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Home bias in officiating: evidence from international cricket

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Home bias in officiating: evidence from international cricket

Summary

We use data on Leg Before Wicket (LBW) decisions from 1,000 Test cricket matches to quantify the systematic bias by officials (umpires) in favour of home teams. We exploit recent changes in the regulation of Test cricket as a series of natural experiments to help identify whether social pressure from crowds has a causal effect on home bias. Using negative binomial regressions, we find that home umpires favour home teams and this effect is more pronounced in the later stages of matches.

Keywords: Bias, Favouritism; Cricket; Negative binomial.

Home bias in officiating: evidence from international cricket

1. Introduction

In this paper, we explore the impact of social pressure exerted by crowds on the decision making of officials (umpires) in sporting contests by using data from Test cricket matches. Previous work (e.g. Garicano et al., 2005 and Buraimo et al., 2010) has identified a tendency for sporting officials to favour home teams. Test cricket is a particularly interesting laboratory for studying this issue for several reasons. First, cricket umpires are able to apply a high level of subjective judgement in decisions that can be critical for match outcomes. Second, regulatory changes to the appointment and functioning of umpires over the last two decades provide a series of natural experiments that can help distinguish the effect of social pressure from other factors such as outright preference from home umpires. Third, Test cricket matches are typically played for up to five days. The fact that crowds are typically larger in the first few days provides another potential source of identification of the effect of social pressure on decision making.

We focus on one particularly controversial area of decision making by umpires – that of deciding whether or not a batsman is dismissed ('out') 'Leg Before Wicket' (LBW). Using data on 1,000 Test matches from 1986 until 2012, we estimate negative binomial regression models to identify the extent and determinants of bias towards the home team. We find strong evidence that umpires have historically made decisions to the advantage of home teams and that the source of this advantage is more likely to be favouritism rather than social pressure from home crowds. We also find that the introduction of neutral umpires has virtually eliminated this bias.

In Section 2, we discuss previous work on the influence of social pressure on decision making and describe the relevant institutional features of Test cricket, drawing out some specific hypotheses. In Section 3 we introduce our data. We present our analysis, including our empirical methodology, in Section 4 and make some concluding comments in Section 5.

2. Social pressure in Test cricket

Test match cricket involves two national teams, where the fielding team is trying to 'bowl' the batting team 'out'. Batsmen can be dismissed in several ways, but the relevant dismissal here is 'Leg Before Wicket' (LBW). If a bowler on the fielding team delivers a ball which strikes a batsman on the leg, the fielding team can appeal for an LBW decision to one of the two on-field umpires, requiring him to judge whether or not the batsman should be given out (see Marylebone Cricket Club [2010] for the current rules underpinning the LBW decision). The umpire has to take into account a number of specific regulations in making his decision but (at least until recent years) has complete discretion over the decision which, once made, is considered final. The LBW dismissal is very common in cricket, with more than four such dismissals occurring in every match, on average.[1]

Given the level of discretion that is afforded to umpires and also the intense time pressure on them (umpires must make their decision within a few seconds), there is clear potential for LBW decisions to favour one team in a systematic way. Indeed, Ringrose (2006) points out that the difficulty of making LBW decisions lends them to conspiracy theories and claims of bias. Chedzoy (1997) statistically examines the effect of umpiring decisions on the performances of Test batsmen and teams, showing that they can alter the match outcome.

A striking feature of Test cricket is that until 1994, both on-field umpires had the same nationality as the home team. In 1994, cricket's governing body, the International Cricket Council (ICC), ruled that one neutral umpire should stand in every Test. Later, in 2002, the ICC ruled that henceforward both umpires would be neutral, chosen from an Elite Panel of umpires. Both of these changes were implemented in these years. From this point onwards, the best performing umpires at lower levels of cricket have been able to receive promotion to the Elite Panel, whilst poorly performing Elite Panel umpires can be demoted: for example, in 2004 three of the original eight Elite Panel umpires did not have their contracts renewed. This shift from fully home to fully neutral officials in Test cricket is rare amongst major team sports (see Andreff and Szymanski, 2006 for a review of major team sports). In the early years of our sample, Test umpires were appointed by each country's board. This hiring process has gradually been centralized towards the ICC.[2] Bryson et al. (2011) observe that a change in payment system impacts referee behaviour and performance in professional football, raising the possibility that the change in terms of conditions for umpires following the Elite Panel may have affected umpire behaviour and performance in Test cricket.

Contemporaneously with these regulatory developments, Test umpiring has also undergone notable technological changes. From the early 2000s, television broadcasters of

[1] As of 1 September 2013, there had been 9,232 LBW dismissals in 2,094 Test matches.
[2] Umpires on the Elite Panel are reportedly paid an annual salary of around GBP 200,000 plus expenses by the ICC (The Telegraph, 2013).

Test matches have used computer-based technology that enables a retrospective judgement to be made on whether an umpire's LBW decision was correct. Recently, this technology has been included in the actual decision making process: in 2008, the ICC began trialling a technological referral system called the Decision Review System (DRS) and then officially introduced it in late 2009. The system works by allowing both the batting and bowling teams to challenge umpires' decisions. Teams are limited to no more than two unsuccessful challenges per innings, but may make any number of successful challenges. At the time of writing, the DRS scheme can be used in any particular match if both teams agree.

Umpires are tasked with making decisions on a pair of teams, of which the home side typically attracts larger live crowds. Certainly, umpires gain utility from making correct decisions. Aside from the inherent pleasure of making a correct decision and the improvement to their professional reputations, the more decisions umpires get correct, the more likely they are to be retained by the ICC. Nevertheless, umpires may be constrained by social pressure to favour the home team, particularly where the 'correct' decision is ambiguous, as is frequently the case with LBW decisions.

Indeed, the limited existing literature provides some support for this hypothesis. Looking at matches played between 1877 and 1980, Sumner and Mobley (1981) noted that home teams suffered significantly fewer LBW decisions than away teams in Australia, India and Pakistan. Crowe and Middeldorp (1996) compare LBW rates for the first six batsmen in a batting line-up in Test matches played in Australia from 1977 to 1994. Using logistic regression models, they find that three of seven opposition teams were given out LBW more frequently than the Australian team, but it was unclear if this was because of umpiring bias. The authors suggest that differentials in LBW rates between the Australian team and its opponents could be explained by differences in playing styles.

More recently, Ringrose (2006) examines Test matches played between 1978 and 2004 for evidence of favouritism towards home teams, finding that location and batting team were significant: home teams suffered fewer LBW decisions than away teams. However, he does not find significant evidence that the introduction of neutral umpires reduced the home bias. We build on this result in two ways. First, in Ringrose (2006) data were only available for the very early years of neutral umpires. We now have the luxury of being able to observe a considerably longer period during which only neutral umpires have been used. Second, we adopt an alternative estimation strategy to Ringrose (2006), who measures LBW dismissals as a rate relative to the total number of dismissals. Such an approach may well understate the true level of home bias as the fewer LBWs awarded by a biased umpire will also reduce the total number of dismissals. Instead we adopt a count data approach which avoids this problem. This is because with each ball that is bowled in an innings, there is the possibility of a dismissal caused by LBW. Using the total number of dismissals in an innings as the exposure variable is problematic because of the endogeneity between total dismissals and LBWs. If there is indeed home bias such that home teams are given out LBW less frequently than away teams then, other things being equal, the value of total dismissals will be lower for home teams (on average) than for away teams. An alternative exposure variable would be the number of LBW appeals, but these data are not available.

Drawing upon Akerlof (1997), Dawson and Dobson (2010) explain that utility for decision makers can be context specific. In the case of Test cricket, utility gained by umpires may differ depending on whether or not they are umpiring a match involving their own country's team. We propose that home umpires may a) prefer the team that shares their own nationality, either consciously or unconsciously and b) be more susceptible to pressure from home crowds.

This leads to an interesting question which has not been explored in the existing empirical literature. What is the origin of the observed preference by home umpires for home teams? Is it inherent favouritism towards their own nation or is it the home crowd exerting pressure on the home umpire? To distinguish between these types of bias, we exploit the fact that Test matches are played over a period of up to five days and that consequently, the size of the crowd (and by proxy the extent of social pressure on umpires) varies with the stage of the match. Given that crowds tend to be very much bigger in the early stages of a Test match (Hynds and Smith, 1994) social pressure from crowds should be greater in the early innings of a match relative to the later innings.

For this reason, in our empirical work, we estimate home bias in LBW decisions both by the type of umpires (home, neutral or a mixture) and by the stage of the match (innings one/two compared to innings three/four). This allows us to identify the origin of the home bias and distinguish between favouritism and social pressure.

3. Data

We use data from all Test matches played between January 1986 and July 2012, excluding two matches that were abandoned without a ball bowled; sixteen matches played at neutral venues and one match played between Australia and a "World XI". This leaves 1,000 matches and 3,601 innings, with each innings treated as one observation. Of these 1,000 Test matches, 206 were played with two home umpires; 348 with one home umpire and one neutral umpire and 446 with two neutral umpires. The data were collected by the authors in their entirety from the ESPNcricinfo web site.

In Table 1, we report the number of LBWs per innings for home and away teams, both for all batsmen and just the top seven batsmen. The mean rate of LBWs is lower for home teams, both for all batsmen and for the top seven batsmen in the team. Standard t-tests suggest that these differences are statistically significant at conventional levels. 136 umpires took to the field in the sample period, with the combined experience of the umpires in each Test ranging between 2 and 201 Tests. The average combined umpire experience per match in the sample is around 53 Test matches.

Also in Table 1, we provide the breakdown of LBW decisions by umpire neutrality, presence of the DRS and host nation. Consistent with home bias, while both home and away teams were given out LBW less often by one home/one neutral umpire compared to two home umpires, away teams benefited more, with 9.6% fewer LBWs per innings as compared to 3.0% fewer LBWs per innings for home teams. With two neutral umpires, the number of LBWs per innings rose for both home and away teams, but considerably more so for home teams. With two neutral umpires, the bias towards home teams is virtually eliminated. One confounding factor is that home teams receive fewer LBWs because of superiority in familiar conditions. If so, the introduction of two neutral umpires may possibly have led to a bias towards away teams should neutral umpires feel pressure to favour away teams. We control for this in the formal analysis in section 4.

We report the rate of LBWs with and without the DRS system (with the latter sample restricted to matches with neutral umpires). Contrary to received wisdom at the time of writing, the mean LBW values have fallen for both home and away teams with the introduction of the DRS. In terms of different stages of the match, the second innings produces the most LBWs per innings, whilst the fourth innings produces the least. The latter is unsurprising as fourth innings of Test matches are, on average, shorter than the others. Although there is evidence of bias towards home teams in each innings, there is no clear trend in the bias between earlier and later stages of matches.

Looking at different venues for Test matches, the most LBWs per innings are given in Pakistan, followed by Bangladesh, India, Sri Lanka and West Indies. The least LBWs per innings are given in South Africa, followed by Australia. As Ringrose (2006) mentions, the slower nature of pitches in Asian countries tends to mean the ball bounces less and makes

LBW decisions more likely, in contrast to quicker and bouncier pitches in Australia and South Africa. The evidence of home bias varies quite considerably across countries. In the West Indies, New Zealand, Zimbabwe and Bangladesh, the mean number of LBWs is notably higher for home teams, whilst in Australia, India, Pakistan and Sri Lanka, the reverse is true. In England and South Africa the mean values are very similar. We will control for this in the subsequent analysis.

In Table 1, we summarize caught behind decisions in our full sample of matches. Caught behind decisions (meaning dismissals caused by the batsman edging the ball to the wicket-keeper behind the stumps) frequently involve an element of judgement by the umpire and, as such, may also be subject to home preference. However, in contrast to LBW decisions, some caught behind decisions do not require adjudication by the umpire and we cannot distinguish in the data which decisions require a formal decision. For this reason, differences in LBW decisions provide a 'cleaner' measure of home advantage. Nonetheless, we observe a clear pattern in the caught behind data, and one which is consistent with the impact of neutral umpires on LBW decisions. With two home umpires, away teams suffer 5.8% more caught behind decisions than home teams. When the one neutral umpire policy is introduced, this advantage to home teams declines to 3.8%. When two neutral umpires are present, the home team's advantage declines yet further to 1.5%.

To summarise, the descriptive statistics are consistent with home teams being favoured by umpires and with this bias being reduced by the presence of neutral umpires. There is also a priori evidence that the bias towards home teams varies considerably by the country in which the Test is being played. However, these differences may well be explained by the relative strengths of particular countries and so we now go on to use multivariate negative binomial regression analysis to see whether differences suggested in the descriptive statistics are robust to the inclusion of our control variables.

4. Analysis

As our aim is to examine how LBW decision making in Test matches is affected by the introduction of neutral umpires, we use the number of LBWs in an innings as the dependent variable. This is a form of count data, so we first consider using a Poisson regression model for our empirical analysis rather than an Ordinary Least Squares (OLS) model. This is because we cannot reasonably assume the dependent variable and the error terms are normally distributed as the count of LBWs is a whole number bounded between zero and ten.

In our sample, the variance of the dependent variable is slightly higher than its mean, suggesting the data vary more than might be expected in a Poisson distribution. Where the data are overdispersed in this way, Koop (2008) suggests that the most common alternative is the use of a negative binomial regression model, which allows the mean to differ from the variance. In the Poisson model, overdispersion can lead to very small standard errors, causing false positives. Although formal tests do not suggest that the overdispersion in our data is statistically significant, we proceed with a negative binomial model on the grounds of generality although, in fact, our conclusions are unaltered by the use of Poisson.

The overdispersion in the binominal model is captured by quadratic variance function which includes the unknown parameter α:

$$V[y|\mu,\alpha] = \mu(1+\ \alpha\mu) \tag{1}$$

From Cameron and Trivedi (2005, p. 675-676), the negative binominal maximises the log likelihood of the following probability mass function:

$$Pr(Y = y|\mu,\alpha) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\mu+\alpha^{-1}}\right)^{y} \tag{2}$$

where μ is parameterised as $\exp(X'\beta)$, as in the standard parameterisation of the Poisson and α is the variance parameter of the gamma distribution which is a constant. The treatment of the variance parameter as gamma distributed is convenient as it allows the analytical expression given in (2). This derives from the usual 'mixture interpretation' given to the overdispersion, meaning it bases the overdispersion as arising from unobserved gamma heterogeneity in a Poisson process. As α tends to zero, the model reduces to the Poisson. While the overdispersion parameter α enters (2) and hence affects the probability distribution, the expectation of the conditional mean is the same as it is in the Poisson model:

$$E[y|\boldsymbol{X}] = exp(\boldsymbol{X}'\boldsymbol{\beta}) \tag{3}$$

In our model, y is the LBW count, $\mathbf{X}$ is the vector of explanatory variables and $\boldsymbol{\beta}$ the corresponding coefficients. The interpretation of the regression coefficients in a negative binomial model remains the same as for a Poisson regression. The marginal effect of the coefficients on the number of LBWs is given by:

$$\frac{\mathrm{dE(Y_i)}}{\mathrm{dX_i}} = \beta\exp(\beta\mathrm{X_i}) \tag{4}$$

As this is a non-linear model, the value of the marginal effects will vary with different values of the covariates. When we calculate the marginal effects we report the "Average Marginal Effect" (AME) as in Cameron and Trivedi (2010, p. 576). This is the average of the marginal effects calculated at the sample values. Since we do not have a specific value of the covariates in mind when we are calculating the marginal effect, we prefer the AME.

To determine whether bias towards home teams occurs in Test cricket we are interested in how the explanatory variable Home batting impacts the LBW count. Home batting is a dummy variable taking the value one if the batting side is playing at home. We estimate equation 3 for the whole sample and then separately for three sub-samples: Tests with two home umpires (Home-Home), Tests with one home and one neutral umpire (Home-Neutral) and Tests with two neutral umpires (Neutral-Neutral). Our hypothesis is that a significantly negative estimate of the coefficient on Home would provide evidence of systematic bias towards home teams. To the extent that home umpires are more likely than neutral umpires to favour home teams, the Home batting coefficient should be highest in magnitude (more negative) when there are two home umpires and lowest (less negative) when there are two neutral umpires.

We consider the top seven batsmen in an innings separately, as social pressure on umpires may differ when making decisions against the specialist batsmen (including all-rounders) as compared to the less skilled lower order batsmen. Period dummies control for changes in the character of Test pitches over time and the effect of the introduction of HawkEye ball-tracking technology to television broadcasts from 2001. Given the possibility of within-match correlation (as up to four innings can be played in one match, with both teams batting up to two times), we cluster the standard errors by match. In the full sample estimates, we also include period dummies based on the neutral umpire rule for the period. We control for the fact that the number of LBWs in each innings will be affected by a number of factors. Some innings are curtailed prematurely due to the end of the match or due to lack of time, leading to the batting captain voluntarily ‘declaring’ the innings closed. As noted above, using the total number of dismissals to control for this is inappropriate as the total number of wickets falling will be directly correlated with any home bias. Hence, we include the log of the number of overs bowled in each innings (ln Overs) as our exposure variable. This does not entirely solve this issue. If wickets are less likely to fall when the home side is batting, the innings is more likely to be extended and the number of overs may be greater. As a robustness check, we control for the length of the innings with the Over dummies variables.

We also include the combined umpire experience in the match (Umpire Experience) and a dummy variable indicating whether the DRS was in use during the match (DRS). In some matches, the DRS has not included ball-tracking technology necessary for LBW referrals. These matches are treated as not having the DRS in place for the purposes of this study.

There may be systematic differences in the number of LBWs across different innings of a match and so we include dummy variables for three of the four innings (Innings2 dummy, Innings3 dummy, Innings4 dummy). Similarly, LBW decisions may be relatively more common in certain countries due to systematic differences in pitches. For example, pitches in Australia and South Africa are traditionally bouncier than in England, making it more likely a ball will bounce over the stumps and so less likely for an LBW decision to be given against the batsman. These impacts will be even more apparent by pitch, for example venues within countries have different characteristics. For this reason, one of our robustness checks below involves including dummy variables for the venue in which the game is being played (*Lord's*, Melbourne Cricket Ground etc.)

Finally, to control for the relative strengths of the teams, we also include two sets of team dummies: one for the batting side and one for the bowling side in each innings. We provide a full description of the variables in Table 3.

We report the estimates for the whole sample and then separately for the first two innings of a match and for the final two innings of a match. As argued above, crowds are generally much larger for the first and second innings of a Test match. Hence, if the evidence of home bias is relatively stronger for the first two innings, this would be consistent with crowd pressure being the source of the bias.[3]

We report the negative binomial regression estimates using the full sample in Table 4. For all four models, we report a likelihood ratio test for overdispersion in the data along with Wald chi-squared and log psuedolikelihood values. Use of Poisson regression (not reported here but available on request) leads to very similar results to those obtained with the negative binomial model.

We first estimate the model on all matches. Consistent with home bias, the coefficient on the key variable of interest, Home batting, is negative and statistically significant, suggesting that over the whole sample home batsmen are given out less often than away batsmen. The marginal effect is 0.128. At the mean value of 1.37 LBWs per innings, this represents approximately a 10% decrease in the number of LBWs per innings. The DRS does

[3] In experiments not reported here, we also use interaction terms to test whether DRS and/or umpire experience has an impact on home bias. We are unable to reject the null hypothesis of no effect in either case. However, it should be noted that the number of tests in which the DRS system has been in operation is relatively small.

not appear to have a significant independent effect on the number of LBWs, but we do observe marginally fewer LBWs as umpire experience increases. We also observe relatively more LBWs in the second and third innings of Tests (compared to the first innings).

Although we control for differences in average team abilities, some of the home advantage might be attributed simply to the home team being better able to avoid LBW decisions, rather than poor decision making by umpires. Put another way, teams may simply play better (and lose fewer wickets) at home than away. Therefore our main identification strategy is to estimate the model separately for Tests with two home umpires, Tests with one home and one neutral umpire and Tests with two neutral umpires. Home advantage due to other factors such as greater familiarity of the pitch should, on average, be constant across the three groups of tests. Any advantage to home teams in LBW decisions made by umpires between the groups can be attributed to home bias. These results are reported in columns 2-4 of Table 4.

There is a very clear pattern. The magnitude of home advantage is biggest when there are two home umpires and smallest when there are two neutral umpires. The marginal effect when there are two home umpires is -0.284, implying a decrease of approximately 19 percentage points in the number of LBWs per innings given against home teams. This is roughly equivalent to one extra LBW decision in favour of the home team in every innings, certainly enough to have a major impact on the outcome of the match. The effect is halved (-0.134) when there is one neutral umpire and reduced again when both umpires are neutral, to the point of statistical insignificance. A Wald test confirms that the coefficient on Home batting is significantly greater when there are two home umpires than when there are two neutral umpires.

So we find strong evidence that the introduction of neutral umpires reduced bias in favour of home teams. Next, we seek to distinguish between the types of bias: does it arise from social pressure or inherent favouritism towards the home team? To do this, we make use of our second source of identification, namely the variation in crowd attendance over the four innings in the Test. To explore the source of this bias, we next estimate the model separately for the first two and the final two innings. If the team's best batsman is incorrectly given out on the first day of the match, this will affect the team's first innings total and impact the outcome. However, the impact of decisions early on is somewhat indirect as there are potentially three more innings left in the match for the team to recover from a flawed decision, lessening the impact a biased umpire can have on match outcome. By contrast, in the final stages of the match (i.e. the final two innings), a similarly flawed decision against the team's best batsman will have a direct impact on the match (to give one example, a biased decision to give the team's best batsman out when the team is chasing a target to win the match in the final innings will very directly impact the final outcome). In these cases, the impact of the umpire's decision on match outcome is more direct and we argue that any home favouritism from umpires is likely to be strongest during these stages of the match for this reason. These estimates are reported in the first two rows of Table 5 (coefficients on the control variables are suppressed here for reasons of space).

In both cases, we see the same pattern as for the whole sample. The coefficient on Home batting is negative and largest when there are two home umpires and smallest when there are two neutral umpires. However, for the first two innings, the coefficient on Home batting is never significant and is much smaller than for the final two innings. Given that crowds tend to be much larger in early stages of Test matches, it is difficult to attribute the bias towards home teams displayed by home umpires as a response to crowd pressure. Instead it appears that home umpires give more LBW decisions in favour of the home team in the later stages of the match, where the decision is more likely to sway the outcome of the game.

Robustness Checks

We next consider a number of alternative specifications to explore how robust these results are. These are as follows:

(i) Inclusion of country-specific time trends to allow for changes in LBW rates in different countries over time. An example of this might be pitches in a particular country becoming generally more (or less) bouncy over time and, as a result, LBW decisions becoming less (or more) common.

(ii) Inclusion, also, of time trends specific to each batting and bowling side. This controls for systematic changes in abilities of particular teams over time.

(iii) Restricting LBWs to the top 7 batsmen only (see Crowe and Middeldorp, 1996).[4] Generally, decisions relating to higher order batsmen are more critical (and hence, potentially more susceptible to social pressure) than for lower order (or 'tail end') batsmen.

[4] In fact Crowe and Middeldorp (1996) use the top 6 batsmen. We use the top 7 as, typically, the seventh is still recognized as an important batting position.

(iv) Inclusion of match fixed effects. In this specification, we include fixed effects for every match. This is a much more restrictive specification which allows for the possibility that match-specific factors (for example atmospheric conditions) may affect the number of LBWs. In this case, the estimates of the coefficient on Home batting are driven solely by within-match variation.

(v) Inclusion of over-dummies. These are included as an alternative approach to controlling for the effect of innings length on LBWs, particularly shorter innings. We include dummy variables for five bands of overs: 1 to 25 overs; 26 to 50 overs; 51 to 100 overs; 101 to 150 overs and more than 150 overs.

(vi) We estimate the model using an alternative specification for the dependent variable, namely the number of LBWs per 100 overs bowled. In this case we use an OLS rather than negative binomial regression.

(vii) To enable a more direct comparison to Ringrose (2006), we estimate the model using the proportion of LBWs to wickets in the innings as the dependent variable.

(viii) We estimate the baseline model using an OLS regression.

(ix) To control for the effect of venue on LBWs, we use ground dummies rather than country dummies. Due to multicollinearity, we exclude team batting and bowling effects from this regression.

The results of the alternative specifications are generally consistent with the baseline model. In every case except (vii), the coefficient on Home batting is significantly negative when there are two home umpires but insignificant (at least at the 10% level) when there are two neutral umpires, whilst the coefficient is larger in size when there is one neutral umpire than when there are two.

The result from (vii), using the proportion of LBWs to wickets as the dependent variable, similar to Ringrose (2006), differs from our other findings. In this case, the coefficient on Home batting is reduced in magnitude and no longer significant. However, the presence of neutral umpires still reduces the magnitude of the coefficient even further. The insignificance of the coefficients when including the number of wickets can be explained by the fact that the number of LBWs is constrained by the number of wickets, so the number of wickets is likely to have a stronger impact on the number of LBWs than other factors. The use of Overs as the exposure variable partially overcomes this difficulty, though decision making by a biased umpire is still likely to alter the number of overs in an innings.

In summary, we find strong evidence that the introduction of one neutral umpire significantly affected LBW rates against home teams, with home teams suffering more LBW decisions with one neutral umpire relative to two home umpires. This finding is generally robust to the inclusion of country and team fixed effects and time trends over the sample period. This indicates that neutral umpires are better able to resist social pressure than home umpires.

Further, our finding that home umpires favour home teams more in the final two innings than in the first two innings provides some insights into the source of the home bias in LBW decisions. Specifically our results are more consistent with home bias arising from favouritism (whether conscious or not) by home umpires for home teams than by crowd pressure.

So how do our results compare with the growing literature on referee and umpire bias in professional sport? North American literature (e.g. Price and Wolfers, 2010 on the National Basketball Association (NBA) and Parsons et al., 2011 on Major League Baseball (MLB)) has tended to focus on ethnicity bias, a type of bias we do not consider in our study. European studies such as Dawson et al. (2007) and Buraimo et al. (2010) look more closely at biased decisions towards home teams and social pressure as proxied by crowd attendance. Our results contribute towards this second strand of the literature by indirectly assessing the impact of social pressure on decision making using stage of match as a proxy for crowd attendance. Our finding that neutral umpiring reduces the extent of home bias is in contrast to Buraimo et al. (2012), who find that home team bias persists in the Champions League even with neutral referees. Buraimo et al. (2012, p.331) note that the appointment neutral match officials in the Champions League is a "…deliberate attempt to combat potential bias" but find that bias persists regardless. One explanation is that crowd pressure acts in different ways on officials in cricket and football. Certainly, referees in football are requested to make decisions more frequently than cricket umpires, meaning instant crowd pressure rather than favouritism may be the main driver of home bias.

5. Conclusions

Our main finding is that there exists evidence of home bias influencing umpires in Test matches in the last two and a half decades. Home teams suffer significantly more LBW decisions when umpired by neutrals, with their advantage significantly declining with the introduction of the one neutral umpire policy and declining further with the introduction of the two neutral umpire policy. Home teams are favoured more by home umpires in the third and fourth innings of Test matches, which suggests favouritism from home umpires, as decisions made in those innings more strongly affect match outcome, even as crowd pressure generally declines.

Recently, some influential commentators have suggested (see, for example, Stewart, 2013) a return to using home umpires on the grounds that this would increase the available pool of high quality umpires, hence reducing errors. If such a proposal were to be followed, it may be the case that the presence of the decision review system (DRS) would mean that favouritism by home umpires would be lower than observed historically. However, the DRS still permits considerable umpiring discretion and, as a result, the results in this paper suggest that any proposal to move away from neutral umpires should be treated with caution.

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References

Akerlof, G.A. (1997). Social distance and social decisions. Econometrica, **65**, 1005-1027.

Andreff, W. and Szymanski, S. (2006). Handbook on the Economics of Sport. Cheltenham: Edward Elgar Publishing.

Buraimo, B., Forrest, D. and Simmons, R. (2010). The twelfth man? Refereeing bias in English and German soccer. Journal of the Royal Statistical Society Series A, **173,** 431-449.

Buraimo, B., Simmons, R. and Maciaszczyk, M. (2012). Favoritism and referee bias in European soccer: Evidence from the Spanish league and the UEFA Champions League. Contemporary Economic Policy, **30**, 329-343.

Cameron, A.C. and Trivedi, P.K. (2010). Microeconometrics using Stata. Texas: StataCorp LP.

Chedzoy, O.B. (1997). The effect of umpiring errors in cricket. The Statistician, **46**, 529-540.

Crowe, S.M. and Middeldorp, J. (1996). A Comparison of Leg Before Wicket Rates Between Australians and Their Visiting Teams for Test Cricket Series Played in Australia, 1977-94. The Statistician, **45**, 255-262.

Dawson, P., Dobson, S., Goddard, J. and Wilson, J. (2007). Are football referees really biased and inconsistent?: evidence on the incidence of disciplinary sanction in the English Premier League. Journal of the Royal Statistical Society Series A, **170**, 231-250.

Dawson, P. and Dobson, S. (2010). The influence of social pressure and nationality on individual decisions: Evidence from the behaviour of referees. Journal of Economic Psychology, **31**, 181-191.

ESPNcricinfo (2010-12). Available from http://www.cricinfo.com (First accessed on December 5 2010).

Garicano, L., Palacios-Huerta, I. and Prendergast, C. (2005). Favoritism under Social Pressure. The Review of Economics and Statistics, **87**, 208-216.

Hynds, M. and Smith, I. (1994). The demand for test match cricket. Applied Economics Letters, **1**, 103-106.

Koop, G. (2008). Introduction to Econometrics. Chichester: John Wiley & Sons.

Marylebone Cricket Club (2010). Laws of Cricket. www.lords.org/mcc/laws-of-cricket, accessed 3rd September, 2013.

Parsons, C.A., Sulaeman, J., Yates, M.C. and Hamermesh, D.S. (2011). Strike Three: Discrimination, Incentives and Evaluation. The American Economic Review, **101**, 1410-1435.

Price, J. and Wolfers, J. (2010). Racial discrimination among NBA referees. Quarterly Journal of Economics, xx, 1859-1887.

Ringrose, T.J. (2006). Neutral umpires and leg before wicket decisions in test cricket. Journal of Royal Statistical Society: Series A (Statistics in Society), **169**, 903-911.

Stewart, A (2013). *Ashes 2013: Bring back 'home' umpires*. www.bbc.co.uk/sport/0/cricket/23683136, accessed 3rd September 2013.

Sumner, J. and Mobley, M. (1981). Are cricket umpires biased? New Scientist, **91**, 29-31.

Table 1: LBWs per innings for home and away teams

	Home	*N*	*Away*	*N*	*Difference*	*All*	*N*
All innings	1.37 (0.03)	1771	1.48 (0.03)	1830	0.11	1.42 (0.02)	3601
All innings, top seven	1.02 (0.02)	1771	1.09 (0.02)	1830	0.07	1.06 (0.02)	3601
Both umpires home	1.32 (0.07)	360	1.57 (0.07)	360	0.25	1.45 (0.05)	720
One neutral umpire	1.28 (0.05)	620	1.42 (0.05)	633	0.14	1.36 (0.04)	1253
Both umpires neutral	1.46 (0.05)	791	1.47 (0.04)	837	0.01	1.46 (0.03)	1628
No DRS	1.47 (0.05)	654	1.48 (0.05)	697	0.01	1.48 (0.03)	1351
With DRS	1.41 (0.12)	134	1.41 (0.11)	143	0.00	1.41 (0.08)	277
First innings	1.33 (0.05)	506	1.43 (0.05)	494	0.10	1.38 (0.04)	1000
Second innings	1.53 (0.07)	490	1.57 (0.05)	498	0.04	1.56 (0.04)	988
Third innings	1.41 (0.06)	455	1.62 (0.06)	503	0.21	1.52 (0.04)	958
Fourth innings	1.13 (0.07)	317	1.18 (0.07)	338	0.05	1.15 (0.05)	655
Australia	0.95 (0.06)	260	1.48 (0.07)	281	0.53	1.23 (0.05)	541
England	1.43 (0.07)	299	1.42 (0.07)	300	-0.01	1.42 (0.05)	599
South Africa	1.23 (0.09)	170	1.15 (0.08)	194	-0.08	1.18 (0.06)	364
New Zealand	1.45 (0.10)	189	1.19 (0.08)	182	-0.26	1.32 (0.07)	371
West Indies	1.77 (0.11)	207	1.27 (0.08)	217	-0.50	1.51 (0.07)	424
India	1.30 (0.10)	178	1.76 (0.09)	195	0.46	1.54 (0.07)	373
Pakistan	1.54 (0.11)	134	2.14 (0.13)	143	0.60	1.85 (0.09)	277
Sri Lanka	1.15 (0.09)	169	1.90 (0.11)	174	0.75	1.53 (0.07)	343
Zimbabwe	1.60 (0.13)	89	1.03 (0.12)	87	-0.47	1.32 (0.09)	176
Bangladesh	1.74 (0.15)	72	1.34 (0.17)	61	-0.40	1.56 (0.11)	133

Notes:
(i) Standard errors in brackets.
(ii) N is the number of innings in each sample.
(iii) The sample of games with no DRS is restricted to matches with both umpires neutral.
(iv) "Difference" is the away average less the home average.

Table 2: Caught behind decisions per innings for home and away teams

	Home	*N*	*Away*	*N*	*Difference*	*All*	*N*
All innings	1.54 (0.03)	1771	1.59 (0.03)	1830	0.05	1.57 (0.02)	3601
Both umpires home	1.47 (0.07)	360	1.56 (0.07)	360	0.09	1.45 (0.05)	720
One neutral umpire	1.55 (0.05)	620	1.60 (0.05)	633	0.05	1.36 (0.04)	1253
Both umpires neutral	1.57 (0.04)	791	1.59 (0.04)	837	0.02	1.58 (0.03)	1628

Notes:
(i) Standard errors in brackets.
(ii) N is the number of innings in each sample.
(iii) "Difference" is the away average less the home average.

Table 3: Variables and definitions

Variable	Definition
LBW	The number of LBWs in the innings
Top seven LBW	The number of LBWs against the first seven batsmen in the innings
Home batting	1 if the batting team was playing at home; 0 otherwise
Away batting team)	1 if the batting team was playing away from home; 0 otherwise
Umpire Experience	The combined number of matches officiated by the two umpires
DRS	1 if the match had the Decision Review System (DRS) in place; 0 otherwise
Time	The number of the match in the sample
Innings1 dummy	1 if first match innings; 0 otherwise
Innings2 dummy	1 if second match innings; 0 otherwise
Innings3 dummy	1 if third match innings; 0 otherwise
Innings4 dummy	1 if fourth match innings; 0 otherwise
Runs	The number of runs scored in the innings
Overs	The number of overs bowled in the innings
ln (Overs)	The log of the number of overs bowled in the innings
Over dummies	Dummy variables for innings length in terms of overs
Umpire period dummies	Period dummies for two home umpires, one neutral and home umpire and two neutral umpires

Table 4: Negative binomial model of number of LBW decisions per innings

	All innings	Innings with two home umpires	Innings with one home umpire	Innings with two neutral umpires
Home batting	**-0.091 (0.030)*****	**-0.196 (0.069) *****	**-0.099 (0.049) ****	**-0.057 (0.044)**
DRS	-0.008 (0.078)			0.005 (0.077)
Umpire Experience	-0.013 (0.0006)**	-0.002 (0.003)	-0.003 (0.001) **	-0.001 (0.0006)
ln (Overs)	0.256 (0.028)***	0.378*** (0.064)	0.287 (0.048)***	0.208 (0.040) ***
Innings2 dummy	0.126 (0.036)***	(0.139)* (0.084)	0.156 (0.058) ***	0.092 (0.054) *
Innings3 dummy	0.138 (0.036)***	0.182 (0.078)**	0.2241731 (0.06) ***	0.054 (0.052)
Innings4 dummy	0.022 (0.053)	0.130 (0.125)	0.111 (0.085)	-0.08 (0.075)
One home and one neutral umpire period dummy	-0.0175 (0.050)			
Two neutral umpires period dummy	0.136 (0.056)**			
Bangladesh (host)	0.407 (0.133)***		0.866 (0.39**)	0.437 (0.155***)
England (host)	0.245 0.070)***	0.208 (0.135)	0.258 (0.144*)	0.272 (0.105***)
India (host)	0.331(0.082)***	0.330 (0.184)*	0.459 (0.174***)	0.260 (0.107**)
New Zealand (host)	0.120 (0.087)	0.198 (0.174)	-0.135 (0.155)	0.287 (0.136**)
Pakistan (host)	0.386 0.087)***	0.425 (0.175**)	0.386 (0.149***)	0.342 (0.136**)
South Africa (host)	0.165 (0.089)*	-0.231 0.447)	0.147 (0.143)	0.192 (0.127)
Sri Lanka (host)	0.257(0.091)***	-0.130 (0.212)	0.282 (0.155*)	0.366 (0.132***)
West Indies (host)	0.309 (0.086)***	0.449 (0.152)***	0.112 (0.174)	0.364 (0.124***)
Zimbabwe (host)	0.060 (0.119)	-0.99 (0.547*)	-0.066 (0.171)	0.530 (0.181***)
Constant	-0.892 (0.156)***	-1.449 (0.357)	-1.008 (0.275)***	-0.583 (0.231)
Batting team effects	yes	yes	yes	yes
Bowling team effects	yes	yes	yes	yes
Number of innings	3,601	720	1,257	1,624
Wald chi-squared		155.24		236.08
Log pseudolikelihood	-5392.1	-1073.3	-1817.9	-2440.7
Likelihood ratio test		0.406		0.485
Home marginal effect	-0.128***	-0.284***	-0.134**	-0.083

Notes:
(i) Robust standard errors in brackets, clustered by match.
(ii) *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
(iii) There is no estimate for Bangladesh in the *Home-Home* estimates because no Test matches were played with two home umpires in Bangladesh.

(iv) "Home marginal effect" is calculated as the Average Marginal Effect as used by Cameron and Trivedi (2010, p.576). Each marginal effect is an average of the marginal effects calculated at the sample values.
(v) "Batting team effects" are a control for the batting side in each innings, and "Bowling team effects" similarly control for the bowling side in each innings. These are included to control for batting and bowling team specific effects.
(vi) The "likelihood ratio test" is a likelihood ratio chi-square test that the dispersion parameter alpha is equal to zero.

Table 5: Estimates of home bias in LBW decisions: alternative specifications

	All	Home-Home	Home-Neutral	Neutral-Neutral
Innings 1&2	-0.054 (0.035)	-0.121 (0.081)	-0.078 (0.059)	-0.031 (0.052)
Innings 3&4	-0.116 (0.048)	-0.336 (0.100)***	-0.102 (0.079)	-0.060 (0.073)
Country-specific trends	-.092 (0.030)***	-0.195 (0.070)***	-0.101 (0.048)**	-0.056 (0.044)
Country, batting & bowling team trends	-0.098 (0.030)***	-0.212 (0.069)***	-0.095 (0.048)**	-0.061 (0.044)
Top 7 batsmen only	-0.083 (0.033)**	-0.163 (0.078)**	0.102 (0.054)*	-0.061 (0.048)
Match fixed effects	-0.091 (0.029)***	-0.192 (0.066)***	-0.099 (0.051)*	-0.063 (0.044)
Over dummies	-0.076 (0.029)***	-0.170 (0.066)***	-0.078 (0.048)	-0.049 (0.04)
LBW/100 overs	-0.21 (0.086)*	-0.592 (0.157)***	-0.136 (0.154)	-0.149 (0.114)
LBW/Wickets	-0.007 (0.005)	-0.023 (0.012)	-0.009 (0.008)	-0.002 (0.008)
OLS	-0.127 (0.042)***	-0.278 (0.101)***	-0.148 (0.063)**	-0.062 (0.062)
Ground dummies	-0.078 (0.031)**	-0.168 (0.072)	-0.116 (0.051)*	-0.017 (0.046)

Notes:
(i) Robust standard errors in brackets, clustered by match.
(ii) *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
(iii) All estimates are based on negative binomial regressions, with the exception of LBW/100 overs, LBW/Wickets and OLS, all three of which are OLS.
(iv) All estimates include the control variables listed in Table 4. These coefficients are suppressed for reasons of space. All estimates except those in the "Match fixed effects" row include country fixed effects and team fixed effects for the batting and bowling sides. For reasons of multicollinearity, the "Match fixed effects" row includes team fixed effects only for the batting side.
(v) In the "ground dummies" row, team batting and bowling effects are not included due to multicollinearity with ground dummies.