings with at least one review:												
% home team												
% bowling team	60.2	63.8		50.77	56.46		9.45	***	7.33	*	-2.12	
N of reviews	3.01	3.97	***	2.99	3.88	***	0.02		0.09		0.07	
N of reviews - batting	1.33	1.61	*	1.52	1.73		-0.19		-0.13		0.06	
N of reviews - bowling	1.68	2.37	***	1.47	2.15	***	-0.21		-0.21		-0.01	
N overturned	0.83	0.86		0.93	1.12		-0.09		-0.26	**	-0.17	
N overturned - batting	0.54	0.51		0.54	0.70	*	0.00		-0.19	*	-0.19	
N overturned - bowling	0.30	0.35		0.39	0.42		0.10		0.07		-0.03	
N umpire's call	0.48	0.82	***	0.51	0.67	*	-0.03		0.14		0.17	
N umpire's call - batting	0.21	0.47	***	0.21	0.32	***	0.00		0.15	**	0.16	
N umpire's call - bowling	0.28	0.35		0.30	0.35		0.03		0.01		-0.02	
% overturned	27.40	18.46	***	30.19	27.39		-2.79		-8.93	**	-6.14	
% overturned - batting review	16.84	9.96	**	16.65	16.27		0.20		-6.31	**	-6.50	*
% overturned - bowling review	10.56	8.50		13.55	11.12		2.99		2.62		-0.37	
% umpires call	14.96	18.69		17.33	16.86		-2.37		1.83		4.20	
% umpires call - batting review	6.94	10.76	*	7.38	6.43		-0.44		4.33	*	4.76	
% umpires call - bowling review	8.02	7.93		9.96	10.42		1.93		2.50		0.56	
N of innings	145	104		166	113							

Notes: author calculations using data from cricketarchive.com/, accessed 28/03/2022. All matches represented in Table 2 that used the decision review system (DRS), with the pre-pandemic period covering matches played between 16 November 2017 and 29 February 2020 and the pandemic period covering matches played 8 July 2020 and 24 March 2022. ***,**,* indicate significant differences in means between matches before and after the COVID-19 pandemic (first match under COVID-19 rules started on 8th July 2020) at 1%, 5% and 10% levels, respectively, two-sided *t*-tests. Difference involving bowling reviews are reversed since the home (away) bowling reviews occur when the away (home) team is batting. Diff-in-Diff refers to: (HomePan - HomePre) - (AwayPan - AwayPre).

There were more umpire's calls during the pandemic, with a significant increase in the number for the home team when batting but not for the away team (last column in Table 5). This is consistent with Hypothesis 2.2. Recall that an umpire's call for a batting team implies that the crucial original subjective decision was deemed upon review to be within a reasonable margin of error, and the umpire's original decision was against the batting team. This finding provides evidence that, for marginal or more difficult decisions, the home umpires may have overcompensated for their natural home bias behaviour, as perceived by the players, commentators, spectators, etc., by giving the home team out more often, compared with when they were previously officiating as neutrals before the pandemic.

Finally, we test for a change in the number of overturned decisions and umpire's calls within an innings, while controlling for other aspects of an innings. In Table 6, we estimate the same model specification as for the LBW models in Table 4, using the counts of decisions overturned and umpire's calls as dependent variables.[26] As in the results above, the model estimates show no significant difference in the numbers of overturned decisions between the home and away team (as in Shivakumar, 2018). This also applies for umpire's calls, which is a new result, since Shivakumar (2018) did not look at umpire's call. Columns (V) and (VI) of Table 6 show that the home team, when bowling during the pre-pandemic period, had fewer decisions overturned (significant at the 10% level) than when the away team bowled. This could again imply, as in Section 4.2, that slightly more decisions by the neutral umpires tended to favour the home team. Moreover, Columns (I) and (II) confirm that the home team, when batting, had fewer decisions against them overturned during the pandemic, but they also faced more umpire's calls (Columns III and IV). This reiterates that marginal decisions against the home team ended up being more likely umpire's call, still leading to a batsman being out, rather than being overturned; the margin of error in the DRS system tended to result in decisions going against the home team more often with home umpires than with neutral umpires. This effect appears to have been strongest in front of crowds, where we might expect the umpires to feel more pressure and scrutiny about their perceived in-group identity and home bias. These findings relating to Hypothesis 2.2 are summarised as follows.

RESULT 2.2 The 'reverse' (or overcompensating) bias against home teams by home umpires, after awareness, appears to be driven by their marginal judgments, which stayed with the on-field decision as 'umpire's call' after technology-assisted review

[26] We also use the percentage overturned and umpire's call as dependent variables, using least squares with venue fixed effects, with the results reported in Appendix Table A3. Our conclusions are robust to doing so.

.**Table 6.** Poisson regression effects (%) of the COVID-19 pandemic and playing behind closed doors on the number of overturned decisions and umpire's call in Test innings

	Batting				Bowling			
	Overturned		Umpire's Call		Overturned		Umpire's Call	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Home team batting (γ_1 or β_1)	-0.135	-0.133	-0.141	-0.142	-0.256*	-0.255*	-0.013	-0.014
	(0.118)	(0.118)	(0.260)	(0.261)	(0.126)	(0.126)	(0.020)	(0.020)
Pandemic (γ_2)	0.2		0.286		0.119		0.170	
	(0.151)		(0.402)		(0.311)		(0.151)	
Home team × Pandemic (γ_3)	-0.205		0.576		0.080		-0.001	
	(0.181)		(0.688)		(0.282)		(0.023)	
Pandemic (ref: pre-pandemic):								
Closed doors (β_2)		0.544***		0.88		0.165		-0.06
		(0.249)		(0.792)		(0.463)		(0.214)
Crowds (β_3)		0.014		-0.057		0.082		0.298*
		(0.167)		(0.240)		(0.299)		(0.202)
Home team × Closed doors (β_4)		-0.500**		0.203		-0.111		0.017
		(0.156)		(0.687)		(0.268)		(0.032)
Home team × Crowds (β_5)		0.045		1.060*		0.211		-0.09
		(0.261)		(0.792)		(0.414)		(0.027)
Umpire experience	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Log overs	1.046***	1.042***	1.233***	1.208***	0.134	0.137	-0.061	-0.059
	(0.278)	(0.278)	(0.451)	(0.462)	(0.166)	(0.168)	(0.054)	(0.053)
ELO predict	-0.201	-0.18	0.818	0.783	0.261	0.301	0.006	0.006
	(0.318)	(0.320)	(1.069)	(1.003)	(0.469)	(0.480)	(0.052)	(0.052)
Innings number (ref: first):								
Second	0.418***	0.420***	0.102	0.085	-0.042	-0.038	-0.003	-0.002
	(0.170)	(0.166)	(0.248)	(0.235)	(0.150)	(0.152)	(0.006)	(0.006)
Third	0.25	0.249	-0.095	-0.106	-0.12	-0.119	-0.012	-0.012
	(0.185)	(0.184)	(0.204)	(0.202)	(0.172)	(0.172)	(0.018)	(0.017)
Fourth	0.395**	0.396**	0.402	0.387	0.014	0.017	0.005	0.005
	(0.229)	(0.232)	(0.426)	(0.418)	(0.214)	(0.215)	(0.029)	(0.029)
Constant	-0.725***	-0.725***	-0.994***	-0.994***	-0.750*	-0.758*	0.750*	0.748*
	(0.017)	(0.017)	(0.005)	(0.006)	(0.202)	(0.196)	(0.551)	(0.535)
p-value: $\gamma_1 + \gamma_3 = 0$	0.02		0.97		0.262		-0.08	
p-value: $\beta_2 = \beta_3$		0.0156		0.1916		0.4558		0.6038
p-value: $\beta_1 + \beta_4 = 0$		0.001		0.942		0.142		0.707
p-value: $\beta_1 + \beta_5 = 0$		-0.49		0.038		0.714		0.725
Venue fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N of innings	527	527	509	509	520	520	526	526

Notes: author calculations using data from cricketarchive.com/, accessed 28/03/2022. All matches represented in Table 2 who used the decision review system (DRS), with the pre-pandemic period covering matches played between 16 November 2017 and 29 February 2020 and the pandemic period covering matches played 8 July 2020 and 24 March 2022. ELO predict is from the perspective of the team batting. Effects shown are $\exp(\hat{\beta}) - 1$, so can be interpreted as percentage effects on the number of LBWs in an innings. ***,**,* indicate significance at 1%, 5% and 10% levels, respectively, two-sided tests, standard errors in parentheses are robust to clusters at the venue and match levels.

6. Discussion

In many situations, people expend effort in competition and the winner is decided by officials. Often the officials make decisions that are wrong due to their inherent identity-driven in-group versus out-group bias. This is observed and documented in various aspects of everyday life, including in the judiciary, workplace feedback, exams, and sports. Such bias can lead to suboptimal outcomes in society and create long-term problems. One of the prescribed tools to deter judgement bias is to raise awareness, make its existence public, and encourage or enable more scrutiny of the officials. There is recent experimental research showing some evidence on the effectiveness of such policies, at least within the timespan of the experiments. However, there is no existing field study that shows the long-term external effectiveness of such policies, especially in terms of unintended consequences. In this study, we used data from international cricket to investigate whether raising awareness can be effective to deter identity driven bias in judgement. We have tested whether the knowledge of one's own potential bias, multiplied by the pressure of public scrutiny, can lead an official to overcompensate with biased judgements in favour of the out-group competitors.

It has been well-documented that the umpires in international cricket historically made decisions consistent with an own home country bias, and the governing body of the sport made rule changes in 2002 permitting only neutral umpires in Test matches – resulting in the removal of the bias. We exploited a temporary rule change due to the COVID-19 pandemic that allowed home country umpires to be re-employed. We found a significant and substantial reduction in the overall match home advantage after this rule change, though there was no evidence that this was further reduced when the potential pressure from home-team supporting stadium crowds was also removed. Going against what people involved in or watching cricket matches might have expected, we found that the substantial pre-pandemic home advantage in the frequency of difficult and important LBW decisions, by neutral umpires, was approximately eliminated when the officials instead plied their trade at home. We further found that home umpires disadvantaged home teams by conservatively judging against them in marginal cases, which might otherwise have been corrected by technology-assisted review.

These results have much broader implications beyond cricket. Existing studies have shown that, at least in an experimental setting, judgement bias can be reduced due to awareness (Alesina et al., 2018; Boring and Philippe, 2021; Mengel, 2021). However, we show that such a policy can also be useful in the field and in the longer run. Judgement bias has been notably documented in the Israeli judiciary Shayo and Zussman (2011). But even after that study was published, a follow-up showed the bias still existed several years later (Shayo and Zussman, 2017). Our results from the cricket field, like those in Pope et al. (2018) for officials' racial bias on the basketball court, suggest that if evidence like that from Shayo and Zussman (2011) is publicised, and if greater scrutiny – even in terms of a social cue such as provided by a well-informed crowd – can be implemented within the system, then the notable bias could be alleviated. The same can be true for other situations where bias relating to race, gender, religion, language, migration status, etc., may affect the judgement of an official.

One important aspect arising from our study is that intensified scrutiny may even reverse the direction of identity-driven judgement bias. This has important implications. Depew et al. (2017) showed that judges in the US courts are harsher to juveniles of their own race. Similarly, Ting et al. (2022) found male professors were more favourable to female music composers. It is important to investigate whether such reverse bias arises due to scrutiny in the courts, or awareness regarding gender bias, as well as whether further awareness can eliminate it. The same can apply for other dimensions of identity, such as gender, ethnicity, and immigration status, in various other aspects of official decisions.

There are several ways our research can be extended. The peculiarity of the game of cricket allows for some results to be revisited. For example, in the pre-pandemic period with two neutral umpires, on average significantly fewer LBW decisions were given to home Test teams. This fits with the observation in other sports that umpires are influenced by the social pressure of the home crowds, although it could also have been explained by other aspects of home advantage, such as familiarity with home playing conditions. During the pandemic, when controlling for the venue and team strengths, there were fewer LBW dismissals overall, which could just reflect the coinciding ban on using saliva to shine the ball or more DRS reviews correcting decisions against the batters. In the pre-pandemic period, it is plausible that the away team batters got more LBWs mainly because home team bowlers were more familiar with the field and weather conditions, thus being better at using saliva on the ball accordingly to exploit their familiarity and trap their opponents. For further validity, other sports and situations can be exploited. There may also be differing impacts on player performance for away and home teams from removing the pressure provided by stadium crowds. For example, in professional football, Ferraresi and Gucciardi (2021) found that the probability of missing a penalty kick increases (decreases) for the home (away) team when playing behind closed doors, compared with in front of crowds. However, we cannot see or find evidence for any obvious reason why the patterns we have described in cricket should be driven by any direct impacts of the pandemic and empty stadiums on player performance.

Till now, we have taken a normative approach in addressing the bias in judging competition, as the bias itself is unacceptable. However, it will also be important to take a positive approach to assess why it is unacceptable, in terms of effort provision by the engaged parties and outcomes for broader society. It will be useful to study how rectification of bias affects effort and other behaviour of contest participants. Experiments may help, along the lines of some recent studies (e.g., Alesina et al., 2018; Boring and Philippe, 2021; Mengel, 2021). Finally, our work sheds light on identity and conflict (Chowdhury, 2021), which could be explored further on the sports field.

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Online Appendix: Additional Tables & Figures

Table A1. Distribution of Test matchups in estimation sample, November 2017 to March 2022, {Pre-pandemic, During COVID-19}

		Home team									
		Australia	Bangladesh	England	India	New Zealand	Pakistan	South Africa	Sri Lanka	West Indies	Zimbabwe
Away team	Afghanistan	{0,0}	{1,0}	{0,0}	{1,0}	{0,0}	{0,0}	{0,0}	{0,0}	{0,0}	{0,0}
	Australia	X	{0,0}	{5,0}	{0,0}	{0,0}	{2,2}	{4,0}	{0,0}	{0,0}	{0,0}
	Bangladesh	{0,0}	X	{0,0}	{1,0}	{2,2}	{1,0}	{0,0}	{0,2}	{2,0}	{0,1}
	England	{4,4}	{0,0}	X	{0,4}	{3,0}	{0,0}	{4,0}	{3,2}	{3,2}	{0,0}
	India	{4,4}	{0,0}	{5,4}	X	{2,0}	{0,0}	{3,3}	{0,0}	{2,0}	{0,0}
	Ireland	{0,0}	{0,0}	{1,0}	{0,0}	{0,0}	{0,0}	{0,0}	{0,0}	{0,0}	{0,0}
	New Zealand	{3,0}	{0,0}	{0,2}	{0,0}	X	{3,0}	{0,0}	{1,0}	{0,0}	{0,0}
	Pakistan	{2,0}	{0,2}	{2,3}	{0,0}	{0,2}	X	{3,0}	{0,0}	{0,2}	{0,2}
	South Africa	{0,0}	{0,0}	{0,0}	{0,0}	{0,2}	{0,2}	X	{2,0}	{0,2}	{0,0}
	Sri Lanka	{1,0}	{2,0}	{0,0}	{1,1}	{2,0}	{2,0}	{2,2}	X	{2,2}	{2,0}
	West Indies	{0,0}	{2,2}	{0,3}	{0,0}	{2,2}	{0,0}	{0,0}	{0,2}	X	{0,0}
	Zimbabwe	{0,0}	{2,0}	{0,0}	{0,0}	{0,0}	{0,0}	{1,0}	{0,0}	{0,0}	X

Table A2. Estimated effects of the COVID-19 pandemic and Test match LBWs: robustness checks

	All Test		Excl. one neutral umpire		LBWs per 100 overs		Inc. new laws dummy		England Effects	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Home team batting (γ_1 or β_1)	-0.264***	-0.265***	-0.262***	-0.262***	-1.056***	-1.059***	-0.263***	-0.266***	-0.242***	-0.241***
	[0.080]	[0.079]	[0.079]	[0.079]	[0.239]	[0.239]	[0.079]	[0.080]	[0.092]	[0.092]
Pandemic (γ_2)	-0.254***		-0.268***		-0.931***		-0.296***		-0.259***	
	[0.084]		[0.088]		[0.272]		[0.090]		[0.097]	
Home team × Pandemic (γ_3)	0.296*		0.265		0.888**		0.291*		0.327*	
	[0.189]		[0.195]		[0.331]		[0.188]		[0.214]	
Pandemic (ref: pre-pandemic):										
Closed doors (β_2)		-0.328**		-0.338**		-1.289***		-0.31**		-0.369**
		[0.105]		[0.119]		[0.423]		[0.110]		[0.104]
Crowds (β_3)		-0.198*		-0.226*		-0.752**		-0.133		-0.166
		[0.105]		[0.106]		[0.288]		[0.152]		[0.133]
Home team × Closed doors (β_4)		0.143		0.052		0.718		0.147		0.256
		[0.272]		[0.289]		[0.576]		[0.273]		[0.373]
Home team × Crowds (β_5)		0.414**		0.401**		0.997***		0.419**		0.374*
		[0.221]		[0.217]		[0.365]		[0.223]		[0.239]
Umpire experience	-0.001	-0.001	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
Log overs	0.253***	0.250***	0.260***	0.254***			0.251***	0.252***	0.253***	0.251***
	[0.087]	[0.087]	[0.088]	[0.089]			[0.088]	[0.088]	[0.087]	[0.088]
ELO predict	-0.329*	-0.323*	-0.299	-0.279	-1.117**	-1.123**	-0.327*	-0.325*	-0.313*	-0.278*
	[0.156]	[0.160]	[0.162]	[0.167]	[0.534]	[0.542]	[0.156]	[0.159]	[0.155]	[0.175]
Innings number (ref: first):										
Second	0.201*	0.198*	0.179*	0.176*	0.465*	0.466*	0.201*	0.198*	0.196*	0.189*
	[0.117]	[0.118]	[0.112]	[0.113]	[0.271]	[0.273]	[0.117]	[0.118]	[0.118]	[0.119]
Third	0.021	0.020	-0.007	-0.008	0.263	0.264	0.021	0.021	0.021	0.021
	[0.110]	[0.111]	[0.107]	[0.107]	[0.231]	[0.233]	[0.110]	[0.111]	[0.110]	[0.111]
Fourth	0.083	0.079	0.052	0.044	0.431	0.427	0.083	0.078	0.08	0.072
	[0.148]	[0.149]	[0.145]	[0.145]	[0.323]	[0.325]	[0.149]	[0.149]	[0.151]	[0.152]
New laws							0.099	-0.089		
							[0.158]	[0.145]		
Home team × England									-0.129	-0.127

									[0.208]	[0.205]
Pandemic × England									0.014	
									[0.192]	
Home Team × Pandemic × England									-0.076	
									[0.275]	
Closed doors ×England										0.216
										[0.454]
Crowds × England										-0.163
										[0.181]
Home team × Closed doors X England										-0.221
										[0.305]
Home team Crowds × England										0.138
										[0.449]
Constant	-0.126	-0.127	-0.182	-0.177	2.958***	2.948***	-0.121	-0.134	-0.135	-0.159
	[0.315]	[0.310]	[0.307]	[0.312]	[0.391]	[0.390]	[0.315]	[0.312]	[0.312]	[0.309]
Venue fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	568	568	543	543	568	568	568	568	568	568

Notes: calculations using data from cricketarchive.com/, accessed 28/03/2022 (see Table 2). Columns (I)-(IV) and (VII)-(X) show Poisson regression estimates of Equations (10) and (11). Effects shown are $\exp(\hat{\beta}) - 1$, so can be interpreted as percentage effects on the number of LBWs in an innings. Columns (V)-(VI) show least squares where the dependent variable is the number of LBWs per 100 overs. ***,**,* indicate significance at 1%, 5% and 10% levels, respectively, two-sided tests, standard errors in parentheses are robust to clusters at the venue and match levels.

Table A3. Least squares regression of the COVID-19 pandemic and playing behind closed doors effects on the percentages of overturned decisions and umpire's calls in Test innings

	Batting				Bowling			
	Overturned		Umpire's call		Overturned		Umpire's call	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Home team batting (γ_1 or β_1)	-0.628	-0.579	-0.718	-0.674	-2.839	-2.826	-2.040	-2.066
	(2.369)	(2.371)	(2.215)	(2.213)	(2.212)	(2.222)	(1.969)	(1.975)
Pandemic (γ_2)	0.227		-2.529		-2.173		-0.166	
	(2.336)		(1.666)		(3.462)		(2.382)	
Home team × Pandemic (γ_3)	-6.243*		4.997*		0.089		-0.158	
	(3.563)		(2.951)		(3.090)		(3.082)	
Pandemic (ref: pre-pandemic):								
Closed doors (β_2)		4.950		0.967		-1.387		-2.141
		(3.144)		(3.015)		(4.428)		(2.684)
Crowds (β_3)		-2.232		-4.297**		-2.550		0.831
		(2.714)		(1.698)		(3.623)		(2.958)
Home team × Closed doors (β_4)		-9.562**		3.819		0.312		0.459
		(4.506)		(5.010)		(3.443)		(3.881)
Home team × Crowds (β_5)		-4.323		5.739**		-0.004		-0.552
		(3.997)		(2.694)		(3.880)		(3.510)
Umpire experience	0.028	0.025	-0.009	-0.011	-0.006	-0.007	-0.001	-0.000
	(0.034)	(0.033)	(0.016)	(0.016)	(0.036)	(0.036)	(0.020)	(0.020)
Log overs	6.358***	6.279***	3.097**	3.013**	-0.560	-0.588	-2.984	-2.936
	(1.584)	(1.554)	(1.395)	(1.409)	(2.142)	(2.132)	(1.778)	(1.770)
ELO predict	-2.874	-2.762	2.583	2.595	-3.923	-3.947	-1.419	-1.423
	(4.777)	(4.813)	(4.234)	(4.204)	(5.606)	(5.630)	(5.427)	(5.427)
Innings Number (ref: first):								
Second	2.586	2.576	-1.767	-1.796	-0.244	-0.259	2.757	2.774
	(2.253)	(2.264)	(2.392)	(2.383)	(1.985)	(1.995)	(1.911)	(1.906)
Third	0.977	0.949	-2.111	-2.152	0.375	0.358	3.283	3.307
	(2.308)	(2.315)	(2.438)	(2.436)	(2.683)	(2.687)	(2.304)	(2.306)
Fourth	1.770	1.699	-0.098	-0.170	-1.202	-1.226	-1.154	-1.113
	(2.777)	(2.783)	(2.606)	(2.601)	(2.160)	(2.152)	(2.470)	(2.476)
Constant	-13.094	-12.662	-4.655	-4.162	18.546	18.722	22.504**	22.219**
	(7.922)	(7.805)	(6.656)	(6.625)	(11.348)	(11.340)	(8.430)	(8.431)
p-value: $\gamma_1 + \gamma_3 = 0$	0.001		0.073		0.224		0.315	
p-value: $\beta_2 = \beta_3$		0.2603		0.676		0.9425		0.8049
p-value: $\beta_1 + \beta_4 = 0$		0.008		0.486		0.396		0.625
p-value: $\beta_1 + \beta_5 = 0$		0.063		0.024		0.373		0.336
Venue fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N of innings	527	527	527	527	527	527	527	527
R^2	0.125	0.129	0.081	0.085	0.079	0.079	0.094	0.096

Notes: author calculations using data from cricketarchive.com/, accessed 28/03/2022. All matches represented in Table 2 who used the decision review system (DRS), with the pre-pandemic period covering matches played between 16 November 2017 and 29 February 2020 and the pandemic period covering matches played 8 July 2020 and 24 March 2022. ELO predict is from the perspective of the team batting. ***,**,* indicate significance at 1%, 5% and 10% levels, respectively, two-sided tests, standard errors in parentheses are robust to clusters at the venue and match levels.

Figure A1. Global distribution of international Test matches in the estimation sample, November 2017 to March 2022, {Pre-pandemic, During COVID-19}