CORRUPTION DOES NOT PAY: AN ANALYSIS OF CONSUMER RESPONSE TO ITALY'S *CALCIOPOLI* SCANDAL

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Corruption does not pay: An analysis of consumer response to Italy's *Calciopoli* scandal

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Abstract

The literature on economics of corruption is lacking in evidence on consumer responses to identifiable scandals. The *Calciopoli* episode affecting Italian football in the 2005/06 season serves as an opportunity for an empirical investigation into consumer (fan) behavior following punishments imposed by the Italian league on clubs whose officials were found guilty of corrupt practices. Using a difference-in-difference estimation method, where the convicted teams are the treatment group, we find that home attendances for treatment teams fell relative to control group teams defined as those clubs not subject to league-imposed punishment. We show further that the fall in attendances identified with *Calciopoli* punishment resulted in non-trivial gate revenue reductions. Our results suggest that a sizable number of fans of the punished clubs were subsequently deterred from supporting their teams inside the stadium.

Keywords: Corruption; consumer demand; Calciopoli; football; attendances.
JEL Classification: L83

1 Introduction

The literature on economics of corruption has not surprisingly tended to focus on behaviour of Governments and related organizations such as the police and the judiciary. The various chapters in edited volumes such as Jain (1998) and Rose-Ackerman (2005) and surveys such as Aidt (2003) tend to deal with issues of corrupt practices performed by public sector employees and representatives. This emphasis on public sector corruption matches the definition of corruption proposed by Jain (2001) as an action in which the power of public office is used for personal gain in a manner that contravenes the rules of the game. Hence,

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researchers have investigated instances of corrupt behaviour such as bribes to politicians to influence the award of tenders in public procurement. But corruption can extend to any organizational form, public or private, where rules of governance could be breached by corrupt practices. Although not in the public sector, sporting competitions have rules of governance; competition rules are clearly set out and are available and known to all participants and stakeholders. Corrupt practices adopted to benefit particular organizations (sporting teams) and individuals (club officials or players) present a threat to the integrity and sustainability of sporting competitions. Sporting competitions, including professional sports leagues would appear to be an excellent environment to study the presence and effects of corrupt behaviour.

In an important contribution to the economics of corruption literature, Duggan and Levitt (2002) identify the presence of corruption in the form of collusion to rig matches in Japanese professional sumo wrestling. Noting that player rankings and earnings rose sharply after the eighth win in the competition, Duggan and Levitt offer evidence to show that wrestlers close to the eight wins margin indulged in match-rigging to enhance their rankings and earnings. Opponents would allow wrestlers to reach the important eighth victory, either via direct bribes or promises that match-fixing will be reciprocated in the future.

A related literature has exposed the presence of favouritism in sports, particularly through the decisions of match officials. This favouritism includes adding more discretionary time at the end of soccer matches to benefit home teams that are behind in score (Garicano et al., 2005), awarding disproportionately more sanctions to players of away soccer teams when fans are placed closer to the field of play (Buraimo et al. 2010), awarding disproportionately more penalty decisions in favour of home soccer teams (Dohmen, 2008) and awarding more foul calls against players of the opposite race in the National Basketball Association (Price and Wolfers, 2010). A common feature of this literature is that the favouritism identified here does not necessarily benefit the match officials concerned and cannot be linked directly to violations of tournament rules. Instead, as Dohmen (2008) points out, such favouritism is likely to be an instinctive, subliminal response to social (fan) pressure. Viewed this way, corruption is distinct from favouritism.

Absent so far from the literature of economics of corruption is any study demonstrating impacts of consumers of revealed episodes of corruption. This research question is not covered in the edited volumes of Jain (1998) and Rose-Ackerman (2005). It can be argued that products or services whose delivery has been revealed to be subject to corrupt practices may be seen as tainted in the views of some consumers. These marginal consumers then decline to purchase these goods or services and the result is loss of consumer demand and revenues for the suppliers. The principle reason for the lack of studies of consumer response to corrupt practices is surely a lack of data.

Our paper will identify- using the now-standard difference-in-difference estimator- an adverse impact on consumer demand from a clear example of corrupt practices in professional team sports: Italy's *Calciopoli* scandal of 2006. In this scandal, officials employed by five Italian clubs were found guilty of attempting to influence referee behaviour so as to enhance the winning potential of their teams in particular League fixtures. The scandal was the subject of a police investigation and important evidence was collected via telephone interceptions of conversations between club officials and referees. Some club officials were given jail sentences while others were banned from further involvement in football. Although the club officials were not public sector employees, the corrupt practices that were proven were found to be in breach of both civil law and the regulations of the Italian Football Association. To extend Jain's (2001) definition of corruption, the club officials convicted in the *Calciopoli* investigation attempted to influence the behaviour of match officials (referees) so as to generate gains for their teams in a manner that contravened the rules of Italian football and also Italian civil law.

Our paper proceeds as follows. Section 2 explains how the *Calciopoli* episode developed and demonstrates the punishments given to the guilty clubs. This section also highlights the product market context for the *Calciopoli* scandal. Section 3 explains our difference-in-difference estimation method. Section 4 details our data set and our model of consumer demand. Section 5 offers our empirical results and section 6 concludes.

2 The *Calciopoli* Scandal

Italian professional football is organised in two divisions, Serie A which has 20 teams and Serie B which has 22 teams. At the end of each season, the three bottom teams are demoted from Serie A and replaced by three promoted teams from Serie B. The title winners from Serie A plus the next two teams qualify for the UEFA Champions' League. The next three teams qualify for less prestigious UEFA Europa League (formerly the UEFA Cup). In any league match, three points are awarded for a win and one for a draw. Allegations of corrupt practices in Italian football predate the *Calciopoli* scandal. Garlando (2005) suggests that 20 matches involving Juventus could be linked to suspicious referee decisions or even outright match-fixing over the period 1994-2004.

The *Calciopoli* scandal was first alerted to the Italian football authorities when prosecutors investigated allegations of player doping at Juventus. A full account of the *Calciopoli* scandal can be found in Boeri and Severgnini (2011). The Juventus General Manager, Luciano Moggi, was revealed to have engaged in mobile phone conversations with referees, Italian football federation officials and journalists aimed at exerting pressure to select referees favourable to Juventus and to provide beneficial media publicity by casting the team in a favourable light. Italian prosecutors took up the case and obtained transcripts of mobile phone conversations during the 2004/05 season between club officials and the panel of former referees (designatori) who were responsible for allocating referees to games. Note that the initial process of referee allocation was non-random and discretionary. Some club officials sought to manipulate this process in favour of their teams.

The process of influence exerted by certain club officials took three forms. First, some referees known to be favourable to Juventus were allocated to important Griglia games of Championship significance. Thus, the referee of the Lazio-Juventus match towards the end of the 2004/05 season was known to be favourable to Juventus. This favouritism was revealed by explicit phone conversations between Juventus officials and the referees concerned. Boeri and Severgnini (2011) report pressures applied to referees such that if the match officials did not comply with the request to make decisions favourable to Juventus then they would not be selected for important Griglia games in the future. Boeri and Severgnini identify this as a career concern. A referee's future career would be undermined, in terms of match income and reputation by failing to accede to the Juventus request for favourable treatment. This applies in the context of a payment system where referees are paid a match fee per match and the fee was higher for Griglia games. Moreover, officiating at Griglia games could lead to appointment to UEFA and International matches thus offering referees further career opportunities. Second, some referees were encouraged to give beneficial decisions to Juventus in important games. Hence, Juventus were given a penalty in their home fixture against Roma despite the fact that their striker who was alleged to have been fouled was clearly in an offside position. Third, and more subtly, players in matches not involving Juventus received unjustified cautions and dismissals that led to suspensions and hence their unavailability for a forthcoming match against Juventus. Half way through the 2004/05 season several Brescia players received unjustified cautions and dismissals in the Messina-Brescia match which meant that Brescia had to field a weakened side in their next game against Juventus. At the end of the 2004/05 season, Juventus was the League winner with 86 points, seven head of nearest rival, AC Milan. Although the investigation initially focused on Juventus, several other teams' officials were found to be undertaking similar corrupt practices. The implicated clubs were Arezzo, Fiorentina, Juventus, Lazio, AC Milan and Reggina. In July 2006, the Italian Football Federation's prosecutor recommended that Juventus be stripped of its 2004/05 and 2005/06 League titles and be demoted two divisions to the regional division C1, Italy's third tier made up of small semi-professional teams. Arezzo were in Serie B (second tier) at the time but the other five implicated clubs were in Serie A. The original recommended and final punishments, awarded after appeal, are set out in Table 1. Appeal cases centred around the attempts to manipulate match results in the case of Juventus as opposed to allegedly more minor offences by the other clubs. Points deductions were applied at the beginning of the 2006/07 season.

In addition to the club-level punishments set out in Table 1, several club officials were banned from taking positions at any level in Italian football for specified periods. These included Luciano Moggi, who subsequently received around 5 year jail sentence for his role in *Calciopoli*. Table 1 reveals that the actual punishments imposed on the five guilty Serie A clubs were much less severe than those initially proposed. In particular, only Juventus was demoted and the actual points penalties were sharply reduced upon appeal. The exclusion from UEFA competitions (Champions' League and UEFA Europa Cup) were agreed after consultation between the Italian Football Federation and UEFA. Faced with a nine point deduction, rather than 30 as recommended initially by the League's prosecutor, Juventus won the Serie B Championship in the 2006/07 therefore giving them promotion back to Serie A at the first opportunity. Juventus lose several star players who joined other European teams. Fiorentina suffered a 15 point deduction but overcame this penalty to finish sixth in Serie A in 2006/07 leading to qualification for the 2007/08 UEFA Europa Cup.

The economic and financial context for *Calciopoli* was one of declining gate attendances and revenues, only partially offset by rising income from sales of television broadcast rights. As Baroncelli and Lago (2006) and Baroncelli and Caruso (2011) report, Italian Serie A clubs after 2000 faced a difficult combination of rising payrolls needed to attract and retain star players in a competitive European market for player talent and with sluggish growth of revenues compared to other European Leagues such as in England and Spain. This led to deteriorating balance sheets for many clubs. Baroncelli and Caruso (2011) point out that for the 2006/07 season, Serie A player payrolls were 62 per cent of total turnover, up from 58 per cent in 1997 and greater than equivalent ratios for other European leagues. This financial pressure may have induced clubs such as Juventus to engage in corrupt practices so as to illegally sustain their positions at the top of the Italian League, win domestic titles and qualify for the lucrative UEFA Champions' League. However, it must be noted that Juventus was one of only two Serie A clubs to post a pre-tax operating profit in the 2002/03 financial year although as a quoted company on the Italian stock exchange it suffered a reduction in market capitalisation from €430m in 2001 to €183m in 2004 (Baroncelli and Lago, 2006). Analysis of corruption in sports such as Forrest and Simmons (2003) and Forrest and McHale (2008) uses an economics of crime model. This suggests that match officials are pivotal figures who can influence games through their decision-making and that these officials are often poorly paid compared to players so their opportunity cost of acceding to requests to influence game outcomes is relatively low. This was one motivation for the English Premier League to switch referee contracts from match fees to substantial annual salaries (Bryson et al. 2011).

3 Econometric Model

Our purpose is to identify the causal effect of corruption (*Calciopoli*) on attendance. We use the fact that some teams have been found guilty, and punished, as a natural experiment. This is possible because we have panel data available before and after *Calciopoli*, and not all the teams received the punishment. Knowing that the corruption took place during the season 2005-06 but punishment was handed out for the season 2006-07, we define the binary variable

$$C_{it} = 0 \quad \text{if team } i \text{ played in t<2006-07}$$
$$C_{it} = 1 \quad \text{if team } i \text{ played in t>2006-07.}$$

This is our parameter of interest, which excludes the season 2006-07 because we want to estimate the effect of corruption on attendance from a pre-treatment period (2002-03 to 2005-06) to a post-treatment period (2007-08 to 2010-11).[1] We observe a drop in attendance in the season 2006-07, and we assume this is mainly due to the lower competitiveness of the punished teams and the absence of Juventus from Serie A. This may have caused a loss of interest in some supporters, at least those defined lukewarm ("tiepidi") and hot ("caldi") by a recent Italian survey[2], which showed that they account for more than 50% of all football fans.

Our treatment variable is

$$P_i = 1 \quad \text{if team } i \text{ has been punished in 2006-07}$$
$$P_i = 0 \quad \text{if team } i \text{ has not been punished in 2006-07.}$$

To estimate the treatment effect we could simply compare the treated teams before and after *Calciopoli*. However, we might pick up the effects of other factors that changed during the post-treatment period. Therefore, we use a control group (teams unaffected by *Calciopoli*) to "difference out" these confounding factors and isolate the treatment effect.

[1] A similar approach is used in Di Tella and Schargrodosky (2004) who study the causal effects of police on crime, using the Buenos Aires terroristic attack in 1994.

[2] Sondaggio Demos, September 2011.

We have four categories: 1) teams not punished before *Calciopoli* that will be punished afterward, 2) teams not punished before *Calciopoli* that will remain unpunished, 3) teams punished after *Calciopoli*, 4) teams unpunished after *Calciopoli*. Since we are using panel data, the teams in categories 1) and 3) and categories 2) and 4) are the same observed before and after *Calciopoli*.

If we take the average attendance of a team i in each category, $\overline{Y}_i$, and compute the change in outcome for the ith team treated $[\overline{Y}_{ia} - \overline{Y}_{ib}|P_i = 1]$ and that for the untreated $[\overline{Y}_{ia} - \overline{Y}_{ib}|P_i = 0]$. A simple *difference-in-differences estimator* of the treatment effect is given by

$$[\overline{Y}_{ia} - \overline{Y}_{ib}|P_i = 1] - [\overline{Y}_{ia} - \overline{Y}_{ib}|P_i = 0] \tag{1}$$

where a and b denote 'after' and 'before' *Calciopoli* .

The same result can be obtained in a regression framework, which uses the level of the attendance as dependent variable

$$Y_{it} = \alpha + \beta_1 P_i + \beta_2 C_{it} + \beta_3 \mathbf{X_{it}} + \phi P_i \times C_{it} + \epsilon_{it} \tag{2}$$

The DID estimator is the pooled OLS estimate of ϕ, the coefficient of the interaction between P_i and C_{it}. The regression based estimator is more flexible, allow us to add controls (i.e. vector $\mathbf{X}_{it}$) and exploit the fact the we have panel data. We perform two types of analysis at seasonal level and match level. Our dependent variable is log of attendance.

We estimate equation 2 together with equation 3, which includes team fixed effects and time dummies. In the analysis at match level we estimate equation 3 assuming first-order autoregressive errors (an AR(1) error model). This is our preferred model because we can control for habit persistence.

$$Y_{it} = \alpha_i + \delta_t + \beta_1 P_i + \beta_2 C_{it} + \beta_3 \mathbf{X_{it}} + \phi P_i \times C_{it} + \epsilon_{it} \tag{3}$$

In general, the validity of the DID estimator relies on the assumption that the underlying 'trends' in the outcome variable (i.e. time effects δ_t in equation 3) are common across treated and untreated team. This assumption is not testable, but with panel data we can get some idea of its plausibility. We provide some graphical evidence below (see Figure 1).

4 Data

Attendance data for Italian clubs are obtained from 'StadiaPostcards', which provides since 2001 a complete report of all matches in Italian Football Serie A, B and Lega Pro on a match-by-match, club-by-club basis.[3] The sources of 'StadiaPostcards' are the main Italian sports newspapers (La Gazzetta dello Sport, TuttoSport, Corriere dello Sport) but also DataSport and the clubs' official websites.

We have data from the season 2002-03 to 2010-11. We exclude the season 2006-07 for the reasons explained in the previous Section. This gives us four seasons of data before *Calciopoli* and four seasons afterwards.

[3]Information on Cagliari is not available on match-by-match basis and we only have aggregate season attendance for this team.

In the analysis at match level, the initial panel includes 2892 observations, where the time dimension is the weekly round of Serie A during a given season, whereas the cross-sectional dimension is the team. During the seasons 2002-3 and 2003-4 Serie A was comprised 18 teams and we observe 306 matches. From 2004-05 the number of teams increased to 20, and the matches played per season that we observe are 380.

In the analysis at season level, we only consider aggregate measure of attendance and controls, that is we compute seasonal averages for each team. The time dimension is now the season and the cross-sectional dimension the team. The initial panel consists of 156 observations which correspond to 18 rounds played from 2002-03 to 2003-4 and 20 rounds afterwards.

The teams included in our treatment group are: Juventus, Milan, Fiorentina, Lazio and Reggina. They all played in Serie A. Arezzo is the only team punished that was playing in Serie B. We have excluded it, and consequently all of Serie B, because we did not have enough observations to perform our estimation in both leagues.

In our control group we can only include teams that have played in Serie A for at least one season before *Calciopoli* and at least one season after *Calciopoli*. This restriction is necessary in order to be able to perform a DID estimation. Moreover, some matches were played behind closed doors due to punishments imposed in response to outbreaks of hooliganism and these matches are excluded from the data set. We therefore end up with a control group formed by 15 teams, that did not play consistently in Serie A from 2002-03 to 2010-11[4]. Thus our final sample is not a balanced panel, and it includes 20 teams for a total of 2292 matches played in 8 seasons. For each team we observe from a minimum of 72 matches to a maximum of 167 (i.e. a team that has always played in Serie A from 2002-03 - e.g. Milan or Roma).

In the sample at seasonal level we still have 20 teams that are observed from a minimum of 4 seasons to a maximum of 8, for a total of 124 observations.

The teams in our sample represent more than 90% of the total supporters. According to a recent survey[5] the distribution of supporters among the "top" teams in Italy has unchanged for many years. Juventus has around 30% of all supporters, then Inter (19%) and Milan (16%). Follow with percentages between 10 and 4.5 were Napoli, Roma and Fiorentina, respectively. The same survey reports that two out of three fans consider '*Calciopoli* scandal' as a case of sport justice 'affected by many errors'. Or manifestly unfair because the investigation was limited to a few teams. And almost half of the fans believed that the title of the season 2005-06 should not have been assigned to anyone.

As we have already mentioned in Section 2, Juventus was relegated in Serie B for the season 2006-07, as punishment for *Calciopoli* scandal. The team has been weakened, because some of its top players moved to other teams. Nevertheless, Juventus was promoted at the earliest opportunity to Serie A in 2007-08, which is the first season in our post-treatment group. Knowing that Juventus always had the highest number and share of fans in Italy, we decide to perform our estimations both including and excluding Juventus. This is a robustness check to verify whether our results are mainly driven by the importance of this team and its attraction of supporters when it plays.

In Table 2 we report the teams included in both treatment and control group and the

[4]This because some teams have been promoted to Serie A and other relegated to Serie B.

[5]Demos & Pi Survey, September 2010

average attendance for all the period 2002-03/2010-11. Figure 1 shows the pattern of attendance at match level, for the treated teams and some controls. We can observe, for example, that Inter, Roma, Udinese, teams that always played in Serie A during the period of our analysis, have similar trend before and after *Calciopoli* . This could provide some evidence that our assumption of common trends across treated and untreated teams has some plausibility.

In general, Serie A has registered a declining attendance trend from the 90s. The average attendance in the season 1991/92 was 34,205 which dropped to 29,883 in 1993-94 with the introduction of the pay-TV. There is a continuous decline down to 26,098 supporters in 2004-05. We should also to mention important changes in the Italian legislation that have also affected attendance. In 2003 the first Pisanu decree[6] allowed the police to arrest a supporter for up to 36 hours after the offence they are accused of, as if they were caught in the act. In 2005, a second Pisanu decree[7] introduced turnstiles and match tickets bearing the user's name. During the season 2005/06 the attendance dropped to 22,476 fans. The lowest level of attendance, 19,711, has been registered during the season 2006-07, when the teams involved in *Calciopoli* scandal were punished. In 2007, following some incidents that saw the death of a police officer and later of a Lazio football fan, a law imposed bans on fans travelling to away games, increased the punishment for those who throw missiles and extended the possibilities of expelling non-Italian nationals.[8] The mean attendance in the season 2007-08 slowly increased to 23,887 and up to 25,570 in 2009/10. We take into account all those shocks that affected treated and untreated teams in the same way, including in our models team and season fixed effects. In the match level analysis, we also include round fixed effects to capture timing effects within season.

4.1 Control variables

Previous literature has established that team success, variously measured as seasonal points or end-of-season position is an important determinant of team seasonal attendance (Simmons, 1996) [9]. We include *Season points* in our model of seasonal attendance. We also include previous season performance, measured here by *previous season position*, to capture habit persistence in team seasonal attendance over time. We use previous season position rather than previous season points to permit inclusion of promoted teams, which are given ranks of 21 to 24 underneath the Serie A ranks of 1 to 20, where 1 denotes Champions.

Promoted teams from Serie B might be predicted to have smaller market size than established and also to have poor prospects of retaining Serie A status. To allow for this possibility, we include a dummy variable for promoted clubs, *promoted.*

At match level, the home and away teams' current performances, *home* and *away points per game*, as measured by the ratio of points to games played prior to the match are included to control for current form of the opposing teams in a given match. In Serie A, three points are awarded for a win, one for a draw and zero for a loss. As points per game cannot be

[6]Decree no. 28 of 24 February 2003.

[7]Decree no. of 17 August 2005.

[8]Law 41/2007 and Amato decree 1 November 2007.

[9]There is just one published article on Italian football attendances, by Di Domizio (2007), but this considers aggregate Italian league attendance over a 44 year period and does not offer disaggregated analysis by club or by match.

computed for the first set of matches in each season, these matches are excluded from the analysis. We predict positive coefficients on *home points per game* and *away points per game*. In the latter case, an away team with more points per game is likely to be more attractive to marginal home fans and will also bring more away fans to the stadium, ceteris paribus.

To further capture other aspects of team performance and strength, the probability of the home team winning, as derived from the bookmaker fixed-odds betting market (*probability home win*) is included. Betting odds on match outcomes were extracted from files in www.football-data.co.uk and transformed into probabilities for each match outcome. The correlation of odds between bookmakers is very high (around 0.95) and we opt for the odds supplied by William Hill, as the source that gives us the greatest coverage of matches. The sum of these probabilities will always exceed unity due to the bookmakerÕs margin. This margin, or 'over-round' is typically around 13.4 per cent. We adjust the probability of each match outcome by dividing by the sum of probabilities. The advantage of using betting odds is that these should capture characteristics that are not easily observed such as player injuries, suspensions and dressing room morale. If the betting market is efficient then betting odds should incorporate all relevant public and private information on the two teams in a match.

There are two hypotheses giving different predictions as to the shape of non-linearity of the attendance-win probability relationship. The first, much discussed in the North American sports economics literature (Humphreys and Watanabe, 2012) postulates that fans want their teams to win but dislike excessively uneven contests. This is known as the uncertainty of outcome hypothesis and proposes that match attendance will rise with home win probability at a decreasing rate. Eventually, for high levels of home win probability, match attendance may even fall. An alternative hypothesis is that the prospect of an easy win will draw more fans to the game and so the match attendance-home win probability relationship will be convex; attendances rise with home win probability at an increasing rate.

Previous research from other European leagues has shown that the match attendance-home win probability relationship exhibits a U-shape as home team *ex ante* win probability increases (see Forrest and Simmons (2002, 2006); Buraimo and Simmons (2008) for England; Buraimo and Simmons (2009) for Spain). In line with this literature, we measure *home win probability* as assessed by fixed-odds bookmakers. In European football betting markets, which are far more open and less restricted than North American sports betting markets, we expect to find that bookmaker betting odds, and hence win probabilities, converge to market efficiency (Forrest, 2008). Hence, home win probabilities taken from bookmaker odds are the best available estimates of likelihood of a home team winning. We also include the home win probability squared to capture any non-linearity in the attendance-home win probability relationship.

Betting odds on match outcomes were extracted from files in www.football-data.co.uk and transformed into probabilities for each match outcome. The correlation of odds between bookmakers is very high (around 0.95) and we opt for the odds supplied by bookmaker William Hill as our source as that gives us the greatest coverage of matches. The sum of these probabilities will always exceed unity due to bookmaker's margin. This margin, or 'over-round', is typically around 12 per cent. We adjust the probability of each match outcome by dividing by the sum of probabilities. The advantage of using betting odds is that these should capture characteristics that are not easily observed such as player injuries, suspensions and dressing room morale. If the betting market is efficient then betting odds should incorporate all relevant public and private information on the two teams in a match.

As with the seasonal attendance model, we include *previous season position* and a dummy variable for promoted clubs, *promoted*. We lack specific information on ticket prices in Italian football, although these are known to show small within-season intra-team variation relative to inter-team variation through a given season. We therefore follow convention in the sports attendance demand model by using team fixed effects.

We finally include *derby*, a dummy variable intended to capture matches of historical rivalry between teams located closer to each other, in the same city or region. Previous studies (e.g. Forrest and Simmons, 2002) have shown that such matches tend to attract greater audiences, *ceteris paribus*, and the coefficient on *derby* is therefore expected to be positive and significant.

5 Results

Table 3 reports raw difference in difference estimates of the effect of *Calciopoli* on the five punished (treated) teams in the sample. We find a statistically significant reduction in attendances of punished clubs relative to unpunished attributable to *Calciopoli*, of the order of 21 to 22 per cent. This is a substantial effect.

Our season level regression results, incorporating control variables and team and season fixed effects, are shown in Table 4. Model (1) reports OLS results while Model (2) shows fixed effects estimates. Model (3) repeats OLS estimation but omits Juventus as a special case which bore the brunt of the *Calciopoli* investigation. Similarly, Model (4) shows fixed effects omitting Juventus. F-tests of joint significance reject the null hypothesis of zero coefficients, in each model. A Hausman test rejects the null hypothesis that the fixed effects are uncorrelated with the regressors. Therefore, we retain the OLS estimates for comparison and focus discussion on the fixed effects estimates. We also adopt robust standard errors clustered by team since without clustering the standard errors are biased downwards.

Looking first at the control variables in Model (2), we see that a better home team performance measured by season points raises seasonal attendance. An improved league position from the previous season is associated with higher attendance (the position variable is measured from one to 23 where one denotes Serie A champion hence an improvement in league position is indicated by a lower value of the position measure). The negative and significant coefficient on the *Calciopoli* dummy variable shows a general reduction in team-season attendances after the 2006/07 season.

The *Calciopoli* -punishment team interaction term in the first row delivers our difference-in-difference estimate of the effect of *Calciopoli* on treated (punished) teams. With Juventus included and adopting the formula $\exp(\beta) - 1$ to obtain the percentage impact of a dummy variable with coefficient β, we find a significant negative effect of *Calciopoli* on treated teams' seasonal attendances of 15.9%. When Juventus is removed from the sample, the treatment effect drops to -13.5% but is still statistically significant.

The match-level estimates in Table 5 reinforce the season-level results. The fixed effects estimates employ an autoregressive error term of order one to capture habit persistence in the dependent variable. As with the seasonal estimates, coefficients of the regressors are found to be jointly significant and fixed effects as well. Focussing on preferred models (6) and (8), match-level control variables perform much as expected. Game attendances are higher for matches of local rivalry, the higher is previous season league position, the greater are home and away team points per game and the higher is ex ante win probability for the home team as assessed by fixed-odds bookmakers. The offsetting negative coefficient on *home win probability squared* is consistent with match attendance results from England (Buraimo and Simmons, 2008) and Spain (Buraimo and Simmons, 2009).

The estimated U-shaped attendance-home probability relationship suggests that games attract larger numbers of fans where the home team has very low probability of winning and very high probability of winning. At low home win probabilities, there is a 'David and Goliath' effect where fans turn up to games, expecting their team to lose but hopeful that they can witness a surprise result in overcoming a better opponent. At high home win probabilities, fans turn up to games to enjoy the glory of their team winning, hopefully for them by a large margin. At intermediate home win probabilities, the Goliath effect is wearing off while the dominant team effect has yet to be revealed. From our results, the home win probability at which home team attendance is minimised is 0.61 (regardless of whether or not Juventus is included) and this is also consistent with Buraimo and Simmons (2008, 2009). Note that this result is inconsistent- indeed diametrically opposed- to the uncertainty of outcome hypothesis in the North American sports economics literature, where fans are proposed to enjoy ex ante winning probability but at a decreasing rate, thus implying a concave relationship between gate attendance and home win probability.

Turning to our *Calciopoli* focus variable, we find substantial negative treatment effects with point estimates of reductions in match attendance of 16.5 per cent with Juventus included and 15 per cent with Juventus excluded. This reinforces the results at seasonal level in Table 4. The use of round as unit of observation enables us to test for a potential negative externality on home teams. Gate attendances might be lower if a punished team is the visitor. Some home fans may express disapproval of a punished away team by staying at home while away fans may be more reluctant to travel. We test for this negative externality by testing for the significance of the coefficient on the interaction term, *Calciopoli*$\times$*away team punished*. We find insignificant coefficients on this term in the fixed effects estimates, regardless of whether or not Juventus is included. This suggests that the burden of *Calciopoli* effects on attendance falls on the home team.

We also test for time-varying effects of *Calciopoli* on treated teams. This is done by restricting the post-*Calciopoli* period to just one season, 2007/08. The pre-*Calciopoli* period is four seasons as before. For the fixed effects model with autoregressive errors, equivalent to Model 6 in Table 5, we obtain difference-in-difference estimates of *Calciopoli* effect on home treated teams of 20.5% with Juventus included and 11.6% with Juventus excluded (coefficients of -0.230 and -0.123 respectively). These results suggest that in the initial post-*Calciopoli* period, the publicity surrounding the malfeasance of Juventus officials led to a stronger effect of punishments on Juventus compared to the other four convicted Serie A clubs. Over the longer four year post-*Calciopoli* period the gap in *Calciopoli* effects between Juventus and the other punished clubs narrows. We find smaller treatment effects over the four season post-punishment period compared to just one season, when Juventus is included. Over time, our estimates also indicate increasing adverse effects of punishment on teams other than Juventus suggesting that fan disillusionment with the smaller punished teams actually increased.

It is useful to assess the economic significance of our results by means of a simple simulation. A 16.5 per cent loss of attendance means 6,190 fewer fans for treated teams in the post-Calciopoli period compared to before. Assuming an average match ticket price in Serie A of €28, the loss of attendance for treated (punished) teams[10] converts into a total loss to these teams of €3.29m for an 'average' punished team in a given post-*Calciopoli* season. In the whole post-*Calciopoli* period the revenue loss is computed at €66m over the five punished clubs and four seasons (over 380 games). This is clearly a non-trivial sum.

The simulated revenue loss is actually understated since it only considers the loss of gate attendance attributable to *Calciopoli* punishment and excludes loss of other sources of revenue such as merchandise sales (replica shirts), loss of sponsorship income as businesses may not wish to give their names to clubs tainted by corruption and loss of sales of broadcast rights as television companies will expect to pay less for a competition that may be undermined by undetected corruption. Moreover, star players may wish to leave punished clubs due to lower expected performances by these clubs (several top players left Juventus in the 2006/07 season as they did not wish to play in the inferior Serie B). Star players will perceive diminished career prospects by staying with punished clubs.

We should stress that our finding of a substantial negative effect of *Calciopoli* on attendances of punished clubs is not necessarily due to moral disapproval by the home fans. A number of alternative explanations are possible. Fans of punished teams may observe that the prospects for success of their clubs are reduced by the punishment, which typically took the form of points deductions. These deductions could have led to a process of downward momentum for the team as it slips down the league standings not just in the punishment season but in later seasons too. Alternatively, fans of punished teams might stay away in protest at the punishments inflicted by the League authorities. Either way, the end result is the same. The punished club loses gate attendances and associated revenues and is in a weaker position to compete effectively against rivals.

6 Conclusion

The *Calciopoli* episode affecting Italian football in the 2005/06 season serves as an opportunity for an empirical investigation into consumer (fan) behaviour following punishments imposed by the Italian league on clubs whose officials were found guilty of corrupt practices. Using a difference-in-difference estimation method, where the convicted teams are the treatment group, we find that home attendances for treatment teams fell relative to control group teams defined as those clubs not subject to league-imposed punishment. The strong advantage of the difference-in-difference method applied here is the identification of *Calciopoli* effects in a context of declining attendances affecting all Italian clubs and not just the punished clubs. Both the raw difference-in-difference in means and the regression-adjusted results support the conjecture of declining attendances for the five punished teams over and above a trend decline in the Italian league as a whole.

[10]We assume mean pre-calciopoli attendance for treated clubs of 37,500, and we use the DID match effect of 16.5%.

Our use of match-level data facilitates a test of a potential adverse effect of punished opposing teams on home teams' attendances. The data do not support the presence of this particular externality.

We show further that the fall in attendances identified with *Calciopoli* punishment resulted in non-trivial gate revenue reductions. Our results suggest that a sizeable number of fans of the punished clubs were subsequently deterred from supporting their teams inside the stadium. Hence, our analysis of the *Calciopoli* episode shows that harmful effects follow for clubs that are detected and punished for engagement in corrupt practices, over and above the direct punishments meted out. Team sports competitions are vulnerable to a number of sources of potential corruption, including explicit match-rigging. Our results suggest that sports leagues can perhaps highlight the additional adverse consequences of punishments as a deterrent for future corrupt practices by club officials who may be open to temptation. The analysis here also serves as a helpful methodology for identifying the consequences of punishments for clubs found guilty of corrupt behaviour. In addition to the punishments imposed on producers (clubs) it appears from our results that consumers (fans) inflicted further punishments in later periods. In this sense, corruption really did not pay in Italian football.

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Figure 1: Punished and Unpunished Teams - Attendance Trends

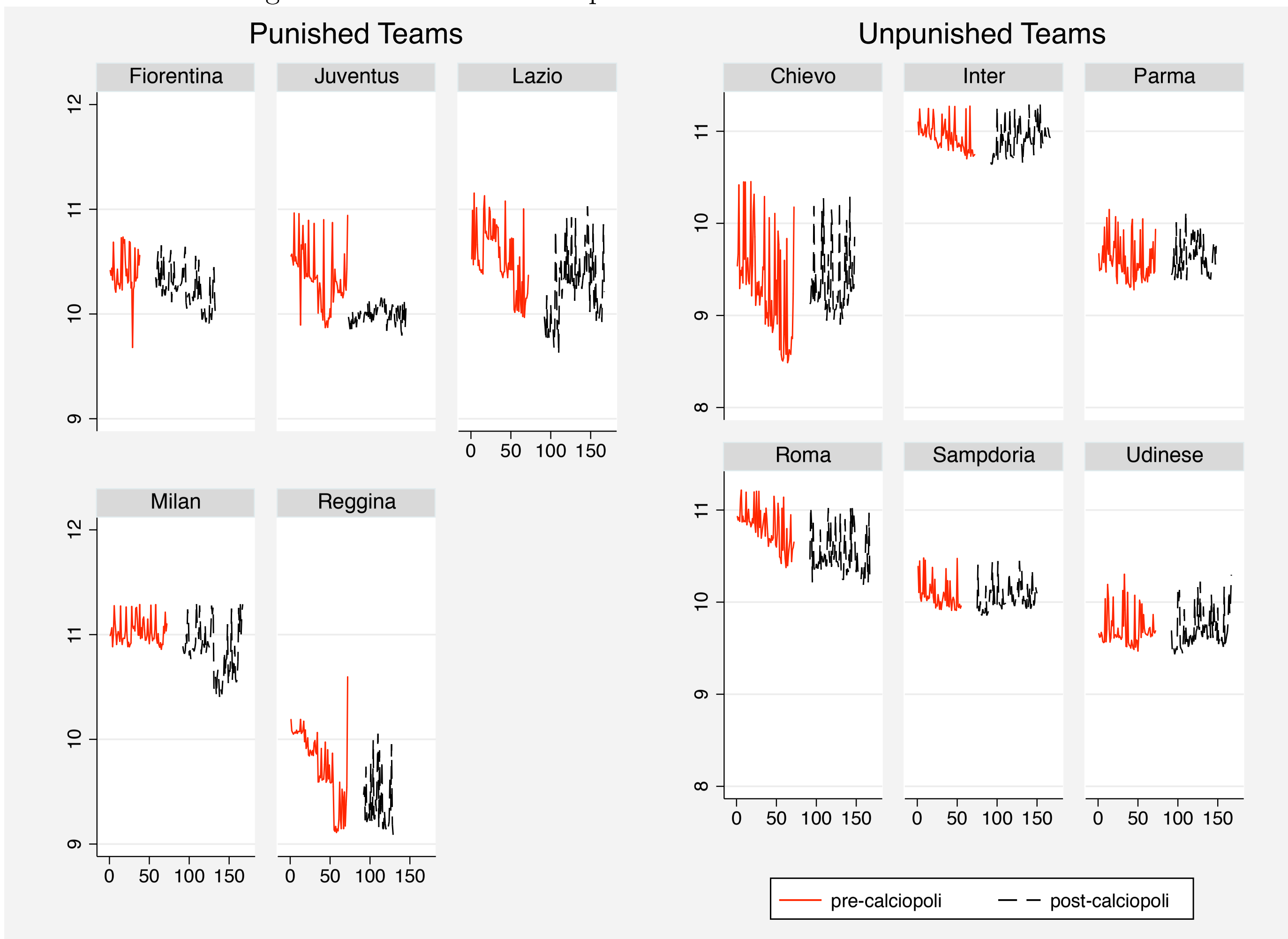

Table 1: *Calciopoli* Punishments

Team	*Original Punishment*	*Final Punishment*
AC Milan		
	Relegated to Serie B	No relegation
	Deduction of 15 points 2006/07	Deduction of 8 points 2006/07
		Ex post deduction of 30 points 2005/06
		1 home game to be played behind closed doors
Fiorentina		
	Relegated to Serie B	No relegation
	Deduction of 12 points 2006/07	Deducted 15 points 2006/07
		Excluded from UEFA Champions' League 2006/07
		2 home games to be played behind closed doors
Juventus		
	Removal of 2004/05 and 2005/06 Serie A titles	Removal of 2004/05 and 2005/06 Serie A titles
	Relegated to Serie C1	Relegated to Serie B
	Deduction of 30 points	Deducted 9 points 2006/07
		Exclude from UEFA Champions' League 2006/07
		3 games to be played behind closed doors
Lazio		
	Relegated to Serie B	No relegation
	Deduction of 7 points	Deducted 3 points 2006/07
	Excluded from UEFA Cup 2006/07	2 games to be played behind closed doors
Reggina		
	No relegation	No relegation
	Deduction of 15 points	Deducted 11 points 2006/07
		£68,000 fine

Table 2: Average attendance at match level

	Seasons from 2002-03 to 2010-11	
Team	*Average attendance*	*N. matches*
Punished		
Fiorentina	30109	132
Juventus	27177	147
Lazio	33614	167
Milan	56368	167
Reggina	15652	129
Unpunished		
Atalanta	13024	110
Bologna	21002	110
Brescia	11238	72
Chievo	12077	147
Empoli	7291	90
Inter	55411	167
Lecce	13523	93
Livorno	11404	94
Palermo	26222	133
Parma	15263	148
Roma	43321	163
Sampdoria	23134	150
Siena	9974	131
Torino	18142	74
Udinese	16524	167
Total	25191	2591

Season 2006-07 excluded.

Table 3: DID - Average Attendance

	Punished	Unpunished	diff	N
		Seasonal data		
Attendance				
post-calciopoli	31182	21953	9229	61
s.d	14054	13567	3849	
pre-calciopoli	37719	22687	15032	63
s.d	16201	15947	4467	
did			-5803	124
s.d			4175	
Log Attendance				
post-calciopoli	10.253	9.845	0.408	61
s.d	0.451	0.535	0.144	
pre-calciopoli	10.442	9.834	0.608	63
s.d	0.468	0.606	0.159	
did			-0.200	124
s.d			0.152	
		Match level data		
Attendance				
post-calciopoli	31208	21967	9241	1,157
s.d	15606	14560	959	
pre-calciopoli	37503	22462	15041	1,135
s.d	17439	16441	1098	
did			-5800	2,292
s.d			1030	
Log Attendance				
post-calciopoli	10.233	9.813	0.419	1,157
s.d	0.484	0.597	0.036	
pre-calciopoli	10.414	9.792	0.622	1,135
s.d	0.506	0.664	0.041	
did			-0.203	2,292
s.d			0.039	

Table 4: Models for *Serie A* Attendance - Seasonal level

Dep var: Log average attendance				
	Mod.1	*Mod.2*	*Mod.3*	*Mod.4*
$C \times P_{home}$	-0.121	-0.174**	-0.163	-0.145**
	(0.113)	(0.061)	(0.135)	(0.059)
promoted	0.449**	0.059	0.533***	0.051
	(0.167)	(0.069)	(0.159)	(0.070)
$\text{points}_{prev\,seas}$	0.017***	0.002	0.020***	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
$\text{position}_{prev\,seas}$	-0.045***	-0.002	-0.049***	-0.001
	(0.011)	(0.004)	(0.011)	(0.004)
N	124	124	116	116
F	8.009	12.511	25.500	11.907

Std.err. in parenthesis. Significance levels: *10% **5% ***1%.

Models 1 and 3 OLS with robust std. err. clustered by Home Team.

Models 2 and 4 Home Team Fixed effects and Season dummies.

Models 3 and 4 exclude Juventus.

Robust std. err. clustered by Home Team.

Table 5: Models for *Serie A* Attendance - Match level

Dep var: Log attendance	*Mod.1*	*Mod.2*	*Mod.3*	*Mod.4*	*Mod.5*	*Mod.6*	*Mod.7*	*Mod.8*
$C \times P_{home}$	-0.140	-0.182***	-0.188	-0.164***	-0.140	-0.181***	-0.184	-0.163***
	(0.115)	(0.033)	(0.145)	(0.038)	(0.113)	(0.033)	(0.143)	(0.038)
$C \times P_{away}$					0.055*	0.014	0.071**	0.016
					(0.030)	(0.019)	(0.029)	(0.020)
promoted	-0.494***	-0.019	-0.493***	-0.002	-0.475***	-0.017	-0.471***	0.001
	(0.153)	(0.037)	(0.151)	(0.042)	(0.149)	(0.037)	(0.146)	(0.042)
$\text{position}_{prev\,seas}$	-0.048***	-0.007***	-0.052***	-0.006**	-0.047***	-0.007***	-0.050***	-0.006**
	(0.014)	(0.003)	(0.013)	(0.003)	(0.014)	(0.003)	(0.013)	(0.003)
home points game	0.265***	0.095***	0.318***	0.098***	0.253***	0.094***	0.305***	0.096***
	(0.064)	(0.015)	(0.056)	(0.016)	(0.063)	(0.015)	(0.054)	(0.016)
away points game	0.269***	0.063***	0.273***	0.059***	0.265***	0.064***	0.269***	0.061***
	(0.036)	(0.011)	(0.037)	(0.011)	(0.035)	(0.011)	(0.037)	(0.011)
home win prob	-1.947*	-3.473***	-2.633**	-3.528***	-1.566	-3.312***	-2.232**	-3.352***
	(0.948)	(0.162)	(0.951)	(0.172)	(0.940)	(0.164)	(0.942)	(0.174)
home win prob^2	2.794**	2.827***	3.678***	2.882***	2.563**	2.737***	3.438***	2.783***
	(1.035)	(0.170)	(1.031)	(0.183)	(1.019)	(0.170)	(1.005)	(0.183)
derby	0.152	0.145***	0.135	0.152***	0.148	0.144***	0.129	0.151***
	(0.090)	(0.020)	(0.091)	(0.020)	(0.092)	(0.020)	(0.092)	(0.020)
N	2178	2158	2037	2018	2178	2158	2037	2018
F	21.025	80.644	32.593	75.774	35.875	81.104	42.968	76.363
F_α		161.581		148.576		159.274		146.437

Std.err. in parenthesis. Significance levels: *10% **5% ***1%. Fu: F test that all $\alpha_i = 0$

Models 1, 3, 5 and 7 OLS with robust std. err. clustered by Home Team.

Models 2, 4, 6 and 8 AR(1) with Home Team Fixed effects, Round and Season dummies.

Models 3, 4, 7 and 8 exclude Juventus. Models 5,6,7 and 8 include Away Team effect.