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UZH Business Working Paper Series

Working Paper No. 376

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August 2018

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http://www.business.uzh.ch/forschung/wps.html

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The Role of Physical Attractiveness in Tennis TV-Viewership*

Helmut Dietl, Anil Özdemir, and Andrew Rendall†

Abstract

What is beautiful is good, the ancient Greek lyric poet Sappho wrote over 2,500 years ago. Studies in social sciences, anthropology, psychology, and economics have shown various effects of physical attractiveness. Physically attractive people are hired more often, receive faster promotion, and generally earn more per hour; thus, there is a beauty premium. However, within the context of sports, little is known about consumer preferences concerning athletes' physical attractiveness.

In this study, we analyze 622 live tennis matches from 66 Grand Slam tournaments between 2000 and 2016, examining the relationship between attractiveness, measured by tennis players' facial symmetry, and TV-viewership. We show that facial symmetry plays a positive role for female matches while there is no significant effect for male matches. The effect persists in several subsample regressions and robustness checks. Our results have important implications for managers in the field of sports. TV-broadcasters will likely acknowledge additional revenue potential from advertising due to increased viewership and change their programming accordingly. We contribute to the sports management and economics literature in that we introduce a new method to measure facial symmetry and show that physical attractiveness plays a positive role in tennis TV-viewership.

JEL Classification: L83, D12, Z2

Keywords: physical attractiveness, demand, consumer discrimination, tennis

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* Earlier versions of this paper were presented at the Business and Economics Research Seminar University of Zurich, the Labor/Political Economy/Development Faculty and Student Breakfast Seminar University Pompeu Fabra, the 12th Gijon Conference on Sports Economics 2017, the 9th ESEA Conference 2017 in Paderborn, and the EASM Conference 2017 in Bern. We would like to thank seminar and conference participants for helpful comments and suggestions. We gratefully acknowledge the comments by Christoph Breuer, Dennis Coates, Egon Franck, Jaume García-Vilar, Brad Humphreys, Alex Krumer, Martin Natter, Robert Simmons, and Pamela Wicker.

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What is beautiful is good (Sappho)

1. Introduction

Several studies in social sciences, anthropology, psychology, and economics have shown various effects of physical attractiveness. Physically attractive people earn more (Hamermesh & Biddle, 1994; Mobius & Rosenblat, 2006); they are hired (Dipboye, Arvey, & Terpstra, 1977) and are trusted more often (Darai & Grätz, 2013; Rosenblat, 2008; Solnick & Schweitzer, 1999; Wilson & Eckel, 2006). Teachers have higher expectations with regards to a student's potential when the student is attractive (Clifford & Walster, 1973); in high school, attractive adolescents score higher grades and are favored by their teachers (Gordon, Crosnoe, & Wang, 2013). In the courtroom, jurors are not only more likely to convict plain people but also to give harsher sentences if defendants are unattractive (Gunnell & Ceci, 2010).

Curiously, however, the concept of beauty has gained little attention in sports. The few exceptions have focused on baseball (Trail & James, 2001), American football (Berri, Simmons, van Gilder, & O'Neill, 2011), European football (Mutz & Meier, 2016), and tennis (Bakkenbüll, 2017; Bakkenbüll & Kiefer, 2015; Meier & Konjer, 2015). A recent attempt by Meier and Konjer (2015) empirically analyzes German TV ratings for tennis games, finding no evidence for a beauty premium in sports consumption. Methodological issues and the rather unexpected results of the paper, call for a new attempt to analyze the effect of physical attractiveness on sports consumption as a taste-based discrimination type (Becker, 1971).

To study the relationship between physical attractiveness and TV-viewership, we analyze 622 live tennis matches from 66 Grand Slams between 2000 and 2016, focusing only on quarterfinal, semi-final, and final matches. We use TV-viewership data from SRG, the Swiss national TV broadcaster. SRG broadcasts on several channels in German, French, and Italian. We use facial symmetry (Perrett et al., 1999; Rhodes, Proffitt, Grady, & Sumich, 1998) as a proxy for physical attractiveness and calculate facial symmetry scores by using a software called *Prettyscale*. The advantage of focusing our research on tennis is straightforward. In comparison to any other sport (especially team sports), the TV camera focuses only on two players, thus, reducing the noise in the data. In contrast to Meier and Konjer (2015), we analyze data over several years and use more reliable methods to derive attractiveness scores. Our analyses indicate that facial symmetry plays a positive and significant role for female tennis matches, while we do not observe any significant effects for male matches.

The remainder of this paper is structured as follows: section 2 provides the necessary theoretical background; section 3 describes our data; section 4 presents our model and hypotheses; section 5 provides regression results and interpretations; and section 6 concludes the paper.

2. Literature

2.1 Physical Attractiveness and the Beauty Premium

Beauty, a concept as old as mankind, has mesmerized societies for centuries[1]. The extant literature in recent decades concludes that (a) facial symmetry plays a significant role in attractiveness ratings (Perrett et al., 1999; Rhodes et al., 1998) and (b) that beauty standards are culturally universal (Cunningham, Roberts, Barbee, Druen, & Wu, 1995; Jones & Hill, 1993; Perrett, May, & Yoshikawa, 1994). Langlois, Ritter, Casey, and Sawin (1995) show that mothers are more affectionate and playful if their infants are more attractive. Infants have a preference for prototyped, that is, mathematically averaged (Rubenstein, Kalakanis, & Langlois, 1999), and attractive faces (Langlois et al., 1987), questioning the conventional wisdom that standards of attractiveness are mainly socialized and driven by media. Hatfield and Sprecher (1986) summarize that societies broadly agree on the standards of beauty and that these standards change slowly over time.

[1] For an extensive summary on physical attractiveness, see Hatfield and Sprecher (1986) or Hamermesh (2011).

Using household data in the US and Canada, Hamermesh and Biddle (1994) analyze how beauty affects labor market outcomes: attractive employees' wages are significantly higher (up to five percent); interestingly, the wage penalty for unattractiveness is harsher (up to eight percent). Similar evidence is found for specific jobs, e.g., lawyers (Biddle & Hamermesh, 1998), and in several other countries, e.g., Britain (Harper, 2000), China (Hamermesh, Meng, & Zhang, 2002), and Australia (Leigh & Borland, 2007).

Mobius and Rosenblat (2006) analyze worker performance in an experimental setting and find that discrimination for attractive workers still remains. When controlling for confidence, attractive workers earn more because of better social and communication skills. Furthermore, the beauty premium persists in experimental game settings: attractive participants receive significantly higher offers in the ultimatum game (Solnick & Schweitzer, 1999), while participants in the dictator game share a greater part of the surplus with players whose voices and pictures are attractive (Rosenblat, 2008). In repeated games, participants find attractive players more trustworthy (Wilson & Eckel, 2006) and players cooperate more often with attractive contestants of the opposite sex in the prisoner's dilemma game (Darai & Grätz, 2013).

There is comparatively little management and economics research on the relationship between physical attractiveness and sports. Some work relies on surveys to derive motivational factors of sports consumers, analyzing aesthetics as the general artistic nature of the sport instead of physical attraction (e.g., Wann, Schrader, & Wilson, 1999). Along similar lines, Trail and James (2001) use surveys to analyze motivational factors for sports consumption in the MLB, thereby distinguishing between the aesthetics of the plays and physical attractiveness of players. Their survey shows that player's physical attractiveness motivates consumers to watch MLB games. The authors also find a positive correlation between physical attractiveness of players and increases in merchandise purchasing. Berri et al. (2011) analyze the facial symmetry of 138 NFL quarterbacks from 1995 to 2009. Their results show that better-looking quarterbacks score significant salary premiums. Mutz and Meier (2016) suggest a positive relationship between football players' attractiveness and the number of Google searches at European Championships.

The results above suggest that physical attractiveness plays a significant role in various fields, yet, in tennis, Meier and Konjer (2015) put forward that there is no beauty premium. Using TV ratings from live telecasts of over 1,000 tennis matches on German free TV, the researchers analyze the relationship between attractiveness and tennis TV-ratings. According to the researchers, attractiveness does not play a significant role when women watch male players while women watch significantly less when attractive female players are playing. The authors interpret that the female audience discriminates against attractive female players. In contrast, men seem to be watching more when attractive females are playing and less when attractive males are playing. We find difficulties with their analyses of the results. The attractiveness variable, by the researchers' definition based on one gender (e.g., the female attractiveness variable is defined as the sum of attractiveness for male players as rated by women), is regressed in both male and female matches. This is problematic for the regression models. The regressions for the female audience include attractiveness ratings of only male players; yet, the researchers interpret the results as if women discriminate against attractive female players. Recalling the researchers' attractiveness definitions, this cannot possible because the attractiveness ratings for male players cannot be regressed in a regression that includes only female players.

Other than Berri et al. (2011), who derive their physical attractiveness scores using software called *Symmeter*, the above-mentioned research papers rely on survey methods to derive physical attractiveness scores. Survey methods have inherent biases. In the case of tennis, we expect these biases to be stronger, e.g., some tennis players are very popular due to their success, hence, the attractiveness scores may be biased towards successful and popular players.

2.2 Sports demand

The extant literature on sports demand largely focuses on team sports (Borland & Macdonald, 2003; García & Rodríguez, 2009), such as European football, baseball, basketball, American football, or ice hockey. Demand is mainly measured as live stadium attendance (e.g., Coates, Humphreys, & Zhou, 2014; García & Rodríguez, 2009) or TV-viewership (e.g., Bizzozero, Flepp, & Franck, 2016; Forrest, Simmons, & Buraimo, 2005; García & Rodríguez, 2006).

While economic and demographic factors have been used as explanatory variables for stadium attendance, research in sports demand particularly focused on consumer preferences that are peculiar to sports. That is, quality of teams and players (i.e., aggregate talent on the field), superstars (Berri, Schmidt, & Brook, 2004; Kahane & Shmanske, 1997), and outcome uncertainty (i.e., matches between competitors with equal strength). Szymanski (2003) summarizes that attendance is highest when the home team is twice as likely to win the game. Fans attend games because they want to see their team win; they prefer to watch strong and skillful players and are more likely to attend a game when their team employs superstars.

There is comparatively less research on demand for individual sports. Rodríguez, Pérez, Puente, and Rodríguez (2013) analyze the determinants of TV-viewership for professional cycling and find that outcome uncertainty plays a significantly positive role for cycling. In tennis, Konjer, Meier, and Wedeking (2015) and Meier and Konjer (2015) control for outcome uncertainty and player quality in their analyses. The authors suggest that player quality and outcome uncertainty, measured by win probabilities via betting odds, attracts more TV-viewers (Meier & Konjer, 2015). Yet, in a larger study over several years Konjer et al. (2015) find that outcome uncertainty plays no role for TV-viewership. Here, they use rankings to measure both player qualities and outcome uncertainty.

3. Data

3.1 TV-Viewership and Tennis

We use TV-viewership data from Mediapulse AG, the official Swiss statistical company for radio and TV usage. Our data consists of TV-viewership numbers for the official Swiss national TV broadcaster SRG that telecasts sports in three languages (German, French, and Italian) and covers all regions in Switzerland. To measure audience size, machines track TV-watching habits of a sample in Switzerland. Whenever a consumer stays on a channel for at least 15 seconds, the machine starts to count. Our TV audience figures are weighted averages throughout the duration of a live tennis match. For instance, if two people each watch a live tennis match for 45 minutes, while the entire duration of the live match is 90 minutes, the machine calculates the weighted average, that is, one person watching for 90 minutes.

Tennis is mainly an individual sport played between two players. Competitive players regularly meet at different tournaments throughout the year and collect ranking points depending on their performance at these tournaments. Grand Slams are the most prestigious tennis tournaments with the largest prizes. The tournaments take place each year in Australia, France, United Kingdom, and USA. To make sure that the best players end up playing each other in the later rounds of the tournaments, organizers use seeding methods based on the Association of Tennis Professionals' (ATP) and the Women's Tennis Association's (WTA) rankings[2]. Grand Slams include 128 participants and winners are decided after seven rounds. For our analysis, we focus only on the last three rounds, i.e., quarterfinal, semi-final, and final matches from Grand Slam tournaments between 2000 and 2016. Match data comes from tennisabstract.com, a website that is run and managed by Jeff Sackmann. In total, this leads to 952 match-observations; however, the sample size reduces to 622 match-

[2] For a detailed description of ATP (https://www.atpworldtour.com/en/corporate/rulebook) and WTA rankings (http://www.wtatennis.com/WTA-RULES) and tournament regulations, the authors refer to the respective websites of the tennis associations.

observations, because SRG does not broadcast all quarterfinal, semi-final, and final matches.

3.2 Facial Symmetry

The extant literature mostly focuses on facial characteristics when analyzing physical attractiveness[3]. In this paper, we will focus only on facial symmetry and use the scores as a proxy for physical attractiveness. To derive attractiveness scores, we use software called *Prettyscale* that calculates facial symmetry scores based on 14 different landmarks that have to be manually placed on the photos of the players. We conduct several rounds of Google picture searches to select three photos for each player. Ideally, a picture is a frontal headshot where players' ears, chin, and hairline are visible and players do not smile or grimace. We then upload each picture to the software, adjust and zoom in the picture if necessary, then place the 14 different landmarks step-by-step via the mouse cursor (see Figure 1).

[Insert Figure 1 here]

For each picture, we document picture anomalies that might occur because the player is smiling or grimacing. Anomalies may also occur because the camera perspective is horizontally or vertically tilted. We deliberately exclude pictures that might have been photo-shopped or are clearly taken outside the career periods of the players. Yet, the pictures might not match the same time the games have been televised. Because attractiveness ratings are consistent over time (Hatfield & Sprecher, 1986), this should not cause any problems for our analysis.

[3] Naturally, beauty perceptions are not only driven by facial characteristics. Anthropometric measures, such as height and weight may also influence beauty perceptions. Bakkenbüll and Kiefer (2015) use the body mass index (BMI) in their analyses. The ATP and the WTA publish height and weight measures of tennis players. However, these measures are self-reported by tennis players, and need to be treated with caution. The BMI is a function of height and weight. While height does not vary within a career lifecycle of an athlete, weight may change dramatically within different points at a time.

In total, we calculate facial symmetry scores for 644 pictures. We then run individual fixed effects regressions, controlling for anomalies, such as horizontal tilts (*Horizontal*), vertical tilts (*Vertical*), smiling (*Smile*) while lips are closed, grimace (*Grimace*); *Grimace* also includes pictures in which players are laughing, i.e., when their lips are open. Some pictures might have horizontal tilts and grimaces (*HoizontalGrimace*) or vertical tilts and grimaces (*VerticalGrimace*)[4].

$$Symmetry_{ij} = \beta_0 + \beta_1 Horizontal_i + \beta_2 Vertical_i + \beta_3 Smile_i + \beta_4 Grimace_i + \beta_5 HorizontalGrimace_i + \beta_6 VerticalGrimace_i + \alpha_j + \varepsilon$$

Table 1 shows the regression results with player fixed effects for the picture corrections. We then predict the individual fixed effects for each player and add the constant of our regressions to the individual fixed effects. Technically, adding a constant to the corrected measures will not change any of the regression results, as this is a simple transformation. This procedure gives us a final corrected measure for facial symmetry, which we will use in our main analyses. Figure 2 shows the histogram of corrected facial symmetry scores: one can see that the average facial symmetry score for male players is slightly higher than the one for female players. Table 2 shows the players with the highest and lowest corrected facial symmetry scores.

[Insert Table 1here]

[Insert Figure 2 here]

[Insert Table 2 here]

[4] We run regressions with more granular clusters of anomalies without any significant differences. Collapsing the anomalies into general clusters is simpler and more appropriate.

4. Model & Hypotheses

To test the relationship between facial attractiveness and TV-viewership, we regress TV-audience size on facial attractiveness scores and a set of control variables for matches (i.e., player quality, outcome uncertainty), and home bias (i.e., Swiss players). We include dummy variables for gender, tournaments, rounds, and matches broadcasted on primetime. We estimate the model, using OLS, as follows:

$$
\begin{aligned}
LN(TV_{ijk}) = {} & \beta_0 + \beta_1 SUMSYMMETRY_i + \beta_2 MALE_i + \beta_3 MALExSUMSYMMETRY_i \\
& + \beta_4 LN(SUMRANK_i) + \beta_5 LN(DELTARANK_i) + \beta_6 SUMGS_i \\
& + \beta_7 NUMBEROFGAMES_i + \beta_8 SWISS_i + \beta_9 PRIMETIME_i \\
& + \beta_{10j} TOURNAMENT_{ij} + \beta_{11k} ROUND_{ik} + \varepsilon
\end{aligned}
$$

The dependent variable *LN(TV)* is the natural logarithm of the absolute TV audience for each match in Switzerland. We summarize the previously corrected facial symmetry scores for each match: *SUMSYMMETRY* controls for the facial symmetry of both players on the field. *MALE* is a dummy variable and takes value 1 if the match is played between male players. We measure the quality of the match *LN(SUMRANK)* by the natural logarithm of the sum of the ATP and WTA rankings of both players; outcome uncertainty *LN(DELTARANK)* is measured by the natural logarithm of the difference of the ATP and WTA rankings of both players[5]. Because the ATP and WTA rankings are regularly updated and hence control for current (short-term) performance, *SUMGS* controls for historic performances (e.g., superstar status) that may not be entirely captured by rankings. *SUMGS* is the sum of Grand Slam wins of both players. To derive the variable, we cumulate the number of Grand Slam wins of each player at the beginning of the respective tournament and then summarize both players' number of Grand Slam wins for each match. Both *LN(SUMRANK)* and *LN(DELTARANK)* measure expected quality and expected outcome uncertainty of the

[5] In some cases, the difference in the ATP or WTA rank might equal one, such that LN(1) equals zero. In such a case, LN(1) is included in the constant. If we were interested in the specific cases where LN(1) equals zero (e.g., a game between two equally talented players), we could add another dummy variable to control for this. Results, however, do not change significantly.

match. Moreover, we also control for in-game outcome uncertainty *(NUMBEROFGAMES)* by counting the number of games throughout the sets. In tennis matches, only two-game leads win sets. A larger number of games indicates a closer match.

SWISS is a dummy variable that takes value 1 if at least one Swiss player is on the field. *PRIMETIME* is a dummy variable that takes value 1 if a match is broadcast in primetime. *TOURNAMENT* is a set of dummy variables that controls for each Grand Slam tournament (Australian Open, French Open, Wimbledon, and US Open), while *ROUND* is a set of dummy variables that controls for the different stages in the tournament, i.e., quarterfinals, semi-finals, and finals. Table 3 lists descriptive statistics for our regression analyses.

[Insert Table 3 here]

Our focus is on the sign and significance of the coefficient β_1. Considering the vast research on beauty, we believe that facial symmetry plays a positive role for TV-viewership, and therefore, we expect β_1 to be positive. Male matches will likely draw more attention relative to female matches. On average, male matches in our sample attract 148,344 viewers while female matches attract 45,819 viewers. However, we are much more interested in the interaction effect between *MALE* and *SUMSYMMETRY*. This will allow us to understand whether there is a significant difference between perceptions of female and male attractiveness for tennis matches.

Depending on the players' world rankings before the tournaments, we believe the audience size will increase when top players are competing, leading to a negative sign for β_4. Previous research is ambiguous with regards to outcome uncertainty, so expected outcome uncertainty might have a positive- negative- or no effect at all. We believe in-game outcome uncertainty will have a positive effect on TV-viewership. The number of games in a match is a direct measure of in-game outcome uncertainty. Therefore, β_7 should have a positive coefficient. The number of Grand Slam wins is an indicator for a player's quality and popularity, leading to a positive sign for β_6. The Swiss TV audience should increase when Swiss tennis players are playing, therefore we expect β_8 to be positive. As for the rest of our control variables, we expect matches on primetime specifically to draw more viewers. The French Open and Wimbledon are likely to draw more viewers, because the local and time distance of these tournaments is closer, i.e., matches are played in similar time zones (most of the games in Australian Open and US Open are broadcast either in the night or very early in the morning). Because match quality and excitement increases with every stage of the tournament, we expect that the coefficients for our round dummies will have positive signs.

5. Results

5.1 Regression Analysis

We run OLS regressions for 622 matches live tennis matches. Our results (see Table 4, regressions 1 to 3) indicate that facial symmetry plays a significantly positive role for female matches. The baseline regression (1) shows an overall positive effect of facial symmetry. However, this regression model controls neither for gender nor for any interaction variables. Regression model (3) controls both for male matches and the interaction effect between *MALE* and *SUMSYMMETRY*. An additional unit in the combined facial symmetry score for female players increases TV-viewership by 2.2%; an increase by one standard deviation in the combined facial symmetry score leads to an increase in TV-viewership by 24.3%, all else being equal. To illustrate a fictional example based on our estimations, consider the Wimbledon 2012 semi-final match between Agnieszka Radwanska and Angelique Kerber. Agnieszka Radwanska's corrected facial symmetry score is 71.2, Angelique Kerber's is 75.3. The predicted results for this match would lead to an audience size of 34,579 people (the actual TV audience size for the match is 21,019). Holding all else constant and only switching Agnieszka Radwanska with Maria Sharapova, who has a corrected facial symmetry score of 84.6, we would predict an additional 12,090 people watching a fictional 2012 Wimbledon semi-final match between Maria Sharapova and Angelique Kerber.

[Insert Table 4 here]

Regression model (3) in Table 4 indicates that facial symmetry does not play a significant role for male matches. The slope for male facial symmetry is -0.0052 (difference between β_1 and β_3) and not significant. However, the results suggest that the beauty bias is significantly different between female and male tennis matches. A marginal analysis depicts the difference in the slopes with regards to facial symmetry between female matches and male matches. Only when *SUMSYMMETRY* is greater than 152, the beauty bias between female and male matches becomes indistinguishable (see Figure 3).

[Insert Figure 3 here]

The TV audience prefers to watch games with higher quality: viewership decreases as the sum of the ordinal ATP or WTA rankings increases, meaning that better ranked players (those with a lower ordinal rank number) draw more viewers. An increase in the ordinal player rankings by one percent leads to a 0.353% decrease in viewership, in line with previous sports demand research. Interestingly, the coefficient for outcome uncertainty has a positive sign and is significant. A one percent increase in the difference of the ATP or WTA rankings leads to a 0.161% increase in audience size. In contrast, the number of games in a match, our in-game outcome uncertainty measure, increases TV-viewership significantly. An additional game in a match leads to 2.2% increase in viewership. Viewers prefer close and undecided matches, but they also prefer to watch games between players with higher rank differences.

A possible interpretation for the contrasting effect of expected outcome uncertainty (difference in rankings) and of in-game outcome uncertainty (number of games) might be that viewers are interested in watching games with surprising outcomes, e.g., when a superstar plays against an underdog. Indeed, Bizzozero et al. (2016) show that both suspense and surprise drive tennis demand, where surprise has a stronger effect. Moreover, the matches in our sample are mostly played between highly competitive and top ranked players. 49% (72%) of the matches in our sample are played between players that are ranked within the top 10 (top 20) ATP or WTA rankings. In the remaining 51% of the matches where at least one player is outside the top ten ranked players, the rank-difference is at least ten or higher in roughly 80% of the matches. This partially explains (1) the relatively small effect of expected quality on TV-viewership and (2) the positive effect of matches that are unbalanced on paper. In 40% of the matches, a top 10 player faces an opponent with a minimum rank-difference of 10; in 20% of the matches, the rank-difference is at least 20. Hence, a match between a top ranked player and an upcoming challenger or underdog attracts more viewers. It is important to note that the matches in our sample are already highly selective: only the best players make it to the last three rounds of Grand Slam tournaments. In this sense, the tournament structure should generally ensure a high quality of the matches.

The combined number of Grand Slam wins has a positive coefficient, yet it is not significant, indicating that our quality and uncertainty measures already capture most of the superstar effects. There is no additional effect of previous Grand Slams wins. As we expected, Swiss players very strongly attract more viewers; whenever a Swiss player is on the field, TV-Viewership more than doubles (increases by 152%), confirming a home bias suggested by previous sports demand studies. Our additional control variables for matches on primetime, tournament specific dummies, and round dummies are all significant. Timing is important: not only do matches on primetime attract more viewers, summer tournaments (French Open and Wimbledon) in France and United Kingdom also increase viewership. Semi-finals and finals increase audience by 46% and 82% respectively, supporting the hypothesis that consumers prefer exciting games.

5.2 Robustness Checks

To test whether the effects of facial symmetry persist, we run several robustness checks. First, we test if our results are robust to outliers with regards to the outcome variable, the audience size. A common approach is to reduce the effects of the tails, that is, we will run two subsample regressions by (a) trimming 5% of the largest and smallest audience sizes and (b) by winsorizing the top and bottom 5% of audience sizes. In contrast to trimming, winsorizing does not eliminate outliers but treats them as if they were within the specified percentiles, i.e., any extreme values are replaced by the maximum specified percentiles. Our results are robust to outliers; the beauty bias for female matches remains significant and positive (see Table 5).

[Insert Table 5 here]

Second, we run a different type of robust regression by applying quantile regressions, to test whether our results are consistent when regressions are run at different points in the conditional distribution of our dependent variable. In contrast to OLS, which focuses on the average relationship between the dependent and independent variables, quantile regressions test this relationship on percentiles and medians; especially the median regression is more robust to outliers in comparison to OLS. We run quantile regressions at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles (see Table 6). Interestingly, the effect of facial symmetry seems to decrease as the percentile of the audience increases from the 10^{th} to the 90^{th} percentile. The effect of expected quality persists, especially in the first quartile, the median, and the 90^{th} percentile distributions. Expected outcome uncertainty is significant in the first quartile and the 90^{th} percentile, while in-game outcome uncertainty is significant for all presented distributions of the TV-audience. Testing whether the coefficients of the quantile regressions are significantly different from our main OLS regression, we conclude that there is no significant difference.

[Insert Table 6 here]

Third, we investigate whether our results persist in matches where Swiss players are excluded. Our viewership data comes from Swiss households and as shown previously, there is a strong home bias towards Swiss players. Swiss players not only attract the most viewers but are also broadcast more often. Out of 622 live tennis matches, 164 include a Swiss player. The average audience size for the entire sample is 243,669 while the average audience size for the subsample without Swiss players is 52,730; and admittedly, Roger Federer mainly drives the Swiss results. The results in our subsample regression for foreign players do not change significantly; the beauty bias for female matches persists (see Table 7).

[Insert Table 7 here]

Fourth, we run separate regressions for female and male matches. Our main regression results might show stronger (weaker) effects depending on several influential factors. In our pooled regression, we are mainly interested in the relationship between TV-audience and facial symmetry for female and male matches. We do not test any additional interaction effects. The results might be driven by either female or male matches. In gender-separated regressions, we can isolate the effects of our explanatory variables and see whether viewers have different consumption patterns depending on the players' gender. We have 261 observations for female matches and 361 observations for male matches. Facial symmetry still plays a significant and positive role for female matches, the coefficient, however is smaller compared to the pooled regression (see Table 8). An increase in the combined symmetry scores for female players leads to a 1.5% increase in TV-viewership. The prediction results indicate a more accurate estimation[6].

Interestingly, neither expected quality nor expected outcome uncertainty play a significant role for female matches. Both effects are significant only for male matches. This does not necessarily mean that female match quality and outcome uncertainty are not of interest for the TV-audience In fact, the coefficients for in-game outcome uncertainty and final round are positive and significant. One possible interpretation is that although viewers are interested in exciting and high quality games, they might not follow the WTA rankings as closely as the ATP rankings, as such they need to rely on other indicators of quality and outcome uncertainty (e.g., number of games, later stages in the tournament). This interpretation is supported by the fact that the ATP top five (top 10, and top 20) ranking remains relatively stable within our sample period, while the WTA top five (top 10, top 20) ranking sees more fluctuation. Moreover, our sample coincides with the emergence of three of the most successful players (Roger Federer, Rafael Nadal, and Novak Djokovic) in ATP's history, thereby intensifying the rivalry between these players and boosting entertainment value for consumers.

[Insert Table 8 here]

Last, we run gender-separate regressions for the women and men audience as well as female and male matches. Men are more likely to watch sports and therefore might mainly drive our results. The average audience size for men is 55,225 while the average audience size for women is 45,383. The results remain consistent with our main regressions. Although it seems as if women viewers have a stronger beauty bias in female matches (coefficient is larger by 0.004), the difference between both coefficients is not significant (see Table 9).

[6] Repeating the point estimation from the previous subsection, our separate regression model predicts 24,148 (the actual TV audience size for the match is 21,019) viewers for the Wimbledon semi-final match between Agnieszka Radwanska and Anqelique Kerber. Switching Agnieszka Radwanska with Maria Sharapova would increase TV-viewership by 5,436 additional viewers, all else being equal.

[Insert Table 9 here]

6. Conclusion

This paper examines whether consumers reward a beauty premium for athletes when watching sports on TV. By analyzing 622 live tennis matches from Grand Slam tournaments and calculating facial symmetry scores of tennis players, we show that consumers do have a beauty bias in that they prefer to watch games with attractive female tennis players more often. Attractiveness does not play any significant role for male tennis matches.

Our results have implications for researchers and managers alike. Other than previous research (Meier & Konjer, 2015) that did not find any positive relationship between attractiveness and TV-viewership in tennis, we contend that a beauty bias in tennis TV-viewership exists, but it is only granted for female tennis players. We thereby extend the literature in sports demand research by (a) applying new methods to calculate physical attractiveness and (b) providing new findings. On the other hand, managers in sports and sports broadcasters will likely exploit consumer biases (taste-based discrimination). For instance, broadcasters with solely ad revenue maximizing, and therefore viewership maximizing objectives, will consider factoring in beauty perceptions as an additional demand determinant and therefore calculate additional revenue generating potential of better-looking athletes for their sports programming. However, this poses the danger of reinforcing non-sports related taste-based discrimination types. Previous research strongly suggests that attractiveness leads to higher salaries. In the case of tennis, this might be translated into higher endorsement deals: the more an athlete is shown on TV, the higher the probability of winning endorsement deals and, thus, the higher is the revenue potential.

Future research will need to delve further into the relationship between consumer preferences and beauty perceptions in sports. Bakkenbüll and Kiefer (2015) suggest that better-looking players are winning more often. One needs to understand whether attractive players are broadcast more often because they win and therefore, are watched more often. In other words, physical attractiveness might be endogenous. A new study with a larger sample size over several years and different tournaments could shed light on these specific effects. Furthermore, future studies could advance the methods provided in this study. Different software algorithms (e.g., Microsoft, Google, and Amazon provide application-programming interfaces to analyze faces) might be used to calculate facial symmetries. Some software algorithms already use artificial intelligence methods based on human ratings to derive attractiveness scores. This would test the facial symmetry and attractiveness scores for robustness.

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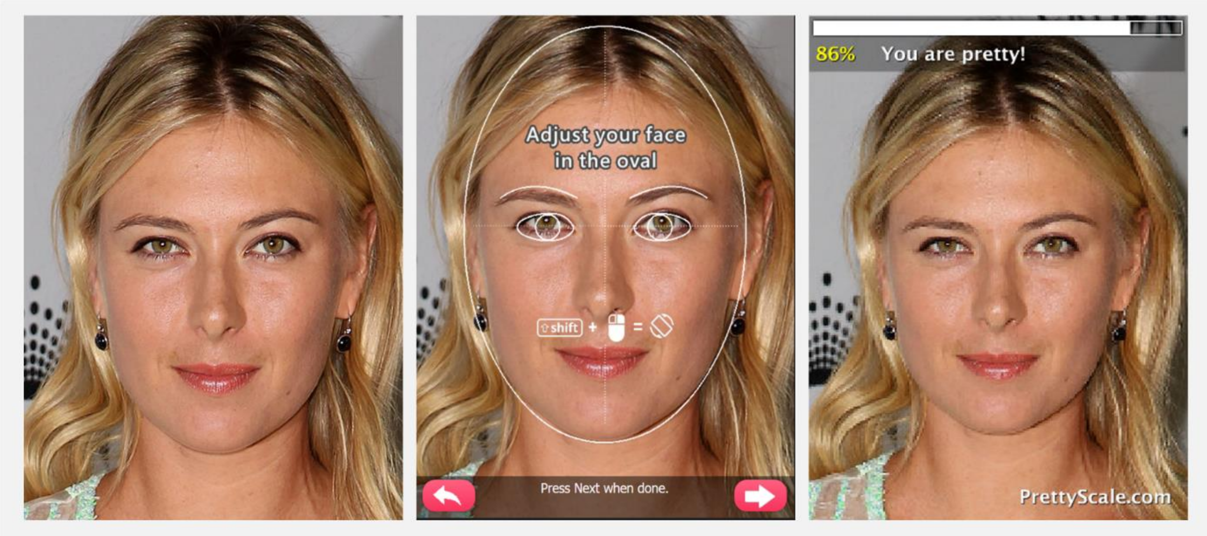

Figure 1: Facial symmetry analysis on prettyscale.com.

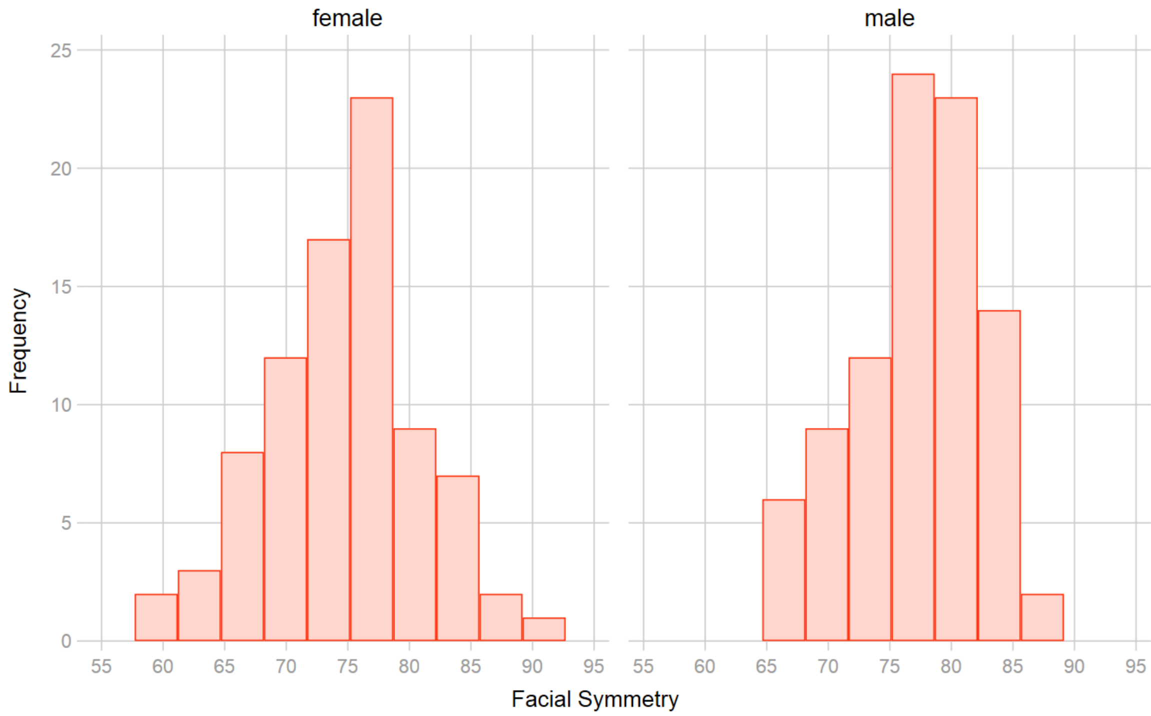

Figure 2: Distribution of facial symmetry scores in the sample by gender.

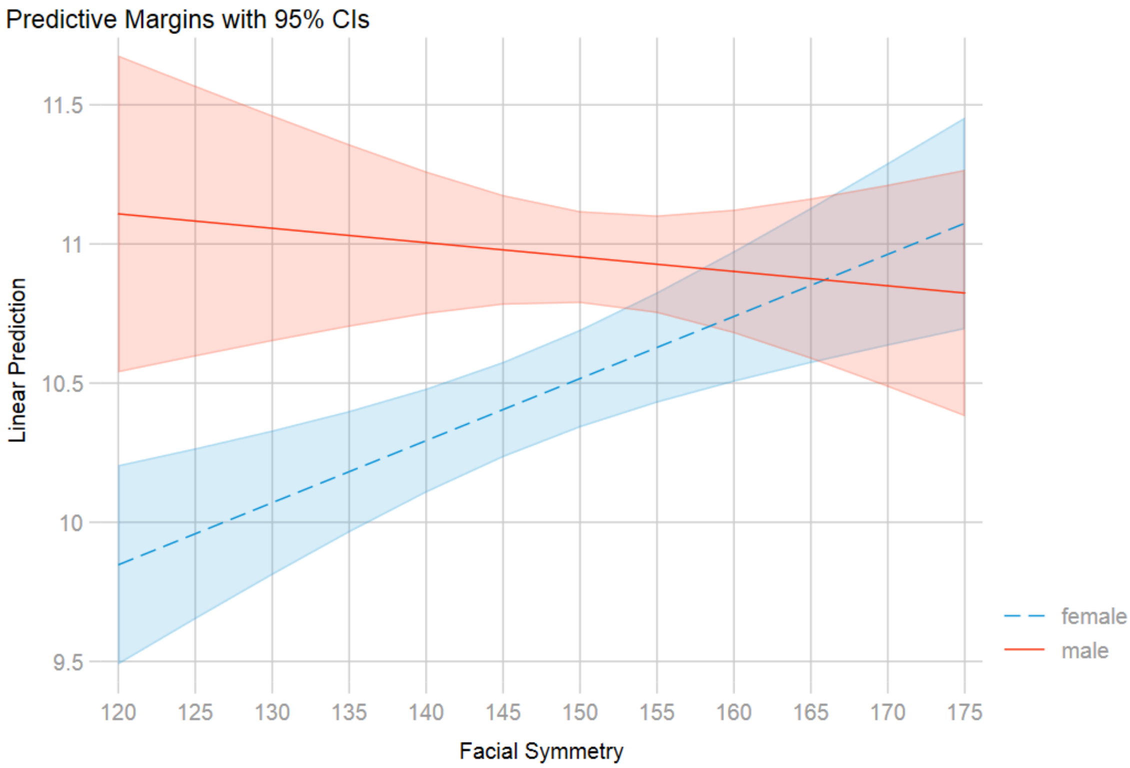

Figure 3: Predictive margins with 95% confidence intervals separated by gender.

Table 1: Regressions with player fixed effects for picture corrections by gender.

Dependent variable: Symmetry	**(1)** **Female**	**(2)** **Male**
Horizontal	-7.752	-0.523
	(5.149)	(1.191)
Vertical	-5.942	-7.546**
	(4.164)	(3.052)
Smile	-3.599*	1.972
	(1.867)	(1.719)
Grimace	-2.690***	-1.643
	(0.978)	(1.059)
HorizontalGrimace	-3.701**	-3.968**
	(1.707)	(1.752)
VerticalGrimace	-3.052	-14.822***
	(3.103)	(2.790)
Constant	75.282***	76.916***
	(0.762)	(0.513)
Observations	313	331
R-squared	0.058	0.102
Number of players	112	114
Player FE	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2: Highest and lowest corrected facial symmetry scores by players' gender.

Female Players	**Score**	**Male Players**	**Score**
Belinda Bencic	89.9	Gaston Gaudio	86.8
Nicole Vaidisova	86.9	Albert Costa	86.2
Dominika Cibulkova	86.9	Sebastien Grosjean	85.1
Samantha Stosur	85.1	Juan Ignacio Chela	85.1
Roberta Vinci	84.7	Kei Nishikori	84.5
Maria Sharapova	84.7	Arnaud Clement	84.2
Tsvetana Pironkova	84.1	Mariano Puerta	84.1
Clarisa Fernandez	83.7	Mardy Fish	84.0
Victoria Azarenka	83.3	Robby Ginepri	84.0
Elena Dementieva	82.4	Vasek Pospisil	83.4
Kim Clijsters	67.5	Gael Monfils	69.2
Mary Pierce	66.7	David Goffin	68.7
Marta Marrero	66.2	Chris Woodruff	68.6
Anna Chakvetadze	65.5	Albert Ramos	68.5
Serena Williams	65.0	Goran Ivanisevic	67.5
Justine Henin	63.8	Martin Verkerk	67.2
Karolina Pliskova	63.7	Todd Martin	66.5
Sabine Lisicki	63.5	Marin Cilic	65.7
Kiki Bertens	59.4	Juan Carlos Ferrero	65.0
Lindsay Davenport	57.7	Gustavo Kuerten	64.6

Table 3: Descriptive statistics of dependent and independent variables.

Variable	Obs.	Mean	SD	Min	Max
LN(TV)	622	10.718	1.516	1.831	13.763
SUMSYMMETRY	622	150.168	9.637	121.512	172.006
MALE	622	0.580	0.494	0	1
LN(SUMRANK)	622	2.752	0.937	1.099	5.861
LN(DELTARANK)	622	2.041	1.229	0	5.849
SUMGS	622	6.241	6.521	0	30
NUMBEROFGAMES	622	30.172	10.703	7	75
SWISS	622	0.264	0.441	0	1
PRIMETIME	622	0.064	0.245	0	1
T. AU OPEN	622	0.209	0.407	0	1
T. FRENCH OPEN	622	0.338	0.473	0	1
T. WIMBLEDON	622	0.262	0.440	0	1
T. US OPEN	622	0.191	0.394	0	1
R. QUARTER-FINAL	622	0.474	0.500	0	1
R. SEMI-FINAL	622	0.338	0.473	0	1
R. FINAL	622	0.188	0.391	0	1

Table 4: Estimation results for OLS regressions.

Dependent variable: LN(TV)	**(1)**	**(2)**	**(3)**
SUMSYMMETRY	0.018***	0.013**	0.022***
	(0.005)	(0.005)	(0.006)
MALE		0.419***	4.560***
		(0.152)	(1.580)
MALE X SUMSYMMETRY			-0.027***
			(0.011)
LN(SUMRANK)	-0.385***	-0.339***	-0.353***
	(0.100)	(0.101)	(0.100)
LN(DELTARANK)	0.184***	0.154**	0.161**
	(0.067)	(0.067)	(0.065)
SUMGS	-0.000	-0.000	0.002
	(0.009)	(0.008)	(0.008)
NUMBEROFGAMES	0.032***	0.022***	0.022***
	(0.005)	(0.007)	(0.007)
SWISS	1.665***	1.583***	1.519***
	(0.101)	(0.108)	(0.107)
PRIMETIME	1.156***	1.186***	1.189***
	(0.207)	(0.205)	(0.203)
T. FRENCH OPEN	0.972***	0.981***	0.946***
	(0.148)	(0.147)	(0.143)
T. WIMBLEDON	1.066***	1.090***	1.056***
	(0.145)	(0.141)	(0.138)
T. US OPEN	-0.350	-0.371*	-0.398*
	(0.213)	(0.213)	(0.211)
R. SEMI-FINAL	0.461***	0.461***	0.469***
	(0.094)	(0.093)	(0.094)
R. FINAL	0.778***	0.796***	0.815***
	(0.132)	(0.132)	(0.130)
Constant	6.302***	7.212***	5.825***
	(0.784)	(0.800)	(0.932)
Observations	622	622	622
R^2	0.510	0.518	0.524
Adj. R^2	0.500	0.508	0.513

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: Robustness checks with trimmed and winsorized outliers.

Dependent variable: LN(TV)	**(1)** trimmed 5th pctile	**(2)** trimmed 10th pctile	**(3)** winsor 5th pctile	**(4)** winsor 10th pctile
SUMSYMMETRY	0.016***	0.010***	0.018***	0.015***
	(0.005)	(0.004)	(0.005)	(0.004)
MALE	2.801**	1.576	3.539**	2.740**
	(1.306)	(1.249)	(1.371)	(1.201)
MALE X SUMSYMMETRY	-0.015*	-0.007	-0.020**	-0.015*
	(0.009)	(0.008)	(0.009)	(0.008)
LN(SUMRANK)	-0.367***	-0.266***	-0.352***	-0.309***
	(0.088)	(0.084)	(0.089)	(0.075)
LN(DELTARANK)	0.204***	0.148**	0.178***	0.162***
	(0.062)	(0.059)	(0.062)	(0.052)
SUMGS	0.012*	0.011*	0.007	0.010*
	(0.006)	(0.006)	(0.006)	(0.005)
NUMBEROFGAMES	0.009**	0.007*	0.013***	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	7.575***	8.644***	6.852***	7.623***
	(0.715)	(0.616)	(0.791)	(0.608)
Observations	560	498	622	622
R^2	0.478	0.389	0.555	0.558
Adj. R^2	0.465	0.371	0.545	0.548
Controls	YES	YES	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6: Robustness checks with quantile regressions.

Dependent variable: LN(TV)	**(1)** 10^{th} pctile	**(2)** 1^{st} qtile	**(3)** Median	**(4)** 3^{rd} qtile	**(5)** 90^{th} pctile
SUMSYMMETRY	0.016	0.025***	0.014**	0.013**	0.012**
	(0.015)	(0.008)	(0.006)	(0.006)	(0.005)
MALE	3.674	4.108**	3.009**	1.546	1.117
	(3.354)	(1.805)	(1.441)	(1.132)	(1.005)
MALE X SUMSYMMETRY	-0.024	-0.025**	-0.016*	-0.006	-0.004
	(0.023)	(0.012)	(0.010)	(0.008)	(0.007)
LN(SUMRANK)	-0.027	-0.437***	-0.284***	-0.121	-0.144**
	(0.219)	(0.097)	(0.089)	(0.082)	(0.058)
LN(DELTARANK)	-0.039	0.140*	0.088	0.072	0.100***
	(0.171)	(0.075)	(0.063)	(0.060)	(0.036)
SUMGS	-0.001	0.003	0.015**	0.011**	0.011**
	(0.015)	(0.009)	(0.007)	(0.005)	(0.005)
NUMBEROFGAMES	0.026***	0.018***	0.014***	0.014***	0.014***
	(0.010)	(0.007)	(0.004)	(0.003)	(0.003)
Constant	4.051*	5.385***	7.470***	8.111***	8.725***
	(2.348)	(1.117)	(0.898)	(0.856)	(0.828)
Observations	622	622	622	622	622
Controls	YES	YES	YES	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: Robustness checks with subsample regressions excluding Swiss players.

Dependent variable: LN(TV)	**(1)** All players	**(2)** Foreign players
SUMSYMMETRY	0.022***	0.021***
	(0.006)	(0.007)
MALE	4.560***	5.159**
	(1.580)	(2.078)
MALE X SUMSYMMETRY	-0.027***	-0.031**
	(0.011)	(0.014)
LN(SUMRANK)	-0.353***	-0.387***
	(0.100)	(0.118)
LN(DELTARANK)	0.161**	0.152**
	(0.065)	(0.075)
SUMGS	0.002	0.003
	(0.008)	(0.013)
NUMBEROFGAMES	0.022***	0.026**
	(0.007)	(0.010)
Constant	5.825***	5.921***
	(0.932)	(1.052)
Observations	622	458
R^2	0.524	0.333
Adj. R^2	0.513	0.313
Controls	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness checks with subsample regressions separated by player gender.

Dependent variable: LN(TV)	**(1)** All players	**(2)** Female players	**(3)** Male players
SUMSYMMETRY	0.022***	0.015**	-0.007
	(0.006)	(0.006)	(0.009)
MALE	4.560***		
	(1.580)		
MALE X SUMSYMMETRY	-0.027***		
	(0.011)		
LN(SUMRANK)	-0.353***	-0.017	-0.683***
	(0.100)	(0.118)	(0.142)
LN(DELTARANK)	0.161**	0.056	0.293***
	(0.065)	(0.077)	(0.092)
SUMGS	0.002	0.010	-0.006
	(0.008)	(0.014)	(0.009)
NUMBEROFGAMES	0.022***	0.048***	0.016*
	(0.007)	(0.010)	(0.009)
Constant	5.825***	5.338***	11.676***
	(0.932)	(0.994)	(1.416)
Observations	622	261	361
R^2	0.524	0.442	0.508
Adj. R^2	0.513	0.415	0.491
Controls	YES	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness checks with subsample regressions separated by player and viewer gender.

Dependent variable: LN(TV)	**(1)** ♀ audience Female matches	**(2)** ♂ audience Female matches	**(3)** ♀ audience Male matches	**(4)** ♂ audience Male matches
SUMSYMMETRY	0.018***	0.014**	-0.003	-0.009
	(0.007)	(0.007)	(0.009)	(0.009)
LN(SUMRANK)	0.080	-0.041	-0.681***	-0.622***
	(0.141)	(0.122)	(0.151)	(0.141)
LN(DELTARANK)	0.019	0.044	0.317***	0.297***
	(0.086)	(0.083)	(0.100)	(0.092)
SUMGS	0.003	0.012	-0.010	-0.004
	(0.018)	(0.013)	(0.012)	(0.009)
NUMBEROFGAMES	0.060***	0.046***	0.008	0.017**
	(0.013)	(0.010)	(0.006)	(0.009)
Constant	3.182**	5.182***	10.372***	11.076***
	(1.261)	(1.065)	(1.510)	(1.384)
Observations	260	261	359	361
R-squared	0.454	0.404	0.470	0.490
AR2	0.428	0.375	0.451	0.473
Controls	YES	YES	YES	YES

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1