The Determinants Of The TV Demand Of Soccer: Empirical Evidence On Italian Serie A For The Period 2008-2015

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Abstract

This paper investigates the determinants of TV audience for Italian soccer. After a review of the literature concerning the key factors driving the demand for sport, we analyse SKY's audience figures for 7 Serie A seasons (from 2008-09 to 2014-15). Applying different OLS specifications, we show that Italian viewers have a committed behaviour and outcome uncertainty does not have a significant impact on TV audience. In addition, when choosing whether to watch a match of teams other than their favourite team, Italian consumers appear to be particularly attracted by both the aggregate quantity of talent present and by matches involving teams at the top of the table. This suggests that, in the Italian context, an increase in the TV demand is mainly driven by an enhancement in the performance of top clubs and in the quality of the entertainment rather than in competitive balance.

Keywords: Broadcasting; Soccer; TV Demand; Uncertainty of Outcome hypothesis; Talent; Serie A.

Introduction

In team sport TV broadcasting rights do constitute the main source of revenue for clubs. In fact, TV networks allocate a substantial amount of money in the most important sport tournaments. In European countries, the most popular sport is soccer: consequently, it is not surprising that in the top five European leagues broadcast revenues increased in the latest years.[1] According to Deloitte Annual Review of Football Finance (2015), broadcast revenue grew by 18% to €5.4 billion in 2013/14, contributing 48% of the total revenues of the big five leagues. The richest league is the English Premier League: their broadcast revenue reached £1.76 billion in 2013/14, accounting for 54% of the league's total revenue, and the value of the domestic rights for the next broadcast cycle (from 2016/17 to 2018/19 seasons) will total over £5.1 billion. However, the Italian *Serie A* was the league that received the highest contribution by broadcast revenue among the big five, as they counted for 59% of cumulative revenue.[2]

What factors are nowadays shaping the demand for soccer? Since Rottenberg (1956) and Neale (1964) the uncertainty of outcome was identified as the key variable of attractiveness. North American professional leagues were inspired by this hypothesis[3]. However, the uncertainty-of outcome hypothesis tends to neglect the impact of the emotional dimension associated with sport fans, that usually are more or less committed to a specific club (Tapp, 2004). In fact, in sport economics it is nowadays a conventional difference between committed and uncommitted fans (Szymanski, 2001). On the one hand, committed fans attend or watch their favorite team matches regardless of the expected final outcome, as their relationship represents a part of their identity and self-image (Robinson & Trail, 2005). On the other hand, uncommitted fans follow a team only if the team performs well and/or has higher probabilities to win, as the association with a successful team makes them feel good and/or repairs a damaged self-esteem. Both types of fans, even though for different reasons, are little interested in the uncertainty of outcome. Moreover, the amount of talent present in a game and the relevance of the game itself are other factors potentially affecting the demand for sport (Kuypers, 1996; Hausman & Leonard, 1997; Hunt, Bristol & Bashaw, 1999; Funk, Mahoney & Havitz, 2003; Buraimo, 2008; Tainsky, 2010); sport fans seeking entertainment may be more attracted by matches involving teams with high-level players or teams battling for the title.

This paper contributes to the debate on the determinants of TV demand of soccer by analysing the Italian *Serie A* from 2008-09 to 2014-15. The results show that uncertainty of outcome does not hold for Italian Serie A. Put differently, the TV demand does not increase when the match outcome is predicted to be very close. Then, it seems that Italian fans have a strongly committed attitude and, when following games not directly involving their favourite team, tend to be attracted by matches characterized by high levels of talent across the two teams and matches involving teams that are at the top end of the table.

Demand for Sports: the Literature Review

The debate about the determinants of the demand for sport has always been central in sport economics since Rottenberg (1956) that identifies the uncertainty of outcome as the key factor to attract customers to a sporting event; the more balanced a competition, the greater the interest of potential spectators, the higher the actual attendance. Further studies (Neale, 1964; El Hodiri & Quirk, 1971) strengthened the idea that sport professional leagues need a balance in competition between teams to maximise profitability. Fort and Quirk (1995) theoretically explored how different cross-subsidization schemes, such as reserve clause, salary cap arrangements, rookie draft, or revenues distribution issues may influence the closeness of the competition, and consequently, the revenues. Other studies (Sloane, 1971; Jennet, 1984; Peel & Thomas, 1988; Hoehn & Szymanski, 1999; Szymanski, 2003) highlighted that both teams and spectators may be not interested in having a well-balanced competition, as teams, especially in the European context, behave as *utility maximizers*[4] rather than as *profit maximizers,* and spectators seem to enjoy watching a game when the team they support have many chances of winning. However, recent literature [Coates & Humphreys, 2010; Fort & Quirk, 2010; Fort & Quirk, 2011; Coates & Humphreys, 2012; Mills & Fort, 2014; Pawlowski, 2014] suggests that additional efforts on theoretical and empirical ground must be done when the uncertainty of outcome hypothesis is tested with respect to the gate attendance.

That hypothesis can be considered crucial for the actual demand in a single game rather than in a whole season, but if commitment of fans emerges as an element able to affect significantly the demand for sports, it is crucial to distinguish between committed and uncommitted fans. Committed fans are loyal and, even though the success of the teams they support is always desirable, display a much greater propensity to attend games featuring their own teams regardless of their on-field performances or the closeness of the competition. Uncommitted fans have low levels of loyalty and may decide to attend a game as attracted by recent or regular successful on-field performances of the teams they support or by the uncertainty of outcome. If uncommitted fans preferring to attend a game when their favourite team is having a great season prevail, teams will prefer winning the championship to the balance of competition; if uncommitted fans that consider attending a close game as appealing prevail, teams will prefer the uncertainty of outcome in order to actually attract them to the games.

But the demand for sport does not correspond simply to gate attendance: advances in broadcast technology occurred especially during the 1990s have significantly increased the number of sport events televised and, consequently, the importance of TV audience within the demand for professional sports; for this reason the sale of TV rights has become the single most important source of revenue to both North American and European professional leagues. TV broadcast provides sport fans with an alternative option to watch a sport event, which can affect negatively attendance but does not represent a contraction of the overall demand. Therefore, Borland and Macdonald (2003) made a first attempt to systematize the sources and determinants of the demand for professional sports meant as not only attendance at sporting events, but also as broadcasting, sponsorship and merchandising. Five potential factors are identified from the literature review: *i*) season-level competitive balance, both within a season and across seasons: there is strong evidence that attendance is related positively to home-team performance and little evidence that it is positively related to match-level uncertainty, but intra-seasonal and inter-seasonal uncertainty seems to affect the demand for sport, which represents a rationale for sporting-league administrators to introduce rules and regulations in order to protect long run competitive balance; *ii*) contest quality: the higher it is, the higher the attendance, so that the number of spectators is lower in lower divisions; *iii*) quality of viewing: attendance is higher at newer stadiums and sport fans are very sensitive to weather conditions and match timing; *iv*) price: attendance sensitivity to price varies among teams yet; *v*) TV: even though the main available evidence suggests that TV broadcast impacts negatively on attendance at a single event, it may also stimulate interest in the sporting competition and increase overall attendance.

Several studies followed Borland and Macdonald's avenue of investigation focusing on the relationship between gate attendance and TV audience, in order to verify how TV broadcast impacts on the number of spectators attending a sport event. Garcia and Rodriguez (2002) estimated an attendance equation using data on individual games played in the Spanish Liga between 1993 and 1996, including all the explanatory variables traditionally considered by the literature. The results show that games broadcast on television and those not played on the weekend are characterized by significantly lower attendance, and this effect is larger when matches are televised on a free-to-air channel rather than on private channels requiring subscription fees.

Forrest, Simmons and Szymanski (2004) analyse the impact of televised matches on English Premier League match-day attendance between 1992 and 2001 by means of a Tobit model. The results show that satellite broadcasting of Premier League matches on Sundays and Mondays did not systematically cause a decline in gate attendance. In general, it emerges a mixed response of attendance to the effects of broadcasting depending on the combination of broadcaster and platform. Buraimo, Forrest and Simmons (2006) replicated the analysis of the relationship between TV broadcast and gate attendance for the Football League Championship, the second tier of English soccer, for the period 1998-2004; they introduced two main innovations: 1) the application of GIS technology, that allows to control for the market size of home and away teams more precisely by including local population measures; 2) the adoption of the Hausman-Taylor random effects estimator in order to take account of the endogeneity of the television coverage variable. They found that free-to-air TV broadcast has an estimated negative impact (over 20%) on the gate attendance that turns out to be significantly higher than pay-tv broadcast (5%), and higher status games (i.e. international or Premier League top-flight games) televised in competition with a Championship fixture at the stadium tend to detract people from attending the game. Buraimo and Simmons (2008), analyzing six seasons of Premier League football from 2001 to 2006, found out that matches televised on Sunday and Monday show a slightly negative effect on the number of spectators, whereas matches televised on other days and on public holidays have no statistically significant impact. Allan and Roy (2008) analysed the 2002-2003 season of Scottish Premier League in order to verify the impact of public television broadcast of soccer games on gate attendance. The main novelty is the decomposition of match-day attendance according to three groups of spectators: *a*) home season ticket holders; *b*) pay-at-the-gate supporters of the home team; *c*) pay-at-the-gate supporters of the visiting team. The main findings are that season ticket holders are loyal supporters and continue to attend also televised matches, that, on the other hand, experience lower attendances (around 30%) by pay-at-the-gate supporters of the home team. The impact of TV broadcast on visiting supporters is, instead, insignificant, probably because many supporters who choose to attend away matches are very likely to be season ticket holders for home matches and to show the same degree of loyalty as the first group of supporters under consideration. Buraimo (2008) shows that the number of stadium spectators positively influences TV audiences, whereas broadcasting, especially if implemented by free-to-air televisions, has a negative impact on match-day attendance. Buraimo and Simmons

(2009) demonstrated that TV broadcast has a significant impact on match-day attendance in the Spanish Liga: this effect is much larger if TV coverage is implemented by public or free-to-air televisions on weekdays.

Fewer empirical studies investigated the determinants of TV demand. Pacey and Wickham (1985) analyzed Nielsen ratings for college soccer assessing the impact of game quality on TV audience. Kuypers (1996) estimated both an attendance equation and a TV audience equation for the 1993-1994 season of the English Premier League. He verified that variables such as the importance of the game for the Championship or the relegation race, the quality of the game, proxied by the number of internationals involved, and the supporters' loyalty to the teams involved can impact positively on both gate attendance and TV demand. Hausman and Leonard (1997) demonstrated that TV ratings for the National Basketball Association (NBA) games are significantly higher when certain players, the so-called superstars, are involved. Kanazawa and Funk (2001) considered the 1996-1997 season of NBA basketball to verify the existence of racially based patterns of TV audience demand, finding that viewership increases when a higher number of white players is involved in the game. Aldrich, Arcidiacono and Vigdor (2005) replicated a similar study for 5 seasons of the National Football League (NFL) and tried to explain the fact that TV audiences of ABC's Monday Night Football are higher when the game involves a black quarterback. Paul and Weinbach (2007) also analysed Monday Night Football audiences for eleven NFL seasons (1992-2002), and found out that fans prefer games characterised by uncertainty of outcome, high quality of the teams playing the game and high-scoring. Salaga and Tainsky (2015) use Nielsen rating to evaluate TV viewer preferences for Bowl Championship Series telecasts between 2006 and 2010; they find that consumers show preferences for games expected to be more certain, but once the game begins, ratings increase uniformly in contests with increased uncertainty. Rodríguez, Pérez, Puente and Rodríguez (2015) focus on the Spanish professional cycling and find that competitive balance is one the best predictor of the potential audience.

According to the role of uncertainty of outcome, in an empirical analysis on eleven seasons of Premier League (1993-2003), Forrest et al. (2005) found a significant positive relationship between uncertainty of outcome and size of television audiences. Buraimo (2008) shows that uncertainty of outcome does not have any significant impact on TV audience, whereas the quality of player talent involved and stadium attendance, that is used as a proxy of the game excitement, are positively related to TV ratings. Moreover, scheduling seems to play an important role: games televised on Sundays and Mondays attract more viewers, and TV audiences are higher in January and February as well. Buraimo and Simmons (2009) tested the importance of outcome uncertainty over four seasons (2004-2007) of the Spanish Liga. Results concerning match-day attendance are very similar to those in Buraimo and Simmons (2008): outcome uncertainty does not have a significant impact on gate attendance, whose relationship with home win probability shows a U-shape, suggesting that fans are attracted only by games in which their favourite team have a very high probability to win and by games where the "David versus Goliath" effect may occur, considering also the presence of two traditional big teams such as Real Madrid and Barcelona. On the other hand, TV audiences are found to have a preference for close matches over games in which outcome is more predictable, and the increased broadcast revenue deriving from higher outcome uncertainty stimulating TV audiences significantly overcome decreased gate revenue. Moreover, stadium attendance and appearance of Real Madrid and Barcelona in any televised game have a significant positive impact on TV ratings. Alavy, Gaskell, Leach and Szymanski (2010) tested the relationship between TV demand for English soccer and outcome uncertainty using minute-by-minute TV viewership figures, showing that the higher the probability of a draw, the more likely viewers to switch channels. Tainsky (2010) estimated demand for 2006 and 2007 NFL games using television broadcast ratings and considering both the home and the visiting teams' markets: many of the factors influencing attendance remain valid with reference to television demand as well. More specifically, team quality, tenure in a market and prime-time broadcast have a positive effect on TV ratings, while sharing a market with one or more teams affect them negatively. Tainsky and McEvoy (2012) replicate the same analysis but considering TV demand in large markets without local teams: team quality and age, games involving the closest team in proximity to the market or more prestigious teams such as the Cowboys and Patriots, and late-season and play-offs contests are found to be significant and positively related determinants of TV ratings, whereas concurrent game telecasts and unbalanced matches are negatively related to viewership. Mongeon and Winfree (2012) identified the quality of their favourite team - proxied by the winning percentage - as a factor that increases sport fans' demand for both gate attendance and TV audiences of NBA games considering six seasons (2000-2005), whereas the existence of other professional franchises representing potential substitutes in the same geographical area has the opposite effect. Moreover, the income of the area where a NBA franchise is located does not have any impact on gate attendance but is negatively related to television viewership. With respect to the Italian context, Di Domizio (2010) analysed the determinants of TV audience for the *Serie A*, considering the 2008-09 season, and found out that uncertainty of outcome has a positive impact of TV demand, but it does not appear to be particularly strong. Feddersen and Rott (2011) analysed all the broadcasts of the German national soccer team from 1993 to 2008 and found that German viewers prefer a national team with established star players and high-quality opponents and factors such as the kick-off time or weather have some influence on TV audience, whereas national team's coaches, implementing more or less attractive playing styles, and student holidays, implying that a large percentage of population is on vacation and may not watch games, are actually insignificant. Buraimo and Simmons (2015), analysing 8 seasons (2001-2008) of the English Premier League, show that competitive balance has a significant impact on TV audience only in the first two seasons under consideration, and it is very likely that over time people developed, in correspondence with an increase in the quality of talent that joined the Premier League, a preference for games involving a significant amount of high-level players or superstars, regardless of the distribution of such talent across the clubs. At last Dang, Booth, Brooks and Schnytzer (2015) show that the uncertainty-of-outcome hypothesis holds for the television viewing of Australian Football League in the period 2009-2011.

The Italian Football Broadcasting Setting and the Dataset

The TV live coverage of *Serie A* is all inclusive, but rather complex/multi-structured. In the period under investigation three broadcasters were involved: the satellite pay-tv platform SKY, and two pay-per-view Digital Terrestrial (DTV) platforms, DAHLIA and PREMIUM. SKY differentiated its proposal in two packages; the first (more expensive), SKY CALCIO, giving to subscribers the opportunity of watching live all matches played in *Serie A*. The second, SKY SPORT, only broadcast matches played in advance/postponed, and two or three self-selected matches played on the traditional Sunday evening date. DAHLIA CALCIO broadcast, for a limited period, a team-selected matches on DTV pay-per-view platform. The DAHLIA channels lost TV rights in February 2011 because of insolvency. PREMIUM provided to the PREMIUM CALCIO package's subscribers team-selected matches.

Although the satellite television started to broadcast matches since 1993, data about TV audiences is limited. The National Professional League (LNP) provides official data from the season 2008/09, but only for matches broadcast on SKY. Data on DTV audiences is provided starting from 2010, but only for PREMIUM platform. In the following table 1 we summarize the number of available observations, by season, associated to each broadcaster.

Table 1 about here

The empirical investigation focuses on matches, and covers eight seasons, from 2008/09 to 2014/15. There are 2559 observations for the following teams: Atalanta, Bari, Bologna, Brescia, Cagliari, Catania, Cesena, Chievo-Verona, Empoli, Fiorentina, Genoa, Hellas-Verona, Inter, Juventus, Lazio, Lecce, Livorno, Milan, Napoli, Novara, Palermo, Parma, Pescara, Reggina, Roma, Sampdoria, Sassuolo, Siena, Torino, and Udinese. The data used for the empirical investigation are drawn from the dataset AUDIBALL (Caruso & Di Domizio, 2015).[5]

As dependent variables we use *sky_audience*, namely the total number of people watching the match on Sky channels, and *sky_share*, the percentage of people watching the match with respect to the people watching TV at the same time, with the exclusion of pub and/or club viewers where matches might be shown. Data on audience are officially provided by LNP on its website; they are based on AGB-Auditel survey, which offers (daily) the most important rating for Italian television programs, taken as a measure of the commercial value of advertising associated to the event.[6] Both *sky_audience* and *sky_share* are obtained by summing audiences of SKY CALCIO and SKY SPORT channels. The exclusion of pay-per-view audience from our empirical investigation is driven by three reasons; first, as indicated in the above-section, data on PREMIUM are available only from 2010, while data on DAHLIA are not available. Second, the two DTV's only broadcast live (DAHLIA until February 2011) a selection of matches, while SKY broadcasts all matches. The third reason is based on price; while the marginal cost of watching football matches on satellite television is null, since the subscribers pay an annual-fixed amount depending on the preferred package, the same is not for pay-per-view spectators. DAHLIA and PREMIUM viewers have (had) actually the double opportunity of subscribing an annual fixed-amount package or, alternatively, paying for a single match by using a prepaid card. In addition, we consider a dummy variable *sky_plus* identifying matches broadcast both on SKY CALCIO and SKY SPORT channels.

The independent variables may be divided into several groups. The first includes three variables modelling the competitive balance: *probs_difference*, *wages_difference* and *points_difference*. *probs_difference* is the uncertainty of outcome related variable obtained from the betting market; it is calculated as the differences (in absolute value) between the home and the away team win probabilities in the match under investigation.[7] Odds are available on line in the archive section dedicated by Football-Data to Italian professional soccer.[8] Given the (almost) perfect linear correlation between odds among the different bookmakers, we selected those provided by *BET365* because it is the most comprehensive set. For matches Bologna-Catania - in the season 2008/09 - Chievo-Bologna and Genoa-Brescia - in the season 2010/11 - we used odds from *Blue Square* and *Bet&Win*, respectively, because *BET365* did not accept bets on. The wages and points related variables are the absolute differences between the home and away team standardized wages and points, respectively.[9] Here standardized wages have to be intended as the ratio between team's payroll and seasonal average payroll, whereas points are the per-game seasonal average points until the match under investigation.[10]

The second group relates to variables associated with match expected relevance; we introduce four variables: *combined_wages*, *points_sum*, *derby* and *fixture*. The variable 'combined wages' does capture the aggregate amount of talent involved in the match. It is used in Hall, Szymanski and Zimbalist (2002), Forrest et al. (2005), Buraimo and Simmons (2008). The *combined_wages* variable is computed by means of the seasonal payroll of teams involved in the match under investigation as follows:

$$combined\_wages = \frac{home\ team\ payroll}{seasonal\ average\ payroll} \times \frac{away\ team\ payroll}{seasonal\ average\ payroll}.$$

The variable *points_sum* is computed by summing the home and the away team average seasonal points up to the match under investigation.[11] *Derby* is a dummy variable identifying the matches played between teams located in the same city or in the same region. Finally *fixture* is the count (spanning from 1 to 38) of matches in each season and is included to verify whether viewers are more interested in early season or late season games.

A variable closely related to the previous group is *occupation*, the ratio between the attendance, measured by the number of tickets sold plus seasonal ticket holders per match, and the stadium capacity. This variable is obtained by cross-checking data provided by the LNP and information on the web.[12] We expect that a more passionate environment, induced by a bigger crowd, may influence positively the TV audience.

The third group refers to variables arranging matches in space and time; the first is *distance*. It is an integer value measuring the distance, in km, between the town centres of the two cities of teams involved in the match.[13] Data are retrieved from Michelin Guide on the site www.viamichelin.it where the shortest way to reach the cities by car is suggested. Then, *combined_market* is introduced to take into account the market size effects.[14] It is computed as follows:

$$combined\_markets = \frac{home\ team\ population}{seasonal\ average\ population} \times \frac{away\ team\ population}{seasonal\ average\ population}.$$

The population data relates to the (team-associated) municipality total residents on the 1st January across the associated seasons; data are provided by the Italian Statistics Institute (ISTAT) on line.[15] The time collocation of matches is defined by a dummy, *working_day*, indicating whether a match is scheduled on a weekday or not. In addition, a set of dummies – *season_08/09*, *season_09/10*, *season_10/11*, *season_11/12*, *season_12/13*, *season_13/14* and *season_14/15* – are introduced to isolate potential seasonal fixed effects.

The fourth group relates to weather conditions associated to a match. Feddersen and Rott (2011), for example, used temperature, rainfall and wind conditions as covariates in the regression analysis of the determinants of demand for televised live soccer in Germany. We have drawn weather information from the website www.ilmeteo.it.[16] Information are listed in two integer variables, *temperature* and *humidity*; the first measures the average daily temperature, and the second the average daily humidity during the day when matches have been played. In addition, four dummy variables are included: *rain*, *storm*, *fog* and *snow*, easily understandable.

The last variable considered in the dataset is an integer value named *substitutes*, ranged between 0 and 9, indicating the number of matches played at the same time of the match under investigation. The inclusion of *substitutes* in the empirical investigation aims at measuring the potential crowding-out effect of competitive matches on our observed event.[17] The description of the whole set of variables is summarized in table 2, whereas their descriptive statistics are listed in table 3.

Tables 2 and 3 about here

Model and Empirical Results

Different OLS estimations have been used to model the Sky audience for a match involving teams i and j in season t ($sky\_audience_{ijt}$) according to the equation:

$$\ln(sky\_audience_{ijt}) = \alpha X_{ijt} + \beta S + \gamma Z + e_{ijt}, \qquad (1)$$

where X_{ijt} is a vector of independent variables, S is a vector of season fixed effects, Z is a vector of dummy variables, α, β and γ are the associated coefficients, and e_{ijt} is the disturbance term.

The specification (1) is based on Buraimo and Simmons (2015) and includes among the explanatory variables: *a*) the variables capturing the competitive balance: *probs_difference,* *wages_difference* and *points_difference; b*) the variables capturing the relevance of the game: *combined_wages,* in order to verify whether viewers are sensitive to the quantity of talent characterizing a certain game, as wages are a good proxy measure for talent; *points_sum,* a measure of the actual relevance of the game based on contemporary information concerning the current performances of the two teams; *derby,* as the rivalry between teams of the same city is traditionally considered more appealing and exciting; and *fixture*, the progressive number of match in each season, in order to verify whether there is a significant difference between early season and late season games audiences, considering that the latter are supposed to be crucial for the determination of the final positions and the achievement of each team's goals; *c*) *pd_cw*, representing the interaction variable between *points_difference* and *combined_wages* and aiming to verify whether games involving teams with a significant point gap but a combined amount of talent above the median tend to record a higher number of viewers; *d*) *substitutes,* the number of matches played at the same time of the match under investigation; *e*) *sky_plus*, a dummy variable equal to 1 if a game was televised by both SKY SPORT and SKY CALCIO and 0 if a game was televised only by SKY CALCIO, in order to capture the fact that some games potentially reach a larger number of fans; *f*) the dummy variable *working_day*, in order to verify whether the TV audience of the games televised during the week is higher or lower compared with those televised on the weekend; *g*) a set of dummy variables capturing seasonal fixed effects.

In specification (2) we have also included two geographical variables: *h*) the *distance* between the town centres of the two cities of teams involved in the match. This is intended to proxy the travel cost for the supporters; *i*) *combined_markets*, as we expect an higher audience for games involving teams with larger local fan-bases. In specification (3) we have included *occupation*, representing the game's attendance as a percentage of stadium capacity and capturing the level of expectations and atmosphere surrounding the game.

Finally, in specification (4) we added the variables related to the weather: *temperature, humidity* and the dummy variables *rain, storm, fog* and *snow*. The aim is to verify whether worse weather conditions urge a significant number of fans not to get to the stadium and to watch the game on TV, sitting comfortably on their couch.

The results of the OLS estimates are shown in table 4. All the explanatory variables are expressed in natural logs, so that the estimated coefficients can be interpreted as elasticities. Moreover, we have considered two alternative log transformations for *wages_difference*: *ln(wages_difference)* is the natural log of the absolute difference between the home and away team relative wages and is included in the *a* columns, whereas *difference_ln(wages)* represents the absolute difference between the natural logs of the home and away team relative wages and is included in the *b* columns.

Table 4 about here

Among the variables modelling the competitive balance, only *wages_difference* shows a positive and substantial influence over the audience in all the specifications: a 1% increase in the gap between the potential amount of talent of the two teams determines an increase in the number of viewers between 0.76% and 0.81% if we consider *ln(wages_difference)*, and between 0.90% and 0.98% if we consider *difference_ln(wages)*, which contradicts the Uncertainty-of-Outcome Hypothesis**.**

First, Italian fans appear to be "committed". Thus they tend to watch mainly games involving the favourite team regardless of the strength of the opponents. Consequently, a game involving a top club, with a very large fan-base, and a lower tier club has systematically more viewers than a potentially more balanced game involving small or medium clubs with significantly lower fan-bases. As the Italian top clubs are mainly located in the Italian biggest cities, the variable *combined_markets* may represent a good proxy to verify this hypothesis: as we can see in specifications (3) and (4), *combined_markets* has significant and positive coefficients, which confirms that games involving teams with larger fan bases record higher TV audiences.

A second explanation concerns the so-called "David vs Goliath" hypothesis; according to this assumption Italian viewers tend to be more attracted by matches played between differently talented teams because they hope in the upset of the top talented/ranked team. Again, *probs_difference* does not show any impact on TV audience, whereas *points_difference* has a significant negative impact, but its coefficient is not very large (between -0.15 and -0.20). The positive and significant coefficients of both *combined_wages* and *points_sum* highlight that TV audience is sensitive to the quality and the importance of the game: Italian fans are attracted by games characterized by high levels of talent and games involving teams that are at the top end of the table. The *combined_wages* coefficients are those most impacted by the inclusion of *difference_ln(wages)* in our model. In fact, a 1% increase in the combined relative seasonal payrolls of teams involved in the match under investigation determines an increase between 0.56% and 0.85% of the total audience in specifications including *ln(wages_difference)* and between 0.68% and 0.96% in specifications including *difference_ln(wages)*, whereas a 1% increase in the sum of the average seasonal points translates into an increase between 0.64% and 0.74% in the number of TV viewers regardless of the wage difference variable employed.

Therefore, following from the previous analysis, it is more likely that an Italian fan, if choosing whether to watch a game not involving the team they support, chooses a match with a large number of top players and/or with teams battling at the top of the table rather than a general balanced game, as close games are not necessarily high-quality nor instrumental to the title race. This result is confirmed by the significance of the interaction variable *pd_cw*: summing the coefficients of *points_difference* and *pd_cw*, we can see that a 1% rise in the point gap between teams involved in the game under investigation determines an increment between 0.22% and 0.28% in the TV audience if the sum of seasonal payrolls is above the median value.

In specifications (2), (3) and (4) also *derby* shows a positive significance, which confirms that the relevance of a game, given in this case by the rivalry between the two teams, is more appealing to Italian viewers than outcome uncertainty. The variable *fixture* shows extremely small negative coefficients, which suggests there is not a substantial difference between early season and late season games audiences: early season games are only slightly more viewed, probably because of the end of the soccer summer break leading more “abstinent” fans to view any type of soccer telecast.

As expected, *substitutes* has negative coefficients, ranged between 0.57 and 0.58: if soccer viewers have a larger set of potential choices, audience will not be focused on a single event but spread across different games and consequently will be, on average, lower for each match. Another expected result is given by *sky_plus* large positive coefficients, as games televised also by SKY SPORT, that usually are the most important of the single fixture and involve at least one top team, reach a larger number of fans. More precisely, a game televised also by SKY SPORT records on average a total audience higher by 74-78% than a match broadcast only by SKY CALCIO.

The variable *working_day* is positively and significantly associated with the dependent variable, showing that games televised during the week have 6-7% more viewers than those televised at the weekend. A possible explanation is that on weekdays a larger number of fans are not able to get to the stadium and, more generally, more people stay home and watch TV rather than go out socially. Finally, *distance*, *occupation* and all the variables related to the meteorological conditions exhibit a weak or no significant impact.

Eventually, we have replicated our estimates by using *sky_share*, the percentage of people watching the associated match with respect to the people watching TV at the same time, as dependent variable. As we can see in table 5, our main findings, concerning the "committed" behaviour of Italian fans and their preference towards high-quality and high-significance games rather than towards generally balanced games, are fully consistent. They are still strengthened by the higher significance of *occupation*, which is closely related to the variables capturing the relevance of the game as it captures, through the game's attendance as a percentage of stadium capacity, the level of expectations and atmosphere surrounding the game; in particular, a 1% increase in the relative attendance seems to be associated with a rise between 0.12% and 0.13% in the TV share. Relevant differences emerge only in relation to the size of the coefficients, that are significantly smaller, and in the sign of *working_day*, that becomes negative. A possible explanation is that audience ratings are inherently influenced by the number of people watching TV in a certain moment and by competitor networks' scheduling: thus, *a*) all the variables considered have a stronger impact on the absolute number of viewers than on their percentage, as the number of people actually watching TV may vary according to factors such as match day, match time, season, competitors' programmes, etc., and *b*) particularly on weekdays, as we have already outlined, more people prefer to stay home and watch TV rather than to go out socially and, at the same time, TV scheduling is richer and provides them with more options, so that it is possible that, even though games televised during the week have a higher absolute number of viewers, their ratings are lower as the number of people watching alternative telecasts is even higher.

Table 5 about here

Conclusion

In this paper we have investigated the factors affecting the TV demand of soccer for the Italian *Serie A*. By means of different OLS specifications we have shown that Italian fans are not particularly interested in the competitive balance of a game, probably because of a strongly "committed" attitude, as they tend to watch mainly games involving their own team regardless of the strength of the opponents. Moreover, when choosing whether to watch a match not directly involving their favourite team, Italian sport consumers appear to be particularly attracted by the aggregate quantity of talent and also by matches involving teams battling at the top of the table. In fact, a 1% increase in the combined payrolls of teams determines an increase between 0.56% and 0.96%, whereas a 1% increase in the sum of the average seasonal points translates into an increase between 0.64% and 0.74% in the number of TV viewers.

This poses intriguing points with regard any novel mechanism to favour competitive balance. In fact, results seem to suggest both committed and uncommitted fans are not likely to demand more soccer in the presence of a higher competitive balance in the league. In fact, larger audience can be expected in the presence of a large number of committed supporters and if teams enrol talented players.

Notes

1. English *Premier League*, German *Bundesliga*, Spanish *Liga*, Italian *Serie A* and French *Ligue 1*.
2. Baroncelli and Caruso (2011) reports accurate figures for Italian Serie A for the period 1998-2008. In those years TV rights increased by 310%.
3. Consider for instance, (i) take revenue sharing systems (ii) maximum wages (iii) transfer restrictions (iv) salary caps (v) luxury taxes (vi) roster limits (vii) reverse order of finish drafts. These policies are actually justified by the will to preserve the competitive balance and, consequently, to maximize profits.
4. Recently Dietl et al. (2011) developed a contest model of a professional sports league in which clubs maximize a weighted sum of profits and wins.
5. The match Cagliari-Roma in the season 2012/13 was not played because of irregularities of the home team's stadium.
6. About composition, organization and mission of Auditel see www.auditel.it.

7. About the use and opportunity of betting odds as a proxy for the uncertainty of outcome see Pope and Thomas (1989), Peel and Thomas (1992), Czarnitzki and Stadtmann (2002), Dobson and Goddard (2008), Buraimo, Forrest and Simmons (2008), Buraimo and Simmons (2009), Rodney, Weinbach, Borghesi and Wilson (2009), Alavy et al. (2010), Štrumbelj (2016).
8. http://www.football-data.co.uk/italym.php.
9. Data on payrolls are those provided by La Gazzetta della Sport in its annual report at the start of each football season. The payroll includes wages paid by teams to the players net of bonus associated to the team and single player performances.
10. As regards the first match of each season, we indicate the average points of the previous season.
11. As for the points differences, data on fixture 1 of each season refer to the last fixture of the previous season.
12. See www.stadiapostcards.com. Note that data about attendance are 2539 on potential 2659; this because of lack of data or their patient inconsistency since Cagliari and Chievo-Verona do not provide official ticketing reports of their home games.
13. About the use of distance as a covariate see Buraimo et al. (2006), Tainsky and McEvoy (2012).
14. On the role of market size see, among others, Cairns (1987), Buraimo and Simmons (2006), Tainsky (2010), Caruso and Di Domizio (2015).
15. Source: http://demo.istat.it/archivio.html.
16. http://www.ilmeteo.it/portale/archivio-meteo.
17. See for example Mongeon and Winfree (2012).

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Tables

Table 1. Available observations of audience on satellite and DTV platforms: 2008/09 - 2014/15

Season	SKY CALCIO	SKY SPORT	PREMIUM
2008/09	380	188	0
2009/10	380	127	138
2010/11	380	144	320
2011/12	380	134	322
2012/13	379	180	323
2013/14	380	180	324
2014/15	380	192	325
Total	2659	1145	1752

Table 2. Description of variables		
Variable	**Description**	**Source**
sky_audience	Total number of people watching a match broadcast by SKY	Lega Calcio
sky_share	Percentage of people watching a match broadcast by SKY with respect to the people watching TV at the same time	
sky_plus	Dummy variable that takes the value of 1 if a match is broadcast both by SKY CALCIO and by SKY SPORT and 0 otherwise	
substitutes	Number of matches played at the same time of the match under investigation	
probs_difference	Absolute difference between the home and the away team win probabilities	Our computation on data www.football-data.co
wages_difference	Absolute difference between the home and away team relative wages, where a team relative wage is given by the team payroll divided by the seasonal average payroll	Our computation on data La Gazzetta dello Sport
combined_wages	Product between the home and the away team relative wages	
points_difference	Absolute difference between the home and away team average seasonal points up to the match under investigation	Almanacco del Calcio - Panini
points_sum	Sum of the home and the away team average seasonal points up to the match under investigation	
derby	Dummy variable that takes the	

	value of 1 if a match is played by teams from the same city and 0 otherwise	
fixture	Progressive number of matches in each season	
working_day	Dummy variable that takes the value of 1 if a match is played on a weekday and 0 otherwise	
occupation	Ratio between the attendance, measured by the number of tickets sold plus seasonal ticket holders per match, and the stadium capacity	Lega Calcio and www.stadiapostcards.com
distance	Distance, in km, between the town centres of the two cities of teams involved in the match	Our computation on data www.viamichelin.it
combined_markets	Product between the home and the away team relative market sizes, where a team relative market size is measured by the ratio between team-associated municipality total residents and seasonal average residents	www.demo.istat.it
temperature	Average temperature degrees during the match day	www.ilmeteo.it/portale/archivio
humidity	Average humidity degrees during the match day	
rain	Dummy variable that takes the value of 1 if there has been rain during the match day and 0 otherwise	
storm	Dummy variable that takes the value of 1 if there has been a storm during the match day and 0	

	otherwise	
fog	Dummy variable that takes the value of 1 if there has been fog during the match day and 0 otherwise	
snow	Dummy variable that takes the value of 1 if there has been snow during the match day and 0 otherwise	

Table 3 - Descriptive statistics of main variables

	Obs.	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
sky_audience	2659	449884.9	250373	528233.7	781	2916186
sky_share	2658	2.083	1.32	2.168	4.5e-05	13.88
sky_plus	2659	0.431	0	0.495	0	1
probs_difference	2659	0.282	0.247	0.190	0	0.824
wages_difference	2660	0.876	0.466	0.888	0	3.431
points_difference	2660	0.575	0.460	0.502	0	3
combined_wages	2660	0.961	0.484	1.297	0.068	12.107
points_sum	2660	2.738	2.723	0.770	0	6
derby	2659	0.052	0	0.222	0	1
fixture	2660	19.5	19.5	10.968	1	38
occupation	2660	0.565	0.569	0.219	0	1.040
distance	2660	496.51	456	317.395	0	1228
working_day	2659	0.139	0	0.346	0	1
combined_markets	2660	0.938	0.313	1.704	0.004	16.344
temperature	2660	12.774	13	6.331	-10	29
humidity	2660	73.061	74	13.687	18	100
rain	2660	0.359	0	0.480	0	1
storm	2660	0.085	0	0.278	0	1
fog	2660	0.133	0	0.340	0	1
snow	2660	0.017	0	0.129	0	1
substitutes	2659	3.298	4	2.797	0	9

Table 4: OLS model for TV audience

Dependent variable: *ln(sky_audience)*	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
ln(probs_difference)	0.058	0.032	0.045	0.001	0.041	0.006	0.052	0.020
	(0.104)	(0.104)	(0.099)	(0.099)	(0.099)	(0.099)	(0.098)	(0.099)
ln(wages_difference)	**0.759******		**0.812******		**0.812******		**0.793******	
	(0.039)		(0.038)		(0.038)		0.039	
difference_ln(wages)		**0.901******		**0.977******		**0.977******		**0.952******
		(0.046)		(0.045)		(0.045)		(0.045)
ln(points_difference)	**-0.202********	**-0.203******	**-0.149********	**-0.147********	**-0.150********	**-0.148********	**-0.159********	**-0.157********
	(0.079)	(0.079)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
ln(combined_wages)	**0.851******	**0.960******	**0.567******	**0.693******	**0.562******	**0.689******	**0.557******	**0.682******
	(0.035)	(0.035)	(0.040)	(0.039)	(0.041)	(0.040)	(0.041)	(0.040)
ln(pd_cw)	**0.483******	**0.464******	**0.393******	**0.363******	**0.392******	**0.363******	**0.399******	**0.372******
	(0.079)	(0.079)	(0.076)	(0.075)	(0.076)	(0.075)	(0.075)	(0.075)
ln(points_sum)	**0.740******	**0.743******	**0.651******	**0.652******	**0.648******	**0.649******	**0.644******	**0.644******
	(0.080)	(0.081)	(0.078)	(0.078)	(0.078)	(0.078)	(0.079)	(0.079)
derby	0.092	0.074	**0.162********	**0.152******	**0.159******	**0.149******	**0.161******	**0.152******
	(0.058)	(0.059)	(0.082)	(0.082)	(0.082)	(0.082)	(0.083)	(0.083)
ln(fixture)	**-0.062******	**-0.063******	**-0.058******	**-0.058******	**-0.058******	**-0.059******	**-0.076******	**-0.076******
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
ln(substitutes)	**-0.573******	**-0.573******	**-0.584******	**-0.584******	**-0.584******	**-0.584******	**-0.582******	**-0.582******
	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
sky_plus	**0.779******	**0.778******	**0.740******	**0.738******	**0.740******	**0.737******	**0.744******	**0.741******
	(0.036)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
working_day	**0.065******	**0.068******	**0.069********	**0.071********	**0.069********	**0.072********	**0.072********	**0.074********
	(0.036)	(0.036)	(0.034)	(0.034)	(0.034)	(0.034)	(0.035)	(0.035)
ln(distance)			0.026	**0.028******	0.026	**0.029******	0.027	0.028
			(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
ln(combined_markets)			**0.573******	**0.585******	**0.574******	**0.586******	**0.593******	**0.604******
			(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
ln(occupation)					0.049	0.041	0.036	0.026
					(0.101)	(0.101)	(0.102)	(0.102)
ln(temperature)							**-0.044******	**-0.044******
							(0.025)	(0.025)
ln(humidity)							-0.114	**-0.119******
							(0.070)	(0.069)
rain							**0.064********	**0.064********
							(0.032)	(0.032)
storm							-0.081	-0.083
							(0.051)	(0.051)
fog							0.039	0.031
							(0.040)	(0.040)

snow							0.046	0.045
							(0.114)	(0.113)
season_09/10	-0.087	-0.085	-0.085	-0.082	-0.085	-0.083	-0.074	-0.072
	(0.056)	(0.056)	(0.053)	(0.052)	(0.053)	(0.052)	(0.053)	(0.053)
season_10/11	0.084	**0.085***	0.074	0.074	0.075	0.075	0.077	0.077
	(0.051)	(0.051)	(0.048)	(0.048)	(0.049)	(0.048)	(0.049)	(0.049)
season_11/12	**0.178*****	**0.180*****	**0.174*****	**0.175*****	**0.175*****	**0.176*****	**0.184*****	**0.185*****
	(0.051)	(0.051)	(0.048)	(0.048)	(0.049)	(0.049)	(0.049)	(0.048)
season_12/13	**0.083***	**0.088***	**0.098****	**0.104****	**0.100****	**0.105****	**0.099****	**0.104****
	(0.048)	(0.048)	(0.046)	(0.045)	(0.046)	(0.045)	(0.046)	(0.046)
season_13/14	0.028	0.036	0.056	0.066	0.056	0.066	0.065	0.076
	(0.047)	(0.047)	(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)
season_14/15	**-0.160*****	**-0.154*****	**-0.141*****	**-0.133*****	**-0.141*****	**-0.133*****	**-0.133*****	**-0.126****
	(0.053)	(0.053)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
constant	**10.73*****	**10.72*****	**10.48*****	**10.45*****	**10.47*****	**10.44*****	**11.10*****	**11.10*****
	(0.129)	(0.129)	(0.168)	(0.168)	(0.172)	(0.172)	(0.354)	(0.354)
Adjusted R-squared	0.801	0.802	0.815	0.816	0.815	0.816	0.815	0.816
Observations	2659	2659	2659	2659	2659	2659	2626	2626

Robust standard errors in parentheses obtained by using the robust or sandwich estimator of variance; p*<0.10, p**<0.05, p***<0.01.

Table 5: OLS model for TV share

Dependent variable: *ln(sky_share)*	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
ln(odds_difference)	0.025	0.013	0.025	0.011	0.0131	-0.000	0.017	0.004
	(0.036)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
ln(wages_difference)	**0.280*****		**0.294*****		**0.293*****		**0.289*****	
	(0.016)		(0.016)		(0.016)		(0.016)	
difference_ln(wages)		**0.336*****		**0.356*****		**0.354*****		**0.348*****
		(0.019)		(0.019)		(0.019)		(0.019)
ln(points_difference)	**-0.044***	**-0.044***	-0.032	-0.031	-0.035	-0.035	-0.035	-0.034
	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
ln(combined_wages)	**0.490*****	**0.535*****	**0.417*****	**0.462*****	**0.404*****	**0.449*****	**0.404*****	**0.450*****
	(0.015)	(0.014)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)
ln(pd_cw)	**0.141*****	**0.132*****	**0.120*****	**0.108*****	**0.118*****	**0.107*****	**0.116*****	**0.105*****
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
ln(points_sum)	**0.239*****	**0.240*****	**0.217*****	**0.217*****	**0.208*****	**0.209*****	**0.207*****	**0.207*****
	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
derby	**0.063*****	**0.057*****	**0.046***	**0.042***	0.040	0.036	0.041	0.038
	(0.021)	(0.021)	(0.026)	(0.025)	(0.026)	(0.025)	(0.026)	(0.026)
ln(fixture)	**-0.047*****	**-0.048*****	**-0.046*****	**-0.046*****	**-0.047*****	**-0.047*****	**-0.049*****	**-0.049*****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)

ln(substitutes)	**-0.280*****	**-0.280*****	**-0.283*****	**-0.283*****	**-0.282*****	**-0.282*****	**-0.283*****	**-0.283*****
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
sky_plus	**0.306*****	**0.305*****	**0.296*****	**0.295*****	**0.294*****	**0.293*****	**0.295*****	**0.294*****
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
working_day	**-0.142*****	**-0.141*****	**-0.141*****	**-0.140*****	**-0.141*****	**-0.140*****	**-0.138*****	**-0.138*****
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ln(distance)			-0.004	-0.003	-0.003	-0.002	-0.003	-0.002
			(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ln(combined_markets)			**0.145*****	**0.150*****	**0.148*****	**0.152*****	**0.154*****	**0.159*****
			(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ln(occupation)					**0.133*****	**0.131*****	**0.125*****	**0.121*****
					(0.035)	(0.035)	(0.036)	(0.035)
ln(temperature)							-0.001	-0.001
							(0.008)	(0.008)
ln(humidity)							-0.031	-0.033
							(0.024)	(0.024)
rain							0.010	0.010
							(0.010)	(0.010)
storm							**-0.031***	**-0.031***
							(0.018)	(0.018)
fog							0.015	0.012
							(0.014)	(0.014)
snow							0.022	0.022
							(0.040)	(0.039)
season_09/10	-0.006	-0.006	-0.007	-0.006	-0.007	-0.006	-0.004	-0.003
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
season_10/11	**0.039****	**0.040****	**0.037****	**0.037****	**0.040****	**0.040****	**0.039****	**0.039****
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
season_11/12	**0.036****	**0.036****	**0.034****	**0.035****	**0.037****	**0.038****	**0.038****	**0.038****
	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
season_12/13	-0.000	0.002	0.002	0.004	0.006	0.008	0.007	0.009
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
season_13/14	**-0.030***	**-0.026***	-0.026	-0.022	-0.026	-0.022	-0.023	-0.019
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
season_14/15	**-0.087*****	**-0.085*****	**-0.085*****	**-0.082*****	**-0.086*****	**-0.083*****	**-0.086*****	**-0.083*****
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
constant	**0.500*****	**0.495*****	**0.504*****	**0.492*****	**0.460*****	**0.449*****	**0.601*****	**0.602*****
	(0.042)	(0.042)	(0.054)	(0.054)	(0.055)	(0.055)	(0.120)	(0.119)
Adjusted R-squared	0.882	0.883	0.887	0.888	0.887	0.888	0.888	0.888
Observations	2658	2658	2658	2658	2658	2658	2625	2625

Robust standard errors in parentheses obtained by using the robust or sandwich estimator of variance; p*<0.10, p**<0.05, p***<0.01.