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Incentives and Economic Decisions: Evidence from Sports Data

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Incentives and Economic Decisions: Evidence from Sports Data

Iuliia Chikish

Dissertation submitted to the
John Chambers College of Business and Economics
at West Virginia University
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy
in
Economics

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2019

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ABSTRACT

Incentives and Economic Decisions: Evidence from Sports Data

Iuliia Chikish

This dissertation presents three essays which demonstrate how sports data can be applied to answer economic questions. Essay 1 explores whether multiple reference points can affect individuals behavior using data from professional figure skating competitions. The second essay examines the role of professional sports facilities and teams in generating local amenities. Using data from eSports tournaments, the third essay aims at understanding whether tournament theory predictions hold in competitions involving mostly mental effort.

The first chapter, “Incentives and Economic Decisions: Evidence from Sports Data” studies the effect of multiple reference points on decisions made by professional athletes. Unique design features present in elite-level figure skating competitions generate two salient reference points: one reflecting rational expectations about the likelihood of success and the other reflecting information on the performance of previous competitors. An analysis of effort decisions and competition outcomes shows that both reference points affect skaters’ decisions; the effect diminishes with experience. The results support the idea that the elimination of market anomalies takes time even for highly-trained professionals and the time required varies depending on the specific reference point.

The second chapter, “Sports Arenas, Teams and Property Values: Temporary and Permanent Shocks to Local Amenity Flows” examines how professional sports facilities and teams generate local amenity flows in cities that may affect property values. Previous research shows evidence of important positive and negative local amenity flows based on case studies of changes in residential property values in specific cities. Changes in residential property values in Oklahoma City are analyzed over a period, 2000 to 2016, where both temporary and permanent exogenous shocks to local sports-related amenities occurred. Results from hedonic price models and repeat sales regression models show that nearby residential property prices increased after the opening of a new arena and the arrival of a new, permanent NBA team in the city. The presence of a temporary NBA team visiting the city also had a positive impact.

The third chapter, “Tournament Incentives and Effort: Evidence from eSports Competitions” studies the relationship between teams’ effort and various measures of skewness of tournament prize money distribution using data from major eSports events tournaments. The results indicate that eSports teams put forth more effort in the Knockout stage of the tournaments with more skewed prize distributions, more specifically with a larger coefficient of variation and larger prize spread between tournament winner and runner-up. Holding skewness of prize distribution constant, the prize pool does not affect the effort provided. These findings are consistent with tournament theory predictions and empirical evidence from “regular sports”. But unlike “regular sports”, difference between next round and current round prizes as well as difference between first prize and the current round prize do not significantly affect the effort exerted by teams in eSports competitions. This distinction might arise from the difference in effort nature in eSports and “regular sports”.

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1 Multiple Reference Points and Economic Decisions: Evidence from Figure Skating Data

1.1 Introduction

Since the concept of reference-dependent preferences was introduced by Kahneman and Tversky (1979), it received considerable attention from both theoretical and empirical research. The main idea of reference-dependence is that people not only assess an outcome itself but also how this outcome compares to some benchmark level called a reference point. Depending on the relationship to this point, an outcome might be treated by an individual as a loss or as a gain. When the outcome is worse than the reference point, individuals being loss-averse, put more effort to improve their position. Almost all existing empirical work considers some specific setting and tests some specific reference point - expectations (e.g., Bartling et al., 2015 ; Card and Dahl, 2011), peers' outcomes (e.g., Card et al., 2012), goals (e.g., Allen et al., 2016; Camerer et al., 1997).

But the question of what happens if an individual faces multiple potential reference points simultaneously remains largely unanswered because it is difficult to identify reference points in real-life interactions. Terzi et al. (2016) attempt to address the matter in the laboratory setting. They expose individuals to several plausible reference points while keeping the decision setting fixed. The results suggest significant heterogeneity in the choice of a particular reference point among the participants of the experiment. Moreover, some participants used several reference points simultaneously and some did not use any.

Also, there is no consensus in the literature on the relationship between experience and salience of reference points in the decision making process. List (2003, 2004) provides evidence that market experience eliminates the endowment effect. The endowment effect is the idea that people value things more merely because they own them. This market anomaly arises from reference-dependent preferences. When people treat ownership status as a reference point, they are willing to pay more to keep an item they own than to get the same item they do not own. Giving this item up would be treated like a loss, so being loss-averse, people are willing to pay extra. Alternatively, Pope and Schweitzer (2011) show that professional golfers exhibit reference-dependent preferences - they are loss-averse attempting a putt relative to a reference point of par. This means that all the experience that is necessary to become a professional golfer does not eliminate the influence of the reference point.

This paper extends the literature by studying the effect of multiple reference points on decisions made by professional athletes in high-stakes competitions and how this effect changes with athletes' experience. I use data on male figure skaters' performance in European and World championships from 2006 to 2016.

This particular dataset choice is driven by the institutional design of elite-level figure skating competitions which provides potential reference points all participants are equally exposed to. The first such point is the participants' competition group. Initially in a competition, groups of competitors are defined according to the figure skaters' World Standing, which utilizes information about athlete's performance for the two previous seasons and the current season up to the competition. Essentially, the starting group number reflects rational expectations about figure skaters' performance in the competition. The second reference point is the previous skater's performance, which the current skater cannot avoid learning just before the beginning of his own program.

I find that both reference points affect figure skaters' effort level. Skaters that move to a worse group after the Short Program (first event), which means they are in the loss-domain, exhibit more effort during the Free Skate (second event). If the previous competitor performs better than the current competitor expects to perform himself, the current skater puts less effort in execution of his own program. This effect is consistent with the notion of disappointment aversion. When a skater knows that his scores are far behind the scores of the previous participant, he wants to minimize the disappointment of trying hard and not win, by exerting less effort.

The results imply that the answer to the question whether market experience eliminates market anomalies is more complicated than a simple yes or no. The elimination of reference points' influence takes time even for highly-trained figure skaters and the time required varies depending on the specific reference point. Figure skaters need more time to overcome the effect of the group-based reference point than the effect of the peer-based reference point. One of the possible explanations is that figure skaters are more incentivized to eliminate some reference points than others. Giving up (putting less effort) after particularly successful performance of the previous competitor has a negative impact on skater's overall performance in a championship, so with time he realizes that and learns to ignore the disruptive reference point. On the other hand, the group-based reference point balances skater's performance. It motivates an athlete to try harder (try less) in the Free Skate if he moved to a worse (better) group after the Short Program. The idea that agents learn faster if a reference point adversely affects their performance is consistent with the findings of List (2003, 2004) - the endowment effect restricts the success of traders in market transactions, and the results of Pope and Schweitzer (2011) - the reference point of par motivates golfers to make more accurate shots when they are "over par" (in the loss-domain).

1.2 Potential Reference Points for Figure Skaters in High Stakes Competitions

1.2.1 Reference Points in Sports

Existing empirical research usually explores some particular reference point in some particular environment. In his review of the theoretical and empirical research on the prospect theory, Barberis (2013) emphasizes the difficulty of defining a reference point in a general setting, because individuals might have different goals and expectations. In the context of sports, the precise rules and regulations coupled with the extensive performance statistics makes the task of defining appropriate reference points much easier. That is why the empirical literature on reference points in sports is relatively extensive.

There are three broad types of reference points for athletes. First, athletes form expectations about their own performance based on the information available to them. The majority of empirical research proxies expectations with betting markets odds data. Card and Dahl (2011), Munyo and Rossi (2013) and Dickson et al. (2016) find the evidence that violation of football or soccer fans' expectations about game outcome make them more prone to violent behavior when the team loses unexpectedly relative to the betting market prediction. Bartling et al. (2015) show that professional soccer players and coaches exhibit reference dependent behavior during matches. Players are more likely to be shown a card and coaches are more likely to implement more offensive substitutions when a team is in a loss domain relative to the betting market predictions. Coates et al. (2014) find that major league baseball fans exhibit aversion to unexpected game outcomes when they make a decision whether to attend.

The common assumption in all these studies is that agents in question (fans, players, coaches) are aware of betting market predictions and their own expectations about the match outcome coincide with the betting market odds. It seems like a fair assumption for players and coaches who undoubtedly analyze all available statistics, but a regular sports fan might be ignorant of betting market odds and might form his or her expectations some other way (for example, believe that a favorite team will always win).

For individual-level sports, it is natural for athletes to compare their own performance with close rivals in a competition. For example, Yamane and Hayashi's (2015) results indicate that swimmers' performance is affected by their adjacent lane competitors. Using data from professional golf tournaments, Brown (2011) shows that participants perform worse when Tiger Woods competes in the tournament. So, the second possible reference point for athletes is peers' performance (ironically, rivals are peers in this context).

Finally, some athletes might use goals as their reference point. Allen et al. (2016) find evidence of significant clustering of marathon runners' finishing times near round numbers (3 hours, 4 hours etc.). Clustering cannot be explained by explicit rewards such as qualifying for the Boston Marathon, peer effects or institutional settings, which leads the authors to conclude that round numbers act as reference-points in

this setting.

In this study I analyze the behavior of elite-level figure skaters participating in the European and World championships. This specific choice is determined by the design of figure skating championships allowing identification of two potential reference points of which all participants are equally aware. These reference points are a skater's group number in the Short Program and the previous competitor's performance. In the next sections I argue that the number of the group in which a skater performs during the Short Program reflects rational expectations about his success in the current competition, and the previous competitor's performance represents peer effects.

1.2.2 Group Number

International figure skating competitions consist of the Short Program which is skated first, and the Free Skate¹. The International Skating Union (ISU) has a specific procedure to determine a starting order for skaters in the Short Program. First, all competitors are divided into two broad approximately equal groups – "skating later" and "skating earlier".² Skaters with higher rank are assigned to the former and skaters with lower rank and no rank are assigned to the latter. Within these two broad groups skaters are divided into smaller groups of a maximum of 6 skaters called starting order groups. The number of these groups depends on number of contestants in a particular competition.³

In the "skating later" broad group, the competitors with the highest World Standing are assigned to the last starting order group, the competitors with the next highest ranks are assigned to the next to the last starting order group and so on.⁴ Within the starting order groups, the skaters are assigned their starting order randomly. A similar mechanism is in place for the "skating earlier" group. The competitors with ranking draw for the later starting numbers compared to competitors without ranking.

According to the procedure described above, the starting group order assignment is correlated with skaters' reputation and performance in previous competitions, but the starting number within the group is random. The first group to skate contains the least experienced skaters, the last group has the most experienced and successful ones. Therefore, for every skater, being placed in a particular group reflects expected outcome of his performance in a competition based on the current and two previous seasons. A higher starting order group number reflects higher expectations for the skaters in that group to win the competition. I assume that all skaters know this information and form their reference points accordingly, which means that the number of a skater's group in the Short Program serves as his reference point further

¹Rule 335 "Segments of competitions", ISU Special Regulation and Technical Rules, 2014

²Rule 520 "Draws for Competition" ISU Special Regulation and Technical Rules, 2014

³Rule 513 "Size of Starting Order Groups" ISU Special Regulation and Technical Rules, 2014

⁴ISU World Standings is a rating of figure skaters based on the two preceding seasons and current season. ISU Communication No.1629 "ISU World Standings for Single and Pair Skating and Ice Dance. ISU Season's World Ranking"

on in a competition.

The results of the Short Program define the starting order for the Free Skate. The figure skaters are divided into groups according to their Short Program score. The athletes with the highest scores skate in the last group, athletes with the lowest scores – in the first. The starting order within groups is again randomly assigned.

After the results of the Short Program become available, a figure skater learns his position relative to the reference point. He compares his group number in the Short Program and in the Free Skate. If the skater moves to a later (better) group after the Short Program, he is in the gain domain because his performance exceeded his expectations. Moving to an earlier (worse) group means that the competitor now is in the loss domain. Due to loss aversion, figure skaters that moved to an earlier group after the Short Program are motivated to make extra effort to exit the loss domain in the Free Program. Treating the starting group number for the Short Program as a reference point for figure skaters generates the following testable hypothesis:

Hypothesis 1: Figure skaters who moved to an earlier group after the Short Program will put forth more effort during the Free Skate than figure skaters who moved to a later group or stayed in the same group.

1.2.3 Previous Competitor's Performance

Another natural reference point might arise as a result of figure skating competitions' design. According to the ISU rules, skaters must take the starting position for each segment of the competition at the latest 30 seconds after their names are called.⁵ With these rules in place, a skater who is about to go on the ice can not avoid learning information about the previous competitor's performance. The skater possesses full information about his own planned program, including its Base Value - the number which summarizes the complexity of the elements in the program and serves as the basis for evaluating the technical side of the program. Judges can add or subtract points from the Base Value depending on the quality of the program's execution.

Before beginning his own Free Skating program, a skater can compare his Base Value with the technical score of the previous competitor. The competitors within the same starting group have roughly similar expectations to win a championship. I assume that they expect to perform at least as good as each other, therefore, their reference point is zero difference between their own Base Value and the technical score of the previous skater. If the Base Value is smaller than the preceding competitor's score then the skater is in the loss domain, and he has an incentive to put more effort into the execution of his Free Skate program. Considering zero difference between the Base Value of a current skater and the technical score of his predecessor as a

⁵Rule350 "Call to Start", ISU Special Regulation and Technical Rules, 2014

reference point generates the following testable hypothesis:

Hypothesis 2: Figure skaters with Free Skate Base Values smaller than the Total Element Scores of their previous competitors will put more effort into Free Skate program execution compared with the skaters with similar or higher Base Values.

1.3 Data and the Model

1.3.1 The Structure of International Figure Skating Competitions

To win a competition a skater must have the highest Final Score among all the participants after Short Program and Free Skate.⁶ Final Score is calculated as a sum of the Total Segment Scores of both programs. Total Segment Score in each segment of a competition is composed of the Total Element Score and the Program Components Scores. The Total Element Score reflects the complexity of skating elements and quality of their execution, while the Program Components Scores are concentrated on skating skills, linking footwork, performance, choreography and interpretation.

Testing both hypotheses requires an objective measure of skaters' effort. That is why I focus only on the Total Elements Score. The Program Components Score includes evaluation of skaters' performance, choreography and music interpretation, which could be based more on judges' personal tastes rather than on skaters' level of effort. Total Elements Score requires evaluation of the execution quality of strictly defined elements by strictly defined rules, which leaves less room for subjectivity. Further details on quantifying skaters' effort are provided in Section 3.2.

The Short Program consists of seven required elements and the Free Skate consists of at most 13 elements.⁷ The required elements are listed in Table 1. The elements performed beyond the list are not counted towards the final score. That way the number of elements is equalized for all competitors, but they have some freedom in choosing the exact elements for a program.

Each element have a Base Value - a number reflecting the element's complexity. Assessing an element performed by a skater, judges select one of seven degrees of execution (-3, -2, -1, 0, 1, 2, 3) which has its own negative or positive numerical value called the Grade of Execution (GOE). This value is added to the Base value of the element and the final number constitutes the Element Score. Part I of the ISU Communication No. 2089 provides the full list of elements' Base Values and Grades of Execution. To define the degree of execution of an element, judges consider first its positive and then negative aspects. Parts III and IV of the ISU Communication No. 2089 explains the procedure in more detail. The sum of the Final Grade of

⁶Rule 353 "ISU Judging System", ISU Special Regulation and Technical Rules, 2014

⁷Rule 611.1 "Short Program Singles" and Rule 612.1 "Free Skating Singles", ISU Special Regulation and Technical Rules, 2014

Execution and Base Values of all elements of the program constitutes the Total Element Score of the section.

1.3.2 Quantifying Effort

The dependent variable in the empirical analysis is the effort provided by the competitors which cannot be observed directly. However the sum of elements' final Degrees of Execution is observable. To maximize his Total Element Score in a segment and, therefore, increase his chance of winning the competition, a figure skater should maximize the GOE for all elements in the program. To do so the athlete needs to make an effort to complete as many positive aspects as possible and to avoid any negative aspects.

Admittedly, the GOE does not directly correspond to skaters' effort. It is also a function of the difficulty of his program, his overall ability, possible judges' biases, and luck. After controlling for all these factors, the effort a figure skater puts into execution of his program should be positively correlated with the sum of final Grades of Execution scores.

Complexity of the program and athlete's ability are the most straightforward to address. The specific control variables are discussed in the data section. I assume the luck is random; it is not correlated with a skater's performance in the Short Program, ability and performance of the previous competitor in the Free Skate. If luck is not correlated with the independent variables then it does not bias the estimated coefficients.

There are several possible sources of judge's biases. First, judges might be biased towards their compatriot figure skaters, which means they will be more likely to give them higher scores than the other judges. This phenomenon is known as nationalistic bias. Seltzer and Glass (1991), Campbell and Galbraith (1996), Zitzewitz (2006), Sala et al. (2007) and Zitzewitz (2014) find evidence to support the claim that figure skating judges favor their compatriots.

The International Judging System (IJS), which became mandatory for all international figure skating competitions in 2006, was aimed to restrict opportunities for nationalistic bias among judges. According to the IJS rules, the highest and the lowest GOE score for each element is not taken into account when the final GOE score is calculated. This procedure should have alleviated nationalistic bias issue, but Zitzewitz (2014) finds that, if anything, the problem became slightly worse after the reform. Therefore, the possibility of nationalistic bias should be taken into account.

Second, judges might exhibit difficulty bias, which means that the skaters who choose to perform more difficult programs might receive higher Final GOEs even though the difficulty of the program has already been reflected in the Base Value. Morgan and Rotthoff (2014) find evidence of difficulty bias in judging elite gymnastics competitions. To account for this possibility, the level of a program's difficulty should be controlled for.

Third, judges might be biased towards well-known athletes. In their experimental study, Findlay and Ste-Marie (2004) found that figure skating judges may have a tendency to rate a participant relative to their expectations of that person's performance. The judges placed athletes known to them higher than unknown ones. The reputation of a figure skater might influence the GOE the skater receives and, therefore, should be controlled for.

Finally, the phenomenon of home advantage in figure skating is very well-known and described in the literature. Home advantage means that the home team or athlete has a better chance of winning than a visiting team or athlete due to psychological effects that crowds and the setting have on the competitors and/or judges. Studies by Courneya and Carron (1992), Nevill and Holder (1999) and Carron et al. (2005) provide the overview of the empirical evidence and potential mechanisms of the occurrence of the home advantage phenomena. Balmer et al. (2001) analyze Winter Olympics data from 1908 to 1998 and find evidence of home advantage in figure skating among other winter disciplines.

1.3.3 Empirical Model

In order to test the first hypothesis I estimate the following regression model:

$$FSGOE_{ict} = \beta_0 + \beta_1 GROUPDIF_{ict} + \beta_2 \mathbf{X}_{ict} + \tau_t + \epsilon_{ict}. \quad (1)$$

where $FSGOE$ is the sum of Final Grades of Execution of the elements included in the Free Skating program of a skater i in year t during competition c ; $GROUPDIF$ is calculated for a skater i as the difference between the starting order group number in the Short Program and the starting order group number in the Free Program in year t during competition c ; $\mathbf{X}$ is a vector of control variables containing individual attributes of the skaters; τ_t captures fixed effects.

The dependent variable $FSGOE$ reflects the level of effort the skater decides to put into executing his Free Skating program. A higher value corresponds to higher level of effort. The main variable of interest is $GROUPDIF$. Initially, higher starting group number for a skater corresponds to higher expectations about his performance. But the difference in the number on contestants in Short Program and Free Skate Program makes it difficult to compare group numbers between programs. Only the 24 best skaters from the Short Program qualify for the Free Skate.

Consider, for example, a competition with 36 entrants. There are 6 groups in the Short Program and 4 groups in the Free Skate. The first group in the Short Program contains the 6 least experienced skaters out of 36, while the first group in the Free Skate will contain the 6 skaters with the lowest scores out of the 24 that remained in the competition after the Short Program. If a skater who started the competition in the

first group ends up in the first group in the Free Skate, nominally he did not change his reference group, but in reality he improved his standing by moving up two groups. In order to make starting order group numbers comparable between the programs, I renumber the group starting order in reverse. The last group becomes first, the group before last becomes second and so on.

After the renumbering, a negative value of *GROUPE* corresponds to a figure skater moving from skating in a later (better) group in the Short Program to skating in an earlier (worse) group in the Free Program, and therefore, means that a figure skater is in the loss domain. According to Hypothesis 1, being in the loss domain motivates skaters to exert more effort. A negative sign of $\hat{\beta}_1$ provides evidence to support Hypothesis 1.

As discussed above, the dependent variable reflects not only effort of the skaters but also the difficulty of their program, their ability, and possible judges' biases. To control for ability I include the total GOE for all elements in the Short Program of a skater i . I choose this variable for two reasons. First, the ability of a skater is positively correlated with the probability of him receiving a higher GOE in the Short Program. Second, the figure skaters are very limited in their choice of elements for the Short Program, so the difficulty of the program will not vary substantially across skaters. The standard deviation of the total elements' Base Values for the Short Program is half that for the Free Skate - 4.5 and 9.3 respectively. This makes the quality of the Short Program execution to be more or less comparable across all championship participants.

To account for the level of program difficulty I include the total of Base Values of all elements in the Free Skating Program of skater i in year t during competition c . A higher total Base Value corresponds to a more difficult program. I include experience to account for the possibility that more experienced skaters might be better in executing some elements or overcoming general nervousness associated with big international competitions. Experience is defined as the number of years a skater i has been training up to year t . Older athletes might have the benefit of experience but younger skaters might have greater physical endurance which is an important determinant of performance in the Free Program, hence I include age and age squared in the regression model. Since younger athletes are expected to get better with training until the peak of their skating career, I expect a positive sign on the linear age term and the negative sign on the quadratic term. I also include dummy variable for World Championship, because the prestige of a competition might affect the effort of the athletes.

As was discussed above, GOE scores might contain judges' biases towards competitors. I try to address the four most common judging biases in the literature: difficulty bias, home advantage bias, nationalistic bias and reputation bias. Difficulty bias would mean that judges tend to give higher GOE scores to the skaters with more difficult elements in the program even though GOE should reflect only execution of elements. Controlling for the Base Value of a skaters' program should account for difficulty bias. I include the binary

variable *HOME* which takes value one if a skater competes in his home country to control for the home advantage bias and the binary variable *COMPATRIOT* which takes value one if a skater has a compatriot judge in the judging panel. Home advantage is not necessarily limited to receiving higher scores from the judges from the same country as a skater. A skater might perform better because of supportive crowd or because he did not have to travel for a long distance.

I control for the group a skater performs in during his Free Skating program by including group indicator variables. I do that for several reasons. First, being in a particular group might motivate athletes to put more or less effort in executing their programs. For example, the skaters in the next to last group might decide to increase their effort level in order to compete for places in the top 10. Second, expectations of the judges about athletes might affect scores. For example, the judges might reserve higher scores until the later groups skate.

I include time fixed effects τ_t because figure skating as a sport develops and changes with time. For example, quadruple jumps have become increasingly common in high-level international ice-skating competitions. Not performing at least one quadruple jump during the European or World championship might signal that the skater is not in the “major league” of the discipline. Younger and less experienced skaters might become increasingly pressured to include quadruple jumps in their routines, which can affect their effort level.

To test the second hypothesis I estimate:

$$FSGOE_{ict} = \beta_0 + \beta_1 SCOREDIF_{ict} + \beta_2 \mathbf{X}_{ict} + \tau_t + \epsilon_{ict}. \quad (2)$$

The dependent variable and individual-level controls are the same as in Equation (6). The main explanatory variable of interest, *SCOREDIF* shows the difference between the previous competitor’s Total Element Score and skater *i*’s Free Skating program Base Value. If positive, it means that the previous skater has a score exceeding the Base Value of the current skater’s program. Therefore, the current skater has an incentive to put more effort into execution of his program in order to catch up with the preceding skater. If the second hypothesis holds I expect positive and significant coefficient estimate on *SCOREDIF*.

The literature identifies two main problems with the estimation of peer effects (see for example Manski, 1993): the reflection problem and endogenous selection. In the context of figure skating competitions, the reflection problem would arise if the Total Element Score of the current skater could affect the performance of the previous skater. But that is impossible because the performance of the previous skater is completed before the current skater begins his program.

In order to avoid endogenous selection, the peers (previous skaters) should be assigned randomly. A skater faces his peer from the same starting order group and the assignment to the groups is not random -

it depends on the athlete's ranking, but the order within one group is defined by a random draw. That way, for the same skater the probability to face weaker or stronger previous competitor depends purely by chance once the starting order groups are controlled for in Equation (2).

1.3.4 Data

In order to test the two formulated hypotheses I use data from World and European championships 2006-2016 and limit my analysis to men singles events only. I do so because the general consensus in the literature is that women are less competitive compared to men even when material interest is involved (Gneezy et al., 2003; Niederle and Vesterlund, 2007; Booth and Nolen, 2014), and they might be less sensitive to reference point influences. Also, pairs skating and ice dancing have different elements and might be judged differently. World and European championships have the same regulations and comparable number of participants with roughly similar level of talent. To collect figure skating performance data I use ISU protocols which contain detailed judges' scores for each championship participant. Overall I have 495 skater-event-year observations. All data on age and experience of the athletes comes from the ISU official website which has short biography pages for each skater participating in the ISU competitions.⁸

The summary statistics are presented in Table 2. I analyze three separate dependent variables. *GOE* - sum of the Final Grades of Execution across all elements, *GOE_Jumps* - sum across all jump elements and *GOE_NonJumps* - sum across all non-jump elements in the Free Program. The mean of total GOE is close to zero (0.27), while it is negative for jumps GOE (-1.50) and positive for non-jumps GOE (1.77), which means that the jump elements are more difficult to execute. The standard deviation for jumps GOE is twice the size of that for non-jumps, which shows that luck might be more important for completing jumps.

About a 40% of the competitors in the sample do not change their reference group. The mean difference between starting groups is positive but close to zero (0.27). The standard deviation is about 1 group. The maximum number of groups a figure skater was able to jump and improve his starting position is 5, but the maximum number of groups that a figure skater was able to fall down is 3. This disparity arises from the fact that only 24 best skaters will qualify for the Free Skate. If a skater changes his position down for more than 3 groups after the Short Program - he is out of the competition.

The mean difference between the previous skater's score and the Base Value of a current skater is close to zero (-0.26), the standard deviation is about 12.7 points. The maximum disparity between two subsequent athletes is about 40 points in both directions. The number of observations is only 473 because the skaters performing their program first in a competition do not have a preceding competitor.

The average Base Value of the Free Skating program is 64 points with a standard deviation of 9 points.

⁸<http://www.isureults.com/bios/>

The most difficult program is worth 95 points, the least - 34 points. The sum of Grades of Execution for the Short Program has a mean value close to zero, the standard deviation is 2.8 which is half of the value for Free Skate GOE.

The average age of participants is 23 years. The oldest skater is 31 years old, the youngest is 15. The average tenure in sport is 17 years. The most experienced skater has been skating for 31 years, the least experienced - for 15. Half of the observations are from the World championships. Only about 6% of the athletes competed in their home country and 37% had a compatriot in the judging panel.

1.4 Results

1.4.1 Group-Based Reference Point

The results of the Equation (6) OLS estimation are presented in Table 3. I estimate separate regressions using all elements' GOE, only jump elements' GOE and only non-jump elements' GOE as a dependent variable. For the overall GOE, the coefficient on the group difference variable is negative and significant at the 1% level (column 1). This means that skaters who moved down from a better group in the Short Program to a worse group in the Free Skate will put more effort in their Free Skating program. The result is consistent with the hypothesis that figure skaters use starting order group number as a reference point for their performance in the Free Skating program.

The GOE for the Short Program, a proxy for skater's ability, has a positive and significant association with the dependent variable. Athletes with higher ability do better in terms of GOE in the Free Skating Program. The coefficient on the Base Value variable is positive and highly significant. The skaters with more complicated programs receive higher GOE. The effect is about five times smaller in magnitude than the effect of ability and consistent with "difficulty bias" theory.

The coefficient on the age term is negative and on the squared term is positive. Both are significant at the 5% level. The signs of the coefficients suggest a U-shape relationship between age and GOE. This finding contradicts the expected inverse U-shaped relationship between age and productivity. The possible explanation for this is that on the one hand, figure skaters are likely to enter elite-level competitions at a relatively young age and if successful they are likely to continue competing until older. So, the oldest figure skaters are probably better than the average skater. On the other hand, if a skater enters at a very young age he is more likely to be very talented to begin with.

Both coefficients on competing in a home country and having a compatriot judge in the panel are insignificant. This finding does not support the home advantage bias and nationalistic bias theories. Moreover, the coefficient on the dummy indicating home championship is negative which might signal that judges push

local weaker figure skaters to qualify for Free Skating program to keep local interest on the competition. The lack of significance might be due to the small number of local athletes - only 6% the sample. The World Championship dummy is positive and significant at 10% level which indicates that athletes exhibit more effort in World than in European Championship.

The specification in column 2 of Table 3 allows the reaction to a change in starting group to differ with experience. The coefficient on the group difference variable is negative and significant on 1% level, while the coefficient on the interaction between the group difference variable and experience is positive and significant at the 5% level. Keeping the status quo starting group is important for all skaters, but the effect diminishes with experience.

Columns 3 and 4 of the Table 3 present the results for the jump elements only, and columns 5 and 6 for non-jump elements only. The signs of the group change variable and interaction remain the same for all specifications, but adding interaction term into non-jump elements regression wipes out significance for both coefficients most likely due to smaller returns on effort for non-jumps.

There is an interesting distinction in estimated coefficients on age variables for jump and non-jump element regressions. Age has a U-shaped relationship with GOE for jump elements, but a reverse U-shaped relationship for non-jump elements. This indicates that young athletes are selected into elite level figure skating competitions based on their ability to perform jumps and older athletes postpone the retirement if better in jumps than average participant. The performance of non-jump elements is consistent with the experience story when skaters get better with training, reach their peak in the discipline and then their performance slightly decays with age.

1.4.2 Peer-Based Reference Point

The results of OLS estimation of Equation (2) are presented in Table 4. Again, I estimate separate models for three dependent variables - GOE, GOE for jump elements and GOE for non-jump elements. Column 1 shows the estimated coefficients for the overall GOE as the dependent variable. The coefficient on the score difference variable is statistically indistinguishable from zero which means that there is no evidence supporting the hypothesis that figure skaters use the performance of the previous competitor as a reference point while making a decision about the optimum effort level to apply to their own program.

One possible explanation is that, despite the fact that information is easily available, the athletes (or their coaches) might choose to ignore it on purpose. It could be the case if this information is disruptive to a figure skaters' performance. If that is indeed so, then an athlete might need time to realize the adverse effects of paying close attention to the previous competitor's performance and time to learn to ignore it.

The columns 2 of Table 4 shows the results of adding experience and score difference interaction in the

Equation 2 specification. The coefficient on the score difference variable becomes negative and significant. It means that, contrary to the predictions of the Hypothesis 2, the bigger advantage his predecessor has the less effort the current skater exerts while performing his Free Skate program. This finding is consistent with the experimental results of Gill and Prowse (2012). They find evidence that agents respond negatively to their rivals' effort in real effort sequential-move tournaments. This effects is known as disappointment aversion. If a preceding competitor has performed much better than the current skater expects to perform, then the current skater tries to minimize potential disappointment of losing to the previous skater by putting less effort into execution of his Free Program.

One might argue that when the previous performer does better than the current competitor expects to perform, the current skater might decide to take more risk by trying harder elements, leading to a higher probability of failure. So, the effect might be not due to effort adjustment but rather due to taking additional risk. But according to the ISU rules⁹, all competitors should set up their program in advance, and performing elements more difficult than stated in the program will not be counted towards skaters technical score. That way the design of figure skating competitions eliminates the possibility of risk adjustment.

The positive and significant coefficient on the interaction term shows that skaters with different levels of experience respond differently to the score difference between them and the previous competitor. The disappointment aversion effect dissipates with an athlete's experience. A possible explanation for this finding is that with time figure skaters realize that negative reaction to the peers' success is detrimental to their own performance and learn to ignore it.

The results for regressions that use only jump elements' and only non-jump elements' GOE as dependent variables are qualitatively identical to overall GOE regressions. The coefficient on score difference variable is negative and the coefficient on the interaction term is positive in the specification accounting for experience. The magnitude of the coefficient is smaller for non-jump elements, which, again, is probably manifestation of different returns on effort for jumps and non-jumps.

1.5 Robustness Checks

1.5.1 Fixed Effects and Random Effects

One might be concerned that OLS estimates of the model do not capture skater-specific effects that might be correlated with the explanatory variables. To address this possibility I estimate random effects and fixed effects models. The random effects model allows ability of each skater to be a random variable with some variance. This might correspond to the case where one thinks of talent as, for example, being able to

⁹Rule 349 "Program Content Sheey" ISU Special Regulations and Technical Rules, 2014

flawlessly perform a Triple Axel 7 out of 10 times. Also, the random effects model seems to be an appropriate specification since the panel is unbalanced - the number of year-championship observations varies from skater to skater.

Table 5 shows the results for the group-based reference point. The random effects model estimates are presented in columns 1 and 2. The coefficients on the group difference variable and interaction term are of the same signs and similar magnitudes as those in the baseline specification. The estimated coefficients for the control variables are also fairly close to those in the OLS model.

The columns 3 and 4 of the Table 5 show the estimated coefficients for the fixed effects model. The fixed effects are supposed to account for ability if each individual skater has his own specific way of dealing with reference points (for example, some skaters are more upset than others when a preceding competitor performs well or when they have to perform in a “worse” group after the Short Program), but this model specification might wipe out the part of the reference point effect. Also, some variation will be lost since the average number of year-championship observations is 3.4 per skater.

The group difference coefficient in column 3 decreases in magnitude and becomes insignificant, at least partly due to the two reasons described above. But in the specification that accounts for experience (column 4) the coefficients on the group difference and on the interaction term are significant and very close in magnitude to the baseline estimates. Also, the coefficient on the compatriot judge dummy becomes significant at the 10% level. Although a weak evidence of nationalistic bias, this result is more in line with the existing literature on judging biases (see for example Zitzewitz, 2006 and Zitzewitz, 2014).

The results of the random and fixed effects models for peer-based reference point are presented in the Table 6. The coefficients on the scores difference and interaction term are significant and close to those in the baseline specification in terms of signs and magnitude.

1.5.2 Effort Adjustment or Mean Reversion

One concern with the group reference point coefficient estimates is that its significance is driven not by effort adjustment but by mean reversion. The idea behind the mean reversion argument is the following: considering two skaters who performed identically in the Short Program, the one whose performance was disappointing and moved to a worse group is more likely to have higher “average performance”. Therefore, he is more likely to reverse to his mean performance in the Free Skate and have higher GOE scores. To understand whether the results are driven by the mean reversion, I start with controlling for the level of “average performance” of each skater. For every athlete in the sample I calculate his mean GOE score across all competitions available in the data and include it in the benchmark regression specification for the group reference point.

Columns 1 and 2 of Table 7 show the results. The “average performance” coefficient is positive and significant as expected, and the coefficient on the group difference variable and its interaction with experience are in line with the benchmark estimation in terms of sign and magnitude which does not support the mean reversion hypothesis.

Further, I can test whether general mean reversion takes place. I create an indicator variable taking value one if a skater’s GOE score for the Short Program of a competition is below skater’s average GOE score. To support the mean reversion hypothesis, athletes who performed below their mean GOE in the Short Program should, on average, perform better in the Free Skate, therefore the coefficient on the below average indicator should be positive. Column 3 of Table 7 presents the results. The coefficient on the below mean dummy indicates that, on average, Free Skate performance of the skaters demonstrated worse than average results in the Short Program does not statistically differs from the performance of the skaters with above the average results.

1.5.3 Other Robustness Checks

If the performance of the current skater is affected by the performance of the previous competitor, I expect the effect to be more salient for the skaters who cannot avoid learning the predecessor’s results right before the beginning of their own program. These skaters will have preceding competitors in their starting group. As a robustness check, I separately estimate Equation (2) for the subsample of such skaters and for the subsample of skaters who perform first in their group and, therefore, do not have peers from the same group performing before them. The latter subsample consists of 62 skaters. To create a comparable reference point for a first skater in a group I calculate the difference between his scores and the scores of a skater performing last in the previous group. Even though the former might choose to learn the results of the latter and form a reference point, I expect the influence of such point to be less pronounced.

The results are presented in columns 1 and 2 of Table 8. I do not include time fixed effects in either model because including them would significantly decrease variation in explanatory and control variables due to a small number of observations per year. The first column reports the estimated coefficients on the score difference variable and its interaction with the experience variable for the subsample of skaters directly observing the result of previous competitors. Both coefficients are of expected signs and significant. For the subsample of competitors who do not have preceding competitors in their group (column 2), neither coefficient is significant at any standard level and the group difference coefficient has a smaller magnitude. Although the small size of the second subsample might potentially be responsible for insignificance of the coefficients, the hypothesis about group difference coefficients being equal in the overall GOE specification is rejected.

Finally, in order to obtain additional evidence supporting the hypothesis that changing starting group after the Short Program affects skaters' effort level in the Free Skate, I consider the subsample of skaters who changed their Free Skate starting number by 5 or less positions compared with their Short Program starting number. Since the size of the group in the Free Skate is 6, this sample contains both figure skaters who changed groups and who stayed in the same group, as opposed to skaters who changed their starting number by 6 places or more, they all would have to change their group as well. There are 254 skaters that satisfy this criteria. If we consider all Then I can separate the effect of changing starting number from the effect of changing group. I include a skater's difference in starting numbers between Short and Free programs as an explanatory variable. The positive value of the Starting Number Difference variable corresponds to the "improvement" of a skaters' position after the Short Program. Since the within-group order is randomly assigned, the change in starting number should not affect an athletes' performance unless he changes group as well. To check this I interact the Starting Number Difference variable with a dummy that takes value 1 if a skater changed group and 0 otherwise.

The estimated coefficients are presented in column 3 of Table 8. The coefficient on the Starting Number Difference variable is statistically indistinguishable from zero, but the coefficient on the interaction term is negative and significant at the 5% level. These results mean that skaters adjust their effort level in response to changing starting number after the Short Program only if they change group as well.

1.6 Conclusion

This paper uses data from elite-level figure skating competitions to study the behavior of professional athletes exposed to multiple reference points. The institutional setting of figure skating championships allows to identify two salient reference points. The first is the group in which each skater competes during the Short Program. This group is defined according to the skater's previous performance and, therefore, reflects rational expectations about his current performance. The second reference point is the results of the previous competitor's performance, which current skater learns just before the beginning of his own program.

The results suggest that both group-based and peer-based reference points affect the effort level exerted by skaters. If a skater moved to an earlier (worse) group after the Short Program he increases his effort level in the Free Skate, and vice versa, if a skater moved to a later (better) group - he decreases his effort level. When a skater observes the previous competitor receiving score that is sufficiently better than his own expected score, he experiences what is known as disappointment aversion and exert less effort.

The effects of both reference points diminish with athletes' experience but group-based reference point seems to be more persistent. It takes an average about 18 years of experience to eliminate the influence of

the previous skater's performance on the effort of the current one, but it takes around 24 years to eliminate the influence of changing the group number. Comparing to the mean value and the maximum value of experience in the sample - 17 and 26 years respectively, one can conclude that skaters get rid of peer-based reference point influence quicker than that of the group-based reference point.

The question of whether market experience eliminates market anomalies is a subject of debate in the literature. The answer provided by List (2003) and List (2004) is yes. He finds that experience eliminates the endowment effect in trading markets - the behavior of ordinary consumers can be explained by prospect theory while the behavior of dealers with intense trading experience is consistent with neoclassical theory. But Pope and Schweitzer (2011) find that professional golfers are loss-averse relative to a reference point of par, despite the fact that golf tournament participants are extremely well-trained and experienced professionals, which implies that market experience does not help them to overcome the effect of the reference point. The findings of the current study provide middle ground between the two findings above. My results suggest that reference points might affect behavior of individuals with significant market experience. It takes time for professional figure skaters to eliminate the effect of the two relevant reference points.

Moreover, it might take a different amount of time to overcome the influence of different reference points. Identifying factors affecting adjustment time is beyond the scope of this paper, but an individuals' incentives to get rid of the influence of a reference point might be one of them. In the case of the group-based reference point, it balances out overall skater's performance in the competition, makes him exert more effort in the Free Skate after a less successful performance in the Short Program, and makes him relax and exert less effort in the Free Skate after an above expected performance in the Short Program. In the case of the peer-based reference point, skaters themselves might perceive it to be detrimental to overall performance more evidently because it does not balance effort level, but instead it makes skaters give up after a very successful performance by the predecessor in a competition. Therefore, athletes might be more incentivized to learn to overcome the influence of the peer-based reference point than that of the group-based one.

Another advantage of the figure skating institutional set up is that competitors cannot change the riskiness of their program. Ozbeklik and Smith (2017) argue that in situations when competitors can choose both risk and effort, it might be difficult to separately identify their effects. They find that golfers take more risk when the relative strength of their opponent increases. In the context of Brown's (2011) and Tanaka and Ishino's (2011) findings, that implies that when playing against a superstar, golfers do not necessarily exert less effort but rather take more risk. The advantage of the figure skating setup is that the elements of the Free Skate program are defined well before a skater finds out the result of the previous competitor. A skater cannot change declared elements, so he has very limited ability to adjust risk. He cannot, for example, decide to perform more difficult elements. Therefore, the effect can be attributed to the change in the skaters' effort

level.

Finally, it seems that one of the side results of this study - I do not find evidence of home advantage and I find at best very weak evidence of nationalistic bias - is at odds with existing studies. Nationalistic bias in figure skating received a lot of attention in the literature. Seltzer and Glass (1991), Campbell and Galbraith (1996), Sala et al. (2007) and Zitzewitz (2006) find evidence that figure skating judges are more likely to give their compatriots higher scores than the other judges. Zitzewitz (2006) underlines that if a skater had a compatriot judge in the panel he is more likely to receive higher scores not only from that judge but also from the rest of the panel, which might reflect vote trading schemes.

The reform of the figure skating judging system in 2006 was designed to reduce the opportunity for judges to trade votes or favor their compatriot skaters, this one of the reasons I have chosen 2006-2016 as a time frame for this study. Zitzewitz (2014) concluded that the reform did not reduce nationalistic bias, if anything the bias slightly increased. But when he looks at men, women, pairs and ice-dancing separately, he finds that the bias is driven mostly by the ice-dancing events, probably because judging technical elements in ice-dancing allows for more subjectivity than in single's and pair's figure skating events. I do not find strong evidence that judges award higher GOE scores to their compatriot competitors after the reform of figure skating judging system, at least for men's events. These results are in line with the findings of Zitzewitz (2014). They also indicate that there is very little place for subjectivity in judging technical elements in the figure skating.

Table 1: Required Elements for the Short Program and the Free Skate

Required Elements	
Short Program (7 elements)	double or triple Axel jump; triple or quadruple jump; jump combination: 2+3 or 3+3 or 4+3 or 4+2; flying spin; camel spin or sit spin; spin combination; step sequence.
Free Skate (maximum of 13 elements)	maximum of 8 jump elements (one must be an Axel jump); maximum of 3 spins; maximum of 1 step sequence; maximum of 1 choreographic sequence.

Table 2: Summary Statistics

Name of the Variable	Description	Mean	Maximum	Minimum	Std. Dev.	Obs.
GOE	Sum across all elements' Final Grades of Execution in the Free Skating Program	0.27	16.99	-10.72	4.78	495
GOE of jump elements	Sum across all jump elements' Final Grades of Execution in the Free Skating Program	-1.50	11.49	-11.22	4.00	495
GOE of non-jump elements	Sum across all non-jump elements' Final Grades of Execution in the Free Skating Program	1.77	7.36	-2.14	1.46	495
Group Difference	Difference between starting groups in the Short Program and the Free Skating Program	0.27	5	-3	1.18	495
Score Difference	Difference between the previous skater's score and the Base Value of the Free Skating Program of a current skater	-0.26	43.25	-39.94	12.69	473
Free Skate Base Value	Free Skate Base Value	64.26	95.13	34.48	9.32	495
Short Program GOE	Final Grade of Execution in Short Program	0.75	10.62	-6.59	2.85	495
Age	Age of a skater	23.10	31	15	3.19	495
Experience	Experience of a skater	17.49	26	6	3.74	495
World	World Championship	0.48	1	0	0.50	495
Home	Championship in the home country of a skater	0.06	1	0	0.24	495
Compatriot Judge	Compatriot judge is in the panel	0.37	1	0	0.48	495

Table 3: Regression results for starting order group number

	GOE		Jump Elements' GOE		Non-jump Elements' GOE	
	(1)	(2)	(3)	(4)	(5)	(6)
Group Difference	-0.437*** (0.135)	-1.659*** (0.563)	-0.296** (0.124)	-1.461*** (0.504)	-0.140*** (0.036)	-0.197 (0.171)
Group Difference * Experience		0.069** (0.031)		0.067** (0.029)		0.003 (0.009)
Free Skate Base Value	0.114*** (0.023)	0.114*** (0.024)	0.103*** (0.020)	0.102*** (0.020)	0.012* (0.007)	0.012* (0.007)
Short Program GOE	0.491*** (0.079)	0.483*** (0.078)	0.419*** (0.073)	0.412*** (0.071)	0.072*** (0.022)	0.072*** (0.022)
Age	-1.645*** (0.631)	-1.648*** (0.613)	-1.934*** (0.561)	-1.937*** (0.546)	0.290* (0.166)	0.290* (0.165)
Age Squared	0.0359*** (0.014)	0.0363*** (0.013)	0.0431*** (0.012)	0.0435*** (0.011)	-0.007** (0.004)	-0.007** (0.004)
Experience	0.008 (0.072)	-0.025 (0.071)	-0.016 (0.068)	-0.046 (0.067)	0.023 (0.018)	0.022 (0.019)
World Championship	0.661* (0.388)	0.688* (0.386)	0.366 (0.356)	0.393 (0.355)	0.294*** (0.103)	0.295*** (0.102)
Compete Home	-0.972 (0.744)	-0.953 (0.729)	-0.934 (0.665)	-0.916 (0.652)	-0.038 (0.150)	-0.037 (0.150)
Compatriot Judge	0.421 (0.349)	0.428 (0.350)	0.520 (0.327)	0.526 (0.328)	-0.099 (0.090)	-0.099 (0.090)
Observations	495	495	495	495	495	495
R-squared	0.436	0.440	0.301	0.306	0.598	0.598

Note: All models include year and group fixed effects.

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 4: Regression results for the peer based reference point

	GOE		Jump Elements' GOE		Non-jump Elements' GOE	
	(1)	(2)	(3)	(4)	(5)	(6)
Score Difference	0.0002 (0.0181)	-0.182*** (0.065)	0.002 (0.017)	-0.145** (0.057)	-0.002 (0.005)	-0.037** (0.018)
Score Difference * Experience		0.010*** (0.004)		0.008*** (0.003)		0.002** (0.001)
Free Skate Base Value	0.118*** (0.032)	0.121*** (0.031)	0.107*** (0.028)	0.110*** (0.028)	0.011 (0.009)	0.011 (0.008)
Short Program GOE	0.487*** (0.082)	0.502*** (0.080)	0.418*** (0.075)	0.430*** (0.075)	0.069*** (0.024)	0.0718*** (0.023)
Age	-1.776*** (0.654)	-1.753*** (0.643)	-1.991*** (0.583)	-1.972*** (0.576)	0.215 (0.170)	0.219 (0.168)
Age Squared	0.039*** (0.014)	0.039*** (0.014)	0.0447*** (0.013)	0.044*** (0.012)	-0.006 (0.004)	-0.006 (0.004)
Experience	0.006 (0.075)	-0.006 (0.075)	-0.020 (0.071)	-0.029 (0.071)	0.026 (0.019)	0.023 (0.019)
World Championship	0.576 (0.444)	0.416 (0.441)	0.291 (0.400)	0.161 (0.400)	0.286** (0.117)	0.254** (0.113)
Compete Home	-1.031 (0.789)	-0.994 (0.759)	-0.968 (0.700)	-0.938 (0.673)	-0.063 (0.167)	-0.056 (0.167)
Compatriot Judge	0.496 (0.365)	0.466 (0.363)	0.571* (0.339)	0.547 (0.338)	-0.075 (0.096)	-0.081 (0.095)
Observations	473	473	473	473	473	473
R-squared	0.421	0.431	0.292	0.301	0.581	0.585

Note: All models include year and group fixed effects.

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 5: Random Effects and Fixed Effects Models

	Random Effects		Fixed Effects	
	(1)	(2)	(3)	(4)
Group Difference	-0.417*** (0.146)	-1.722*** (0.646)	-0.234 (0.177)	-1.611** (0.772)
Group Difference * Experience		0.075** (0.036)		0.078* (0.043)
Free Skate Base Value	0.121*** (0.023)	0.121*** (0.023)	0.126*** (0.030)	0.125*** (0.030)
Short Program GOE	0.452*** (0.079)	0.445*** (0.079)	0.319*** (0.092)	0.323*** (0.092)
Age	-1.398** (0.675)	-1.396** (0.673)	-1.005 (1.351)	-0.976 (1.347)
Age Squared	0.030** (0.014)	0.031** (0.014)	-0.007 (0.023)	-0.008 (0.023)
Experience	0.011 (0.086)	-0.025 (0.087)	1.251* (0.700)	1.262* (0.698)
World Championship	0.561 (0.374)	0.576 (0.373)	0.074 (0.454)	-0.020 (0.455)
Compete Home	-0.821 (0.693)	-0.792 (0.691)	0.225 (0.833)	0.257 (0.831)
Compatriot Judge	0.477 (0.350)	0.481 (0.349)	0.696* (0.407)	0.675* (0.405)
Observations	495	495	495	495
R-squared			0.259	0.266

Note: All models include year and group fixed effects.

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 6: Random Effects and Fixed Effects Models

	Random Effects		Fixed Effects	
	(1)	(2)	(3)	(4)
Scores Difference	0.006 (0.018)	-0.168** (0.068)	0.011 (0.021)	-0.193** (0.085)
Scores Difference * Experience		0.010*** (0.004)		0.011** (0.005)
Free Skate Base Value	0.131*** (0.032)	0.135*** (0.031)	0.139*** (0.040)	0.145*** (0.040)
Short Program GOE	0.444*** (0.082)	0.455*** (0.082)	0.319*** (0.095)	0.332*** (0.095)
Age	-1.418** (0.713)	-1.350* (0.710)	-0.972 (1.411)	-0.508 (1.412)
Age Squared	0.031** (0.015)	0.030** (0.015)	-0.011 (0.024)	-0.023 (0.025)
Experience	0.002 (0.092)	-0.012 (0.092)	1.422** (0.709)	1.499** (0.704)
World Championship	0.398 (0.426)	0.232 (0.427)	-0.191 (0.502)	-0.382 (0.504)
Compete Home	-0.822 (0.724)	-0.788 (0.718)	0.216 (0.847)	0.183 (0.840)
Compatriot Judge	0.569 (0.366)	0.559 (0.363)	0.780* (0.422)	0.800* (0.419)
Observations	473	473	473	473
R-squared			0.259	0.273

Note: All models include year and group fixed effects.

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 7: Robustness Checks for Mean Reversion Possibility

	(1)	(2)	(3)
Group Difference	-0.463*** (0.131)	-1.465** (0.573)	-0.400*** (0.143)
Group Difference * Experience		0.057* (0.032)	
Average SP GOE	0.230*** (0.083)	0.227*** (0.083)	
Below Average			-0.467 (0.360)
Observations	495	495	495
R-squared	0.440	0.442	0.391

Note: All models include benchmark controls and year fixed effects.

Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 8: Robustness Checks

	Competitor	No Competitor	Changed Number
	(1)	(2)	(3)
Score Difference	-0.183** (0.074)	-0.147 (0.157)	
Score Difference * Experience	0.012*** (0.004)	0.014 (0.009)	
Starting Number Difference			0.064 (0.135)
Starting Number Difference * Changed Group			-0.393** (0.188)
Free Skate Base Value	0.163*** (0.031)	0.274*** (0.084)	0.095*** (0.034)
Short Program GOE	0.577*** (0.086)	0.527*** (0.182)	0.467*** (0.106)
Age	-1.364* (0.697)	-3.708** (1.819)	-0.899 (0.928)
Age Squared	0.030** (0.015)	0.0810* (0.041)	0.020 (0.020)
Experience	0.023 (0.087)	-0.075 (0.214)	-0.034 (0.099)
World Championship	0.022 (0.449)	-0.742 (1.061)	1.112* (0.582)
Compete Home	-1.011 (0.918)	-1.185 (2.514)	-0.295 (1.112)
Compatriot Judge	0.550 (0.404)	-1.849** (0.912)	0.661 (0.527)
Observations	411	62	254
R-squared	0.371	0.270	0.419

Note: All models include group fixed effects. Model (3) includes year fixed effects.

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

2 Sports Arenas, Teams and Property Values: Temporary and Permanent Shocks to Local Amenity Flows

2.1 Introduction

A number of recent papers examine the effect of professional sports teams and facilities on nearby property values, a line of research with important economic policy implications. North America recently experienced a boom in new sports facility construction. Sixty-four new stadiums and arenas were built for National Basketball Association (NBA), Major League Baseball (MLB), National Football League (NFL) and National Hockey League (NHL) teams over the period 1991 to 2006; most involved substantial public subsidies. An increasing number new sports facility projects use Tax Increment Financing (TIF) to generate funds for these subsidies. TIFs issue bonds to pay for infrastructure, land, and facility construction costs, and use new property tax revenues generated by the construction projects to pay the principle and interest on the bonds. The Rogers Centre in Edmonton, the KFC Yum! Center in Louisville, and proposed new arenas in Chicago and Milwaukee all use TIF financing.

In this paper, we exploit two natural experiments, the unexpected, temporary presence of the New Orleans Hornets in the Chesapeake Energy Arena in downtown Oklahoma City from November 2005 through April 2007, and the arrival of the Oklahoma City Thunder, *née* Seattle SuperSonics, in the arena in 2008, to generate evidence on the effect of the presence of a professional sports team, but not the construction of a new facility, on nearby property values. We also estimate the presence of the arena on nearby housing prices. We exploit the arrival of NBA teams to an existing arena that hosted other events like minor league hockey, arena football, and concerts, before the team arrivals to generate exogenous variation in the external amenities and disamenities generated by professional sports teams.

Several recent papers exploit the opening of new sports facilities to estimate the impact of facilities and teams on nearby residential property values. Tu (2005) analyzed the opening of FedEx Field outside Washington DC; Ahlfeldt and Maennig (2009) use the opening of two new sports facilities in Berlin, Germany for a similar analysis. Ahlfeldt and Kavetsos (2014) exploit the opening of a new stadium built for the 2012 Summer Olympic Games in London. All report evidence that residential property values increase with distance, and generally find that properties close to facilities experience no price increases after opening.¹⁰ In these papers, the natural experiment involves new facility construction and the presence of sport and non-sport events in the new facility. The results in these papers suggest that nearby property values may be affected by negative externalities (traffic, noise, trash, crowds etc.) generated by customers attending events

¹⁰Propheter (2017) shows that commercial rent increased near a new NBA arena in Brooklyn, New York.

in the facility while property values farther away reflect only positive amenities like the perception of “world class city” status from hosting a team in a top professional sports league.¹¹

Most research examines only the overall impact of both new facilities and new games played in these facilities on economic outcomes like property values. The impact of a new facility and the games played in it may generate different amenity flows. For example, a new sports facility might be architecturally pleasing and become a local landmark, increasing the amenity flow in the area near the facility. Traffic noise associated with fans coming and going from games played in the facility would reduce the amenity flow. Increased traffic near the facility on game day makes it difficult for local residents to get around by car or foot during games reducing the amenity flow. Fans attending games who park on the street would reduce parking available to residents, reducing the amenity flow from the facility. Garbage generated by fans walking to and from the facility, in the form of trash on the streets or overflowing trash cans, would be a eyesore, reducing the amenity flow.

This paper contributes to the literature by analyzing a novel sequence of plausibly exogenous events related to sports teams and facilities in a single city, at least in terms of the timing of the arrival of the teams in the city. These events include an NBA team playing games in the city on a temporary basis due to a natural disaster and the unexpected permanent move of a different NBA team to the city as a result of a court case with an unpredictable outcome. These events, along with the opening of the new arena during the sample period, represent novel shocks to local amenity flows unlike others analyzed in the literature.

Results from hedonic price regression models and repeat sales regression models indicate that residential property values near the Chesapeake Energy Arena increased significantly only following the opening of the arena. The repeat sales regression model results also indicate a positive impact following the opening and arrival of both teams, suggesting that unobservable property- or neighborhood-specific factors play an important role in this setting. These results suggest that the playing of games in a high profile sports league is not the most important factor driving observed property value increases documented in the existing literature. The mere presence of an arena, and the non-sports related events in the arena, play an equally important role in generating increased property values.

2.2 The Chesapeake Energy Arena, the Hornets, and the Thunder

Chesapeake Energy Arena is a multi-purpose sports arena located in Oklahoma City, Oklahoma. Ground breaking occurred 11 May 1999 and the facility opened on 8 June 2002; it cost \$89 million to build (\$120 million in 2017 dollars). Construction was 100% publicly financed. The arena seats 18,203 spectators for

¹¹A recent paper, Stitzel and Rogers (2018), analyze a novel data set containing detailed geo-coded spatial sales data at the establishment level from Oklahoma City. This paper finds evidence of spatial displacement in restaurant sales toward the arena and spatial displacement in entertainment establishment sales away from the arena after the Thunder relocated to the city.

basketball games, 15,152 for ice hockey games, and 16,591 for concerts. Oklahoma City owns the facility. From 2002 through 2009 it was home to a minor league hockey team, the OKC Blazers; from 2004 through 2008 it was home to an Arena Football League team, the Yard Dawgz.

The arena represents a key component of a larger long-term urban revitalization project, the Metropolitan Area Projects, or MAPS, that began in 1993. MAPS includes both financing mechanisms, in the form of temporary increases in sales taxes to finance construction projects, and the construction of structures for cultural, sports, recreation, entertainment, and convention events designed to revitalize downtown Oklahoma City. Other MAPS-funded projects include the Chickasaw Bricktown Ballpark (cost \$34 million, opened 1998), a minor league baseball stadium, the Cox Convention Center (cost \$60 million, opened 1999), the Ronald J. Norick Downtown Library (cost \$21.5 million, opened 2004), an interior renovation of the Civic Center Music Hall (originally opened in 1934, cost \$53 million, completed 2001), and renovations to the Oklahoma State Fairgrounds in 1998. MAPS also included arena renovations and upgrades put in place over the period 2008-2010 and the construction of a practice facility for the Thunder in 2012.

Some MAPS investments likely affected property values in downtown Oklahoma City. The sales tax increases were temporary and probably did not affect property values. Only the new library and renovations to the Civic Center Music Hall and the practice facility occurred during our analysis period. The other large MAPS projects occurred before, and should be capitalized into property values throughout our period of analysis. The Music Hall, located about 0.6 miles from the arena, renovations changed only the interior of the building which likely had a minimal impact on nearby property values. The library is located about 0.5 miles from the arena; little evidence exist on the impact of libraries on nearby property values. The practice facility is not a recreation or entertainment venue.

From November 2005 through April 2007 the arena was the temporary home of the New Orleans Hornets (now called the Pelicans). Hurricane Katrina struck New Orleans on 29 August 2005 and severely damaged the New Orleans Arena, home to the Hornets. While some early reports suggested that the facility would soon be usable, on 22 September the NBA announced that the team would play 35 games in Oklahoma City in the 2005/06 season, and 6 games in New Orleans, if the arena was ready. Repairs lagged, and on 31 January 2006 the NBA announced that the Hornets would play the entire 2006/07 season in Oklahoma City. The team again played 35 games in Oklahoma City, and 6 games in New Orleans, in the 2006/07 season. Their final game in Oklahoma City was 13 April 2007.

In November 2007, the owner of the Seattle SuperSonics, Clay Bennett, announced that he intended to move the team to Oklahoma City as soon as he could get out of the existing lease on Key Arena and requested arbitration to terminate the lease. When denied arbitration, the city sued to force the team to play in Seattle until 2010. The trial began in late June and on 2 July 2008 the team and city reached an

agreement before a verdict was announced that allowed the team to move to Oklahoma City in exchange for a \$45 million payment by the team.¹² The team moved to Oklahoma City, and began play in October 2008 as the Thunder. Seattle kept the SuperSonics name and team history under the terms of the settlement.

The temporary move of the Hornets/Pelicans, and the permanent move of the SuperSonics/Thunder to Oklahoma City following the 2 July 2008 settlement represent “natural experiments” that motivate a quasi-experimental differences-in-differences analysis of the effect of the presence of an NBA team playing games in Oklahoma City on nearby residential property transaction prices. The presence of two different teams in Oklahoma City reflect the impact of an unexpected natural disaster and the unexpected outcome of a court trial that could not be forecasted until shortly before each team arrived.

We assume that the Hornets/Pelicans could have been expected to play the 2005/06 season in New Orleans and the SuperSonics could have been reasonably expected to remain in Seattle until 2010, and perhaps beyond, had these unexpected events not occurred. Dehring et al. (2007) exploit similar unexpected events, in terms of several announcements about the location of a new facility to analyze the effects of a planned new football stadium on property values in Arlington, Texas.

2.3 Prior Literature

A number of papers analyze the impact of proximity of sports teams and facilities on residential property values. Ahlfeldt and Kavetsos (2012) show how standard bid-rent functions representing utility maximizing decisions by consumers on where to live motivate this relationship. Humphreys and Zhou (2015) develop a formal spatial general equilibrium model that generates predictions about spatial patterns of residential property values near sports facilities. Utility maximizing consumers maximize well-being by choosing where they live, and utility from housing depends on the size and quality of dwellings and locational quality in this model. Location-specific quality can be thought of as a composite good reflecting access to jobs, natural amenities like environmental quality, publicly provided services, and potentially access to a professional sports team in a stadium or arena.

In competitive real estate and goods and services markets, residents’ utility depends on proximity to sports facilities and teams and other location and non-location characteristics associated with their place of residence. At the margin, an increase in utility from location-specific or non-location-specific property characteristics offset any corresponding increase in rents or dwelling prices, implying the standard bid-rent function in urban economics linking rent to specific location-specific and non-location-specific characteristics, including proximity to sports facilities.

¹²One of the authors of this paper, Humphreys, was employed by the SuperSonics to provide expert testimony during this trial. This research is unrelated to that trial, and no part of this research is related to his testimony.

Ahlfeldt and Kavetsos (2012) observe that identification of proximity effects depends on the ability to separate facility effects from other observable and unobservable locational characteristics; these other factors could be correlated with distance to a facility. Correlation could arise from the fact that sports facilities are often located downtown in large cities. If the facility impact cannot be separately identified from the impact of other location-based factors, then the estimated hedonic impact price will be biased. Ahlfeldt and Kavetsos (2012) propose a quasi experimental approaches to reduce bias: pooling housing price data into space-time cells and performing before-and-after tests around specific events like openings or renovations. Ahlfeldt and Kavetsos (2012) further recommend conditioning on observable dwelling characteristics.

Tu (2005), Dehring et al. (2007), Ahlfeldt and Maennig (2009), Ahlfeldt and Maennig (2010), Kavetsos (2012) and Ahlfeldt and Kavetsos (2014) employ difference-in-difference methods to estimate the effect of new sports facilities on housing prices using data from before and after different facility openings. Humphreys and Nowak (2017) employ similar methods to estimate the impact of the departure of NBA teams from existing arenas in Seattle and Charlotte. Tu (2005) focuses on the opening of a new stadium with a team playing in the facility. Dehring et al. (2007) and Kavetsos (2012) focus on announcements, not actual facility openings.

Tu (2005) reported a 13% increase following the 1997 opening of FedEx Field. Dehring et al. (2007) reported a 1.5% decrease after 2004 and 2005 announcements about two alternative locations for a new football stadium in Arlington Texas. Ahlfeldt and Maennig (2009) and Ahlfeldt and Maennig (2010) reported a 2.5% increase in property values after the opening a cycling venue in Berlin, Germany, and a 15% increase after the opening of an arena in Berlin in the 1990s. Kavetsos (2012) reported a 2.5% to 3% increase after the 2007 opening of a new Olympic Stadium in London. Ahlfeldt and Kavetsos (2014) reported a 15% increase after the 2007 opening of a new stadium in London. In all cases, the opening of new facilities coincided with the arrival of new sport franchises or other sporting events; the price effect estimated in these papers can not be separated from the price effect of a facility and non-sporting events occurring inside it. Humphreys and Nowak (2017) report an increase of about 7% in nearby property values after NBA teams left Seattle and Charlotte; the arena remained in use after these team departures.

Humphreys and Nowak (2017) estimate the impact of NBA team departures on nearby property values in Seattle and Charlotte. They report evidence that the departure of an NBA team generated increases in nearby residential property values, suggesting that these teams generates local congestion disamenities like crime or traffic that were capitalized into residential property values. No prior research has investigated the impact of a new team moving into an existing facility on residential property prices.

2.4 Empirical Analysis

2.4.1 Econometric Approach

We estimate the effect of proximity to the arena before and after the arrival of two NBA teams and before the opening of the arena over the period 2000-2016. The tests are based on an difference-in-differences hedonic price model (DDHPM) and an augmented repeat sales regression (RSR) model. RSR models can be easily derived from hedonic price models. DDHPMs assume that the quality, quantity and price of characteristics of a dwelling determine observed transaction prices. In a DDHPM the log price of property j transacted at time t is

$$p_{jt} = \delta_t + f(X_{jt}, Z_j, \beta_t) + d_j \times 1(t \geq Year) \times \theta + u_{jt} \quad (3)$$

where, p_{jt} captures the log of the transaction price, δ_t all time-varying average price levels in the local property market, $f(X_{jt}, Z_j, \beta_t)$ relates time-varying and -invariant property-specific characteristics, X_{jt} and Z_j , to service flows from the characteristics, d_j reflects the distance between residential property j and the arena, $1(t \geq Year)$ is an indicator variable equal to one the property transaction occurred after point in time when the teams arrived and 0 otherwise, θ reflects changes in the amenity value of the arena after team arrivals, and u_{jt} represents an unobserved equation error term that reflects other factors that affect transaction prices. Since we observe transaction prices before and after the arena was built and the teams arrived, this represents a difference-in-differences approach.

Repeat sales are dwellings for which multiple sales during the sample period are observed. For dwelling j sold in period s and again in period $s \leq t$, the price change across transactions is simply the difference of Equation (3)

$$\Delta p_{jt} = p_{jt} - p_{js} = \delta_t - \delta_s + f_{jt}(X_{jt}, Z_j, \beta_t) - f_{js}(X_{js}, Z_j, \beta_s) + d_j \times 1(t \geq Year > s) \times \theta + u_{jt} - u_{js}. \quad (4)$$

In Equation (4) $1(t \geq Year \geq s)$ is an indicator variable equal to one if the second observed sale occurred after a given team arrived and the first observed sale occurs before a given team arrived. This indicator function equals zero if both sales occurred before a given team arrived or if both sales occurred after a given team arrived. Repeat sales where $1(t \geq Year \geq s) = 1$ constitute the identifying sales in the data. These repeat transactions allow us to identify θ , the parameter of interest in a RSR.

RSR models can be used instead of HPMS like Equation (3) because the RSR approach eliminates the need to specify a specific functional form for the DDHPM as well as the need to collect data on property

characteristics in X_{jt} and Z_j . These relaxed requirements are important because of the presence of difficult to quantify time-invariant factors affecting property values in the area near the arena. RSR model estimation requires only that

$$f_{jt}(X_{jt}, Z_j, \beta_t) - f_{js}(X_{js}, Z_j, \beta_s) = \omega_{jt}.$$

This is a simple functional form where ω_{jt} is a well-behaved random variable and $E[\omega_{jt}] = 0$. Estimation of unobservable parameters in Equation (4) proceeds using an unbalanced panel of residential transaction prices from Oklahoma City; some dwellings have multiple repeat sales but most have only one. Using differenced sales prices removes any unobserved time-invariant factors from u_{jt} .

The covariance matrix for Δu_{jt} is not diagonal. For dwellings with one repeat sale, Δu_{jt} contains unobserved factors associated with residence j and is assumed to be uncorrelated with all other $\Delta u_{k \neq jt}$ s. Under these conditions, Δu_{jt} 's covariance matrix is a band matrix with non-zero values on the first off-diagonal. All RSR results reported here come from the ordinary least-squares estimator using the White-Huber correction on estimated standard errors.

Regardless of the estimator used, Equation (4) can be written

$$\Delta p_{jt} = p_{jt} - p_{js} = \delta_t - \delta_s + d_j \times 1(t \geq Year > s) \times \theta + \Delta u_{jt}. \quad (5)$$

Rewriting in this form highlights that price changes for residence j reflect market-wide changes in prices, distance to the arena, repeat sale timing, and an unobservable error term $\Delta u_{jt} = \omega_{jt} + u_{jt} - u_{js}$. Repeat sales when $1(t \geq Year > s) = 0$ represent sales where expected price appreciation is simply equal to market-wide changes over time: $\delta_t - \delta_s$. Excess price appreciation is captured by $d_j \times \theta$ for identifying sales.

2.4.2 Data

The data come from the Oklahoma County Assessor's office which collects comprehensive information on property transactions. We analyze only residential property – single family homes and condos – sales. The street address for all transacted properties in the Assessor's office data were geocoded by latitude and longitude using the Google Maps API. We filtered the data to remove all transactions listing an LLC as buyer or seller to eliminate the sale of vacant properties, all transactions where the buyer and seller has the same last name to eliminate non-arms length transactions, and all repeat sales where the absolute value of the price change was greater than 100%. Following Linden and Rockoff (2008) we also trim the smallest and largest 1% of the transactions in the sample to remove the effects of outliers. The final data set contains all 106,828 residential property transactions in Oklahoma City over the period 1 December 2000 through 25

July 2016 within 10 miles of the arena location.

Geocoding the latitude and longitude of each transaction permits the estimation of the straight-line distance between the arena and each residential property in miles. To illustrate the geography of transactions we graph 20% of the transactions in the sample. Figure 1 shows the location of the arena as a black circle in the middle, and the location of transactions in the data set within 10 miles of the arena. The inner light gray circle identifies transactions within two miles from the arena, then the gray shading gets progressively darker for transactions within 3, 4, 5 and 10 miles of the arena. Transactions in Oklahoma City more than 10 miles from the arena were not included in the sample.

We restrict the impact area of arena-based amenities to properties within ten miles of the arena. Since the arena was used for concerts and minor league sporting events before the arrival of the two NBA teams, we assume that the arrival of the teams affected foot and car traffic near the arena on game day, including both positive and negative externalities generated by fans. Such externalities more likely affect properties near the arena; parked cars, crowds, trash, and noise tend to be concentrated there. Since these externalities increase in strength with proximity to the arena, we divide the sample into rings or donuts at two mile, three mile, four mile and five mile distances from the facility.

Table 9 contains summary statistics for the 106,828 residential property transactions in the sample. The sale price of each transaction was deflated to real 2016 dollars using the Consumer Price Index for All Urban Residents (CPI-U). The average sale price was \$79,807 and the average transacted property had about 1,400 square feet of living space. Unfortunately, the Assessor's office data does not contain additional characteristics of the dwellings like the number of bedrooms and bathrooms, or indicators for dwelling types like detached single family homes or condos. However, square feet of living space is correlated with the number of bedrooms and bathrooms in a dwelling, and can also control for differences in dwelling type, since condos are generally smaller than single family homes.

The residential transactions data begin in 2000, the Chesapeake Energy Arena opened in June 2002, the Hornets played temporarily in the arena from November 2005 through April 2007, and the Thunder began play in the arena in October 2008. These events represent the points in time where we identify changes in the external amenities and disamenities generated by the arena and the games taking place in the arena. From Table 9 about 85% of the transactions occurred after the opening of the arena, about 11% occurred while the Hornets were playing in the arena, and about 43% occurred when the Thunder were playing in the arena.

From Figure 1, relatively few transactions occurred very close to the arena. The arena is located on the southern fringe of downtown Oklahoma City and the area south of the arena is an industrial area with many vacant lots, surface parking lots, and an interstate highway. From Table 9, only 3.9% of the transactions

in the sample occurred within two miles of the arena. In practical terms, a two mile radius impact area provides relatively few transactions to analyze.

2.4.3 DDHPM Results

Table 10 contains the DDHPM results based on Equation (3) using the sample of residential property transaction prices within 10 miles of the arena over the period 2000 to 2016. We present DDHPM results primarily to demonstrate the superiority of the RSR results, which represent our preferred specification. The log of the transaction price is the dependent variable. Table 10 reports results for four different treatment areas around the arena: all transactions within two miles, all transactions within three miles, all transactions within four miles and all transactions within five miles. Each of these models is estimated separately and each model increases the treatment area for arena proximity.

As expected, the parameter estimate on the dwelling size variable is positive and statistically different from zero. Larger dwellings sell for higher prices. Residential property near the arena sold at a substantial discount relative to residential property in the rest of Oklahoma City. Dwellings within two miles of the arena sell at a discount of -0.515 log points, about 50% less, relative to dwellings in the rest of Oklahoma City. The arena was built in an area with low housing prices. For the largest impact area, within five miles of the arena, the estimated coefficient drops to -0.314.

The DDHPM results on Table 10 contain three different difference-in-differences (DD) events: transactions close to the arena after the arena opened (Arena Opens $\times$ Close), transactions close to the arena while the Hornets played in the arena (Hornets on OKC $\times$ close), and transactions close to the arena after the Thunder arrived in Oklahoma to play in the arena (Thunder Arrives $\times$ Close). The parameters on these three variables, the parameters of interest, reflect the impact of each event on nearby residential property prices.

From Table 10, the opening of the arena increased nearby residential home prices, but the temporary move of the Hornets and the arrival of the Thunder had little impact. The results show that the opening of the arena increased prices in the three largest treatment areas by between 0.06 log points (0.06%) and 0.043 log points (0.04%). The estimated impact declines as the treatment area gets larger. Again, this can be interpreted as an increase in the amenities generated by the arena location after the opening of the arena compared to before, perhaps due to access to the events held in the arena or gentrification due to the presence of the arena. Recall that dwellings within two miles of the arena sold for prices substantially below the average price in Oklahoma City, so the increase in prices of nearby homes did not raise them above the average across the rest of the city.

The temporary arrival of the New Orleans Hornets and the permanent arrival of the Thunder had no

effect on nearby local residential property values. The Hornets were clearly not making a permanent move to the city which likely explains the lack of impact on local residential property values. This result suggests that the impact of a professional sports team playing games in an arena on nearby property values may stem from factors unrelated to the actual playing of games, which include crowds of fans and traffic. Hornets games were being played in the arena over the period November 2005 through April 2007 and Thunder games after October 2008 but the playing of games appears to have had no impact on local real estate prices.

2.4.4 RSR Model Results

The DDHPM results may suffer from some econometric problems, most notably the presence of unobservable property-specific and neighborhood-specific factors correlated with the treatments. Repeat sale regression models represent one way to address the presence of unobservable property-specific characteristics in econometric analysis of residential real estate price data. RSR models use multiple observations for the same dwellings to eliminate the impact of time-invariant unobservable factors. Of course some dwelling characteristics can change between repeat sales, and renovated houses may be more likely to resell in any given time period, which would be a source of mis-specification in RSR models (Billings, 2015).

The number of repeated observations represents one key to implementing RSR models. Table 11 shows the number of repeat sales that identify each of the three arena-related events in the sample (opening, Hornets tenure, and arrival of the Thunder) for each treatment area. Identifying repeat sales represent dwellings that sell before and after one of the events. Repeat sales occurring in the same time bin cannot identify the impact of team arrivals. They effectively represent the control group in RSR models.

As expected, relatively few identifying transactions exist in the treatment area defined as transactions within two miles of the arena, since few houses exist in that small area. The other treatment areas contain relatively large numbers of repeat sales of the same dwelling. This should provide enough variation in repeat sales to identify the effect of the arena-related events in this sample.

Table 12 shows results from estimating Equation (4) using repeat sales in the Oklahoma City data. RSR models do not include property characteristics like square footage, since the effect of these time-invariant characteristics on prices are differenced out. The effects of all unobservable time-invariant local factors are also differenced out.

The results on Table 12 generally resemble those from the DDHPM reported on Table 10 in terms of the opening of the arena. Residential property prices increased near the arena after opening and the impact diminishes as the impact area increases in size. The impact of the Thunder on nearby property values is also positive for three of the treatment areas. But this is not uniform, and the estimated effect is negative when the treatment area expands to include all transactions within five miles of the arena. This could reflect

the idea that the five mile treatment area is too large and reflects the impact of other factors affecting the Oklahoma City real estate market after the Thunder moved to town.

RSR model results on Table 12 also reveal a positive effect of the Hornets during their temporary stay in the city from late 2005 through April 2007. However, this positive impact only appears in the larger treatment areas (within 3, 4, and 5 miles). These results may reflect broader market-wide increases during the period the Hornets played in the city, and not the effect of the games. Or the lack of an estimated effect in the two mile treatment area may reflect the small number of identifying transactions in that area.

The results from the RSR model confirm the results from the DDHPM specification shown on Table 10 for the arena opening and also indicate that the presence of NBA teams in the city increased nearby property values. The building of a new arena, and the attraction of an NBA team to Oklahoma City both increased property values in a relatively large area downtown. The strongest impact generally occurs in treatment areas closest to the arena and dissipates across larger treatment areas. These results likely reflect important positive amenity values flowing from the arena, and the games played by the teams in the arena, and impacting nearby residential property values. These amenity values could take the form of increased civic pride and an enhanced local image attributable to a major sporting venue and high-profile professional sports team in the city. They could also reflect gentrification of the neighborhood following the arrival of the teams. Since the opening of the arena generated increases in local residential property values independent of the presence of a team, some of the amenity values appear to be unrelated to the playing of NBA games in the arena alone.

Note that the estimated size of the impact of a new arena on Table 12 is substantially smaller than the DDHPM results on Table 10. For example, the effect of the opening of the new arena on property values within two miles falls from 14.5% to 7.7%. Effect sizes near 15% appear implausibly large in the context of the existing literature on positive and negative shocks to residential property prices. The DDHPM results likely reflect unobservable property-specific and neighborhood-specific factors that hedonic price models cannot adequately account for. The RSM approach addresses this limitation and represents our preferred model specification.

As a robustness check, we re-estimated the DDHPM and RSR models using a sub-sample that also dropped all transactions involving LLCs and between buyers and sellers with the same last name. This should remove un-occupied dwellings and within-family sales from the sample. We also dropped all repeat sale transactions with absolute price change greater than 100%. This dropped about 3,000 transactions from the samples. The results were nearly identical to those on Table 10 and Table 12 with respect to estimated parameter signs and significance.

2.5 Conclusions

Understanding the dimensions of local amenity flows generated by sports facilities and the playing of games in these facilities, and the associated impact of these amenity flows on local property values, represents an important component for developing effective local economic development policies. New professional sports facilities and teams often represent key elements in local redevelopment plans, and local government frequently subsidizes the construction of new sports facilities. These subsidies often take the form of Tax Increment Financing (TIF) districts located around the new facilities, further highlighting the importance of understanding how new sports facilities and teams affect nearby property values.

Tension exists in the literature. Some studies find increases in residential property values following the opening of a new sports facility (Tu, 2005; Ahlfeldt and Maennig, 2009, 2010; Ahlfeldt and Kavetsos, 2014) suggesting important local amenity flows while other studies (Humphreys and Nowak, 2017) find increases in residential property values following the *departure* of teams from a city, suggesting important local disamenity flows. Since research in this area consists of case studies from one or two cities, new sources of shocks to local sports-related amenity or disamenity flows need to be analyzed to move the literature forward.

This paper focuses on a novel set of shocks to the professional sports environment in Oklahoma City to help disentangle the effect of a facility from the effect of NBA games played in that facility. The evidence suggests that the presence of an arena and both a permanent and temporary NBA team amenity flows in nearby areas. Civic pride, “world class city” status, and other intangible factors represent the most likely source of these amenity flows. Arena-related gentrification could also generate these increases in property values. Evidence using stated preference data and the Contingent Valuation Method also finds strong evidence that the presence of a professional sports facility and team in a city generate important intangible benefits (Johnson et al., 2001, 2007; Fenn and Crooker, 2009). Patterns in voting on sports facility subsidy referendums also support the presence of local intangible benefits (Coates and Humphreys, 2006; Horn et al., 2015).

The results show that both a new arena and the arrival of a permanent and a temporary NBA team generated increases in local residential real estate prices. The strongest impact occurred relatively near the arena in treatment areas of between two and four miles out. The impact of temporary games played by an NBA team relocated to the city because of a natural disaster also generated amenity flows and property value increases. Increases in residential property values benefit home owners, but could generate economic harm to renters if rents increase because of the increase in property values. The limited impact area of this increase in residential property values argues for the use of relatively small TIF districts to finance those new facilities that must be subsidized.

Table 9: Summary Statistics for Transactions within 10 Miles of the Arena

Variable	Mean	Std. Dev.	Min	Max
Sale Price (2016 dollars)	79,807	75,255	2,232	1,908,793
Square Footage	1,427.65	667.58	204	17,412
Post Arena Opening	0.857	0.350	0	1
Hornets	0.113	0.316	0	1
Thunder	0.426	0.495	0	1
Arena Proximity < 2 miles	0.039	0.195	0	1
Arena Proximity < 3 miles	0.136	0.343	0	1
Arena Proximity < 4 miles	0.296	0.456	0	1
Arena Proximity < 5 miles	0.479	0.500	0	1
Observations	106,828			

Table 10: DDHPM Results - Transactions within 10 Miles of Arena

	Treatment Area			
	≤2 miles	≤3 miles	≤4 miles	≤5 miles
Log Square Footage	1.434*** (0.005)	1.399*** (0.004)	1.361*** (0.005)	1.318*** (0.005)
Close to Arena	-0.515*** (0.027)	-0.560*** (0.014)	-0.404*** (0.010)	-0.314*** (0.008)
Arena Opens	0.069*** (0.012)	0.067*** (0.011)	0.057*** (0.011)	0.055*** (0.012)
Arena Opens × Close	0.027 (0.033)	0.060*** (0.017)	0.043*** (0.012)	0.026*** (0.009)
Hornets in OKC	0.014 (0.009)	0.0148 (0.009)	0.023** (0.009)	0.013 (0.009)
Hornets in OKC × Close	-0.032 (0.038)	0.010 (0.019)	0.002 (0.013)	0.018 (0.010)
Thunder Arrives	-0.011 (0.015)	-0.014 (0.014)	-0.014 (0.014)	0.003 (0.014)
Thunder Arrives × Close	0.039 (0.028)	0.013 (0.014)	-0.001 (0.010)	-0.032*** (0.008)
Observations	106,828	106,828	106,828	106,828
R-squared	0.560	0.591	0.588	0.579

Note: Robust standard errors in parentheses, *** p<0.01, **p <0.05

Table 11: Number of Identifying Sales

Distance	Arena Opens	Hornets in OKC	Thunder Arrive
2 miles	289	352	562
3 miles	918	1,194	1,895
4 miles	2,137	2,627	4,305
5 miles	3,609	4,225	7,030
10 miles	7,896	8,641	15,385
Total Repeat Sales	41,701		

Table 12: Repeat Sales Regression Results - Transactions within 10 Miles of the Arena

	2 miles	3 miles	4 miles	5 miles
Arena Opens	0.0057 (0.006)	0.002 (0.006)	-0.001 (0.006)	-0.0039 (0.007)
Arena Opens $\times$ Close	0.065*** (0.020)	0.039*** (0.011)	0.027*** (0.006)	0.020*** (0.005)
Hornets	0.016*** (0.004)	0.013*** (0.004)	0.009** (0.004)	0.005 (0.005)
Hornets in OKC $\times$ Close	0.009 (0.0179)	0.024** (0.010)	0.022*** (0.006)	0.023*** (0.005)
Thunder Arrive	-0.001 (0.0065)	-0.011 (0.0065)	-0.013** (0.0065)	-0.004 (0.0066)
Thunder Arrive $\times$ Close	0.039*** (0.015)	0.018** (0.008)	0.015*** (0.005)	-0.010** (0.004)

Note: Robust standard errors in parentheses, *** p<0.01, **p <0.05

Figure 1: Arena and Property Sale Locations, 2000-2016

3 Tournament Incentives and Effort: Evidence from eSports Competitions

3.1 Introduction

The model developed by Rosen (1986) predicts that in elimination tournaments prizes must be highly skewed towards top ranking contestants in order to maximize effort level exerted by every participant. Empirical tests of tournament theory are complicated because it is difficult to measure both individuals' effort level and incentive structures they face in real life situations.

eSports, or competitive video gaming, provides an opportune environment for testing tournament theory in non-experimental setting. For a researcher, eSports has a “classic” sports’ advantage of detailed data on prize structure and match outcomes being freely available for most major events. Furthermore, as Wagner (2006) points out, effort in eSports is related to “mental or physical abilities in the use of information and communication technologies.” So, studying eSports tournaments might provide some insight as to whether mental effort is responsive to payoff differentials in the same way as physical effort. The results might be more applicable to modern labor markets which are mainly concerned with employees’ mental effort, often in a computerized environment.

I use data from major League of Legends (LoL) events - tournaments of World Championship Cycle, Demacia Cup, KeSPA Cup, National Electronic Sports Tournament (NEST) and Intel Extreme Masters (IEM) events from 2015 - 2017 to test whether teams’ effort depends on skewness of tournament prize money distribution between top performing participants. The results indicate that eSports teams put forth more effort in the Knockout stage of the tournaments with more skewed prize distributions, more specifically with a larger coefficient of variation and larger prize spread between tournament winner and runner-up. There is no evidence that total prize pool affects the effort of the teams. These results are consistent with tournament theory predictions. But, marginal win (difference between the next round and the current round prizes) and the difference between the first prize and the current round prize do not affect the effort provided by teams. This finding might be explained by the difference in the nature of effort in eSports and “regular sports” competitions.

LoL is one of the largest eSports, with various annual tournaments taking place worldwide. The prize money awarded from 2010 to present day amount to \$48,611,177. The prize pool of the 2017 LoL World Championship totaled \$4,596,591 with fans’ direct contributions accounting for roughly half of the amount (\$1,850,000)¹³. The final game was held in Beijing National Stadium with the capacity of 80,000 and more

¹³https://www.lolesports.com/en_US/articles/update-fan-contribution-worlds-2017-prize-pool-0

than 75,000,000 people watched it online¹⁴. Some agents are directly interested in making LoL matches as competitive and entertaining as possible - tournament organizers, sponsors, broadcasters and fans. Therefore, the results of this study not only will be interesting as an insight in some general labor markets, but also as a guideline for designing eSports tournament reward system which maximizes players' effort levels.

3.2 Tournament Theory and eSports

Using the framework developed by Szymanski (2003), I assume that eSports tournament organizers aim to maximize profit from selling tickets, merchandise, online banners, name sponsorship, etc. Therefore, they are concerned with attracting as many spectators (including online viewers) as they can. The demand for eSports tournaments depends on team quality and the effort they exert in every game. It is interesting to note, that unlike "regular" sport teams, eSports teams usually do not attach themselves to particular geographical locations, at least within a country. So, their fan base might be more sensitive to the teams' performance. Organizers want to design the reward structure that provides teams with an incentive to exert effort levels maximizing organizers' expected profit.

Output of an eSports team depends on deterministic and random components. The deterministic component is associated with team's effort and skill, and is positively but not perfectly correlated with probability of winning a larger prize. The random component is everything beyond teams' control, such as luck. Teams' preferences are described by separable utility function increasing in prize money and decreasing in effort. The interactions between teams and tournament organizer can be represented as the following game. First, given the structure of rewards, each team chooses the effort level which optimizes its utility. Then, the organizer uses teams' best responses to set the optimal prize structure.

Frick (2003) summarizes the predictions of Rosen (1981) in the context of sporting competitions. If all tournament participants are equally skilled and endowed, there exists a symmetric pure strategy equilibrium in which effort is an increasing function of the prize spread. In order to maintain constant level of effort, the organizer should set up prize the structure with a constant interranks spread from second place down and larger spread at the top. On the other hand, if teams have heterogeneous abilities, some teams are more likely to win a game than others. When tournament participants have full information about each other's abilities incentives to exert effort are undermined. The worse teams know that the chance to win is weak, therefore the expected payoff is smaller which, in turn, leads to the team reducing the effort. The better teams are aware that the chance to win is above average, therefore there is no need for the team to try very hard. The model predicts that in order to increase the level of competition, the tournament organizer must adjust the rewards distribution by skewing it more heavily towards the higher ranks. The main testable

¹⁴<https://esc.watch/tournaments/lol/2017-world-championship>

prediction emerging from tournament theory is that effort depends on skewness of prize distribution but not on absolute value of prizes.

There are several works that found evidence of participants of “regular sports” tournaments (tennis, golf, NASCAR, marathon and foot running) adjusting their effort in accordance with tournament theory predictions (Ehrenberg and Bognanno, 1990 (a,b); Gilsdorf and Sukhatme, 2008; Lallemand et al., 2008; Becker and Huselid, 1992; Frick and Humphreys, 2011; Frick and Prinz, 2007; Maloney and McCormick, 2000).

The question is: how effort in eSports competitions different from one in “regular sports”? Partaking in eSports involves a sizable mental effort component (Wagner, 2006) along with physical effort. The definition of physical effort is relatively straightforward. According to Shenhav et al.(2017), physical effort regulates engagement of muscles. In the case of eSports - small groups of muscles (fine motor skills), therefore, competitors experience very little physical exertion (Chikish et al., 2019).

Defining mental effort is more complicated task. Mental effort allows an individual to override of default actions or habits, engage reasoning, maintain working memory and switch between tasks with different demands (Shenhav et al., 2017). All cognitive processes can be thought as belonging to a continuum of automaticity. At the one end of this spectrum are all processes that could be performed without much cognitive control, for example, driving from home to work taking a familiar route does not usually require much thinking. Processes on the other end of this continuum require a person to increase cognitive control to reconfigure information processing away from default (Botvinick and Cohen, 2015). Therefore, the increase in cognitive control can be viewed as an “instrument” through which mental effort is exerted.

Despite the lack of physical exertion, mental effort is still costly to an individual. Shenhav et al.(2017) describe two types of costs associated with cognitive control: intrinsic costs and opportunity costs. Intrinsic costs involve limited capacity metabolic resources in the brain and constraints on the capacity to maintain task-relevant information. Opportunity costs mean that when an individual decides to allocate control to one set of processes he or she forgoes pursuit of other processes that may also have value. Empirical literature suggests that mental effort responds to incentives (Krebs et al. 2010, Engelmann et al. 2009, Duckworth et al. 2011, etc.) This paper extends the tournament theory literature by looking at how prize structure affects mental effort of tournament participants.

eSports tournaments context differs from most existing empirical studies in another respect - effort is exerted on a team-level. Various tasks can be more efficiently accomplished by coordinated contribution of people (Freeman and Wohn, 2018). eSports setting allows to investigate whether such activities coordinated through computer technology respond to a change in prize structure. Moreover, eSports is an interesting and unique case with regards to cooperation in teams. According to DeChurch and Mesmer-Magnus (2010),

there are two extremes of teams: action-oriented teams (firefighters, trauma teams, etc.) that perform highly interdependent and time sensitive tasks in stressful and risky environments, and decision/knowledge-oriented teams (teams in business, software development, etc.) that perform tasks in the relatively calm environment of traditional workplace settings. For eSports teams, on the one hand, teamwork is taskbased—similar to that of a traditional organizational setting. On the other hand, eSports teamwork happens in a highly competitive, stressful, and intense virtual environment that requires fast decision-making, making them action-oriented.

To my knowledge, there is only one empirical study connecting eSports and tournament theory. Using data¹⁵ on monetary prizes of eSports tournaments, Coates and Parshakov (2015) find that tournaments' reward schemes are designed so that the function reflecting the relationship between prize and player/team's tournament rank is convex. It means that each subsequent move up the tournament ranking brings sharper increase to team/player's reward.

Coates and Parshakov's results indicate that tournament organizers aim to maximize participants' effort by structuring the reward scheme according to Lazear and Rosen (1981) and Rosen (1986) predictions, but no conclusions can be made whether such reward design indeed affects the effort provided by the eSports tournament participants. In this study I test whether an increase in prize money differentials between ranks of eSports tournaments has an effect on teams' effort provision. In order to have some clear measure of effort I concentrate on one particular game - League of Legends (LoL).

League of Legends is a third-person multiplayer online battle arena game. Two teams of five players compete against each other in matches, lasting, on average, from 20 to 60 minutes. Each team starts at opposing sides of a map, near its' core building called Nexus, and the match lasts until either team destroys the Nexus of the opponent. Along the way players earn gold by taking down enemy units and structures which requires effort on the players' part. Gold is one of the main ways for a player to increase the power of his character over the course of the game, so both teams are motivated to obtain as much gold as they can¹⁶. The gold acquired by a team at the end of a match can proxy for the team's effort once abilities of the team and the opponent are accounted for. The main advantage of this proxy is that it is (almost) continuous compared, for example, to match result - win or loss.

3.3 Empirical Approach

The basic empirical hypothesis is that observable factors related to the skewness of the LoL tournaments' prize distribution provide incentives for teams to exert more effort. All tournaments consist of matches

¹⁵Available at <https://www.esportsearnings.com>

¹⁶LoL New Player Guide <https://na.leagueoflegends.com/en/game-info/get-started/new-player-guide/>

between two teams. The matches can be best of one, two, three or five games. My basic model for the game-level data is:

$$GOLD_{ijgnty} = \beta_0 + \beta_1 z_{ty} + \beta_2 \mathbf{X}_{ijgnty} + \theta_y + \psi_{iy} + \phi_{jy} + \epsilon_{ijgnty}. \quad (6)$$

The dependent variable $GOLD_{ijgnty}$ shows the amount of gold collected by team i when playing against team j in game g of match m in tournament t during year y . Gold is used by players as a currency allowing them to obtain additional abilities and increase the power of their champions over the course of the game. For a team, obtaining more gold might shift the game balance to its favor. The results of a simple linear regression (with team-year and opponent-year fixed effects) suggest that a unit difference in total gold per game between two teams corresponds to 3% increase in probability of the team with the gold advantage to win the game¹⁷. At the beginning of every game, players from both teams are given some fixed equal amount of gold. During the game, they are earning gold passively, which means that no action from players is required. A player can actively increase his gold by performing certain actions, such as obtaining gold-increasing items; destroying structures; and killing neutral monsters, enemy minions, or enemy champions. I assume that any active option requires some mental and physical effort from the player. Therefore, total gold collected by a team per game can serve as a proxy for team's effort. Also, it is important to note that gold collection is not a zero-sum game for two teams. The gold collected by a team is not subtracted from the opponents' gold. Rather, the amount of gold reflects the teams' progress in a game.

The independent variable z_{ty} reflects the skewness of tournament's t prize distribution in year y . In the basic specification I use the coefficient of variation (CV) and first prize as tournament's pool percentage as measures of skewness. Higher values of both variables correspond to a distribution which is more skewed towards top-ranked teams. If tournament theory predictions hold for the LoL setting, then an increase in z_{ty} should motivate teams to exert more effort, which means obtaining more gold. Thus, I expect the coefficient β_1 to be positive.

Vector $\mathbf{X}$ contains control variables. Since gold could be earned without any effort from a player, I include *GameMinutes* variable which accounts for the duration of the game in minutes and, therefore, for the gold earned passively. *Pool* controls for the total tournament t prize money in year y . According to tournament theory, the absolute level of prizes should not affect the effort exerted by the participants, but tournaments with a larger pool might be associated with more prestige.

Teams' effort might also depend on the number of rival teams participating in a tournament and the number of prize places available. Holding everything else constant a team is likely to exert less effort if it

¹⁷The coefficient is significant at 1% level

competes for a prize with a larger number of teams since the probability to win decreases with the number of tournament participants. If the number of top-performing participants receiving monetary prizes increases it creates disincentive for the teams to put forth effort since the probability to win a monetary compensation increases. Variables *Teams* and *PrizePlaces* control for the number of teams participating in a tournament and the number of top-performing teams that receive cash prizes respectively.

Finally, effort of a team might reflect strategies employed in a particular game by the team's opponent. The opposing team might choose strategy to be more aggressive. To account for this I include variable, *OpponentKills*, which reflects the number of times team i player's champions were killed by the player of the opposing team. I do so to control for the aggressiveness of opponents' play style which complicates gold collection for the team.

One of the main challenges is to separate the effect of prize distribution on effort from the selection bias that occurs in cases when higher-ranked tournaments have less equal prize distribution schemes, and at the same time above average teams select themselves into such tournaments. Therefore, a positive correlation between the standard deviation of the prize distribution and effort might be purely due to the selection of better teams into top-rank tournaments. In order to control for teams' abilities, I use team fixed effects and opponent fixed effects - ϕ_{iy} and ψ_{jy} - respectively. I also estimate a version of equation (6) with team-year and opponent-year fixed effects because teams tend to have stable roster during a season. Finally θ_y is year fixed effects and ϵ_{ijgmt_y} is an error term that captures all other unobservable factors affecting effort exerted by teams.

3.4 Data

For the analysis I use data from major League of Legends events - tournaments of World Championship Cycle, Demacia Cup, KeSPA Cup, National Electronic Sports Tournament (NEST), and Intel Extreme Masters (IEM) events from 2015 to 2017. The choice of the time frame can be explained by availability of match scoreboards containing detailed statistics. A typical LoL tournament consists of group and elimination stages. In the group stage each group plays a round robin tournament, in which each team plays against every other team in the group. Usually, the matches are best of one. Then, top performing teams in their respective groups are seeded to the knockout stage where they play against each other in one-off matches. Those matches are usually best of three or best of five.

The data on tournaments' prize structures comes from esportsearnings.com and the data on game statistics comes from lol.esportswikis.com. Table 13 shows summary statistics. The first panel of the table reports tournament-level information. Overall, 53 tournaments are used in the analysis. I collect information on

the prize pool, number of teams participating, and number of top-performing teams that receive monetary prizes, as well as the amount of each prize. An average tournament’s prize pool is about \$430,000 with the minimum pool amounting \$50,000 and the maximum pool reaching \$5,000,000. The number of participating teams varies from 4 to 29 averaging 11, and the number of prize places varies from 4 to 24 with the average of top 7 teams receiving monetary rewards.

Using the data on tournaments’ prize structure I construct independent variables reflecting skewness of prize distribution within tournament ranks. The variable *CV* denotes coefficient of variation (CV) which is calculated as the ratio of the standard deviation to the mean. CV describes the dispersion of the prize money between the eligible ranks. A higher value corresponds to a more unequal distribution of the tournament pool. To create a measure of variation that is less sensitive to outliers, I create a variable, *IQR/Median*, which is the interquartile range divided by the median. The interquartile range is calculated as the difference between the 75th percentile and the 25th percentile of a tournament’s prize distribution.

One of the main concerns of tournament organizers is whether the remuneration scheme in place maximizes the effort provided by all teams at all levels of the tournament. To elicit the highest level of effort possible from each team, organizers usually put disproportionately high weight in terms of prize money to the tournament winner. The last two rows of the first panel of Table 13 present two variables that reflect this skewness towards the first place. *1st Pool %* is the ratio of the winner’s prize to the total prize pool, and *1st to 2nd* is the ratio of the winner’s prize to the runner-up’s prize. The winner receives on average about 47% of the pool money with the minimum of 20% and the maximum of 83%. On average, the winner receives twice as much money as the runner-up.

OpponentKills provides information about how many times the players from the opposing team kill champions of the current team. This variable proxies the aggressiveness of the opponent’s strategy in a particular match. *GameMinutes* provides information about the duration of each game. On average, games last about 36 minutes in the Group stage and 35.5 minutes in the Knockout stage. The final sample is comprised of 12,732 game-level observations, with 10,674 and 2,058 observations coming from tournaments’ Group stage and Knockout stage respectively.

Since in the Knockout stage of a tournament the order of teams’ elimination is observed, I am able to construct two additional variables *MarginalWin* and *1st – Current*. Marginal win reflects additional money a team earns if it loses the next round conditionally on winning the current match as opposed to losing the current match. The average amount of marginal win is around \$52,000. The variable *1st – Current* shows additional prize money a team gets if it wins the tournament as opposed to losing the current game. The average value of the variable amounts to \$187,000.

3.5 Results

Table 15 reports the estimates for Equation 6. The coefficient of variation is used as an independent variable of interest in the first four columns of the table. The analysis is conducted separately for Group stage and Knockout stages. Equation specification in the odd columns uses team and opponent fixed effects, and specification in the even columns uses team-year and opponent-year fixed effects. The results presented in columns 1 and 2 show that changes in the coefficient of variation of tournament's prize money does not affect the effort exerted by teams in the Group stage, but it has positive and significant effect in the Knockout stage (columns 3 and 4). If the coefficient of variation increases by one unit then each team, on average, obtains 5 more units of gold in the Knockout stage (in the team-year and opponent-year regression specification). This unit increase is equivalent, for example, for a tournament with \$100,000 pool and 4 prize places, changing prize money distribution scheme from \$50,000, \$25,000, \$15,000, \$10,000 for the first, second, third and fourth place respectively to the \$90,000, \$6,000, \$3,000, \$1,000.

The results suggest that tournament organizers can potentially incentivize teams to exert more effort in the Knockout stage by changing prize structure without increasing prize pool. Moreover, the coefficient estimates on the prize pool variable are not significant with the exception of team-year and opponent-year specification for the Group stage matches. In that case, the effect is negative but very small, a \$1,000,000 increase in the pool money is associated with a 0.5 unit decrease in gold collected by teams in the Group stage.

GameMinutes coefficient is positive and significant across all specifications. On average, one additional minute of a game brings about 1.9 additional units of gold to the teams in part due to the passive gold generation. The number of prize places has a negative effect on teams' effort in the Knockout stage but has no significant effect in the Group stage. Having an additional prize place in a tournament is associated with teams decreasing gold collection by 0.4 units. Holding everything else constant (including the number of participants), if more top-ranked teams receive monetary prizes then all participants have a higher chance to receive a prize. This, in term, leads teams to a decrease in their effort. Usually LoL tournaments are designed in a such way that only the teams qualified to the Knockout stage have a chance to win cash prizes. In the Group stage teams compete for the qualification but not for prizes, therefore variables related to the tournaments' prize structures, such as the coefficient of variation and number of prize places, are most likely to have an effect on effort only in the Knockout stage.

The coefficient on the number of tournament participants variable is positive across all specifications but significant only in some Group stage specifications. Having an additional team participating in a tournament increases competition in the Group stage hence increases the effort level. If an opposing team chooses to

act more aggressively than it makes it harder for a team to obtain gold, therefore the coefficient on the *OpponentKills* variable is negative and significant for all specifications.

Columns 5-8 report estimation results of Equation (6) with a different variable characterizing tournaments' prize structure - first prize as a percentage of the prize pool. Higher value of the variable corresponds to the prize distribution being more skewed towards the winner. The coefficient on the *1stPool%* is not statistically significant for the Group stage, but it is positive and statistically significant at the 5% level in the Knockout stage. Again, in the Groups stage teams are fighting for seeding to the Knockout stage, but once they do, their incentive changes to winning the first prize. As the prize increases (as a share of the pool) teams put forth more effort in winning individual games. Having additional 10% of the pool money allocated to the tournament winner, on average, increases the effort of all teams by about 0.7 units of gold.

Table 14 provides results for some alternative measures of prize distribution skewness. Only Knockout stage estimates are reported¹⁸. Columns 1-2 presents the estimates for interquartile range divided by the median. Similar to the coefficient of variation, it measures dispersion of prize ranks. Since the interquartile range is calculated as a difference between the 75th percentile and the 25th percentile, the variable is less sensitive to outliers - top prize and bottom prize ranks - than the coefficient of variation. The estimate of the coefficient on *IQR/Median* is not statistically different from zero in both specifications.

Skewness of prize distribution measured as *IQR/Median* does not affect on effort. Therefore, the positive effect of the *CV* is most likely driven by the disproportionate amounts of money allocated to the winners. I consider another variable reflecting skewness of prize distribution towards the winner - the ratio of the first prize to the second prize. Columns 3-4 show the results. The coefficients are positive and significant at the 5% level in both specifications. Increasing the ratio by one unit is associated with increase in teams' gold by 0.95 units.

Finally, I test whether monetary incentives to improve teams' current position in the Knockout stage of a tournament affect effort. First, I look at the marginal win - gain in the prize money from winning the current round and losing the next round versus losing the current round. The results are reported in columns 5 and 6. A marginal win of \$1,000 does not have a significant effect on teams' effort. The estimates in columns 7-8 show that monetary gain from winning the tournament versus losing the current match does not affect the gold collected by teams either. Taking all these findings together, there is no evidence that average effort responds to marginal change in prize money corresponding to winning next round in the Knockout stage, rather effort responds to the proportion of tournament pool money allocated to the winner team.

There might be the case that the effort increase in the Knockout stage is driven by some other factors

¹⁸For the upper panel the Group stage estimates are insignificant, for the lower panel the independent variables can only be constructed for the Knockout stage observations

rather than the tournaments’ prize structure. For example, by different average ability of teams qualifying to the Knockout stage in different tournaments. As a robustness check I re-estimate the benchmark specification for the teams in the Group stage which would subsequently qualify to the Knockout stage. This allows to limit the sample by the same teams competing against each other in the Group and the Knockout stages. If teams increase their effort in response to change in the tournament prize distribution, I would expect this effect to be more prominent in the Knockout stage where the teams compete for the prizes, than in the Group Stage where the teams compete for a chance to compete for the prizes.

Table 16 presents the results. The coefficients on both measures of prize distribution skewness - coefficient of variation and first prize as a percentage of the pool - are statistically indistinguishable from zero. For the same teams, prize money distribution does not affect the effort of teams in the Group stage (Table 16), but has a positive effect in the Knockout stage Table 15. Therefore, teams increase their effort in response to prize distributions that are more skewed towards tournament winner only in the Knockout stage where incentives to win the first prize are straightforward, but not in the Group stage where winning the first prize seems somewhere down the line.

3.6 Conclusion

This paper examines the relationship between prize structure and team effort in eSports competitions. Combining detailed data on League of Legends match outcomes for major LoL tournaments from 2015 to 2017 with data on eSports teams’ tournament earnings, I find that prize distribution affects the effort level provided by the teams in the competition. Prize distributions more skewed towards the top ranks are associated with higher average level of effort provided by teams in the Knockout stage of the tournaments. This suggests that individuals/teams can adjust mental effort in response to monetary incentives. Holding skewness of prize distribution constant, the prize pool does not affect the effort provided. The results support tournament theory predictions in non-experimental environment more closely resembling the original “workplace” Rosen and Lazear (1981) setup than “regular sports” studies.

Testing alternative measures of skewness, I find that both, marginal win (difference between the next stage and current prize) and the difference between the first prize and the current prize do not have a significant effect on effort, while “regular sports” empirical studies find positive effects (see Ehrenberg and Bognanno, 1990; Gilsdorf and Sukhatme, 2008). This difference might be possibly explained by mostly mental nature of effort in the eSports competitions. All teams qualified to the Knockout stage might aim not just to proceed to the next round, but to win the first prize, since the cost of mental effort might not increase so sharply with the effort level as does the cost of physical effort - in a eSports tournament there is

a little chance to get an injury even while competing against the favorites.

My findings are subject to at least two limitations. First, I assume that teams are driven only by tournament monetary compensations, which is not necessary the case. Winning a tournament can provide some additional benefits, for example, new sponsorship deals. Second, I assume that teams behave like a single player. There might be cases in which incentives of a player or of a group of players contradict the incentives of the team to maximize the probability to win. The most evident example of this possibility is match-fixing. Preston and Szymanski (2003) describe match-fixing as the situation when one team makes side payments to the opposing team to exert less effort, or situations when players can gain monetary benefits from gambling on the outcome of a competition. Such factors as an exponentially growing betting market (Grove, 2017) and the computerized environment of eSports, allowing easy communications between team players and betting sites stakeholders, make eSports especially susceptible to match-fixing. Considering the tournaments in the sample, they are all major League of Legends event with major prizes which should minimize teams' incentives to cheat.

Finally, the current study is focused on one particular game (League of Legends) and very skilled players. Other games might have different mechanics as well as different social norms. Thus, further research using data from various games and player skill levels is required. The number of eSports tournaments have increased dramatically during the last decade, and more detailed game-level data on team and individual players performance are becoming available. One of the possible direction future research can take is to study the relationship between effort and prize distributions for tournaments with different levels of talent heterogeneity.

Table 13: Summary Statistics

	Obs	Mean	Variance	Min	Max
Tournament-level Data					
Pool	53	426492.2	952471.1	50000	5070000
Teams	53	11.26	5.97	4	29
Prize Places	53	6.98	3.97	2	24
CV	53	0.98	0.299	0.471	1.848
IQR/Median	53	1.238	0.515	0.6	3.5
1st Pool %	53	0.466	0.095	0.2	0.83
1st to 2nd	53	2.083	0.336	1.6	4
Game-level Data					
Group Stage					
Team Gold	10674	63.61	15.47	8.9	153
Opponent Kills	10674	12.64	6.99	0	58
GameMinutes	10674	36.13	7.87	18	80
Knockout Stage					
Team Gold	2058	62.87	14.59	20	134.8
Opponent Kills	2058	13.05	6.98	0	41
GameMinutes	2058	35.61	7.25	20	71
Marginal Win (1000s)	1838	51.60	134.49	0	1267.50
1st - Current (1000s)	1838	187.76	378.69	14	1825.20

Table 15: Results for Coefficient of Variation and First Prize as a Percentage of Prize Pool

	Coefficient of Variation				1st Pool %			
	Group Stage		Knockout Stage		Group Stage		Knockout Stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Measure of Skewness	-1.560 (1.118)	1.149 (1.148)	3.784** (1.579)	5.053*** (1.916)	-1.119 (2.604)	0.468 (2.907)	5.141** (2.453)	6.639** (3.099)
Pool (1000s)	-0.0003 (0.0002)	-0.0005** (0.0002)	0.00004 (0.00027)	0.00015 (0.00032)	-0.0003 (0.0002)	-0.0005** (0.0002)	-0.0001 (0.0003)	-0.00005 (0.0004)
Game Minutes	1.890*** (0.008)	1.894*** (0.008)	1.868*** (0.019)	1.872*** (0.020)	1.890*** (0.008)	1.894*** (0.008)	1.869*** (0.019)	1.871*** (0.020)
Prize Places	0.080 (0.072)	-0.084 (0.092)	-0.351*** (0.121)	-0.448*** (0.147)	-0.015 (0.054)	-0.007 (0.063)	-0.041 (0.079)	-0.030 (0.099)
Teams	0.083 (0.051)	0.180*** (0.037)	0.041 (0.039)	0.059 (0.047)	0.096* (0.049)	0.172*** (0.037)	0.015 (0.032)	0.030 (0.040)
Opponent Kills	-0.513*** (0.009)	-0.512*** (0.009)	-0.534*** (0.020)	-0.548*** (0.020)	-0.513*** (0.009)	-0.511*** (0.009)	-0.533*** (0.020)	-0.546*** (0.020)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	No	Yes	No	Yes	No	Yes	No
Opponent FE	No	No	Yes	No	Yes	No	Yes	No
Team-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Opponent-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,674	10,674	2,058	2,058	10,674	10,674	2,058	2,058
R-squared	0.881	0.887	0.870	0.879	0.881	0.887	0.869	0.878

Note: The dependent variable is the amount of gold collected by a team
Robust standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.10

Table 14: Results for Alternative Measures of Prize Distribution Skewness

	IQR/Median		1st/2nd	
	(1)	(2)	(3)	(4)
Measure of Skewness	-0.055	0.459	0.796**	0.952**
	(0.357)	(0.474)	(0.315)	(0.372)
Observations	2,058	2,058	2,058	2,058
R-squared	0.869	0.878	0.870	0.879
	Marginal Win		First - Current	
	(5)	(6)	(7)	(8)
Measure of Skewness	-0.001	-0.001	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.003)
Observations	1,838	1,838	1,838	1,838
R-squared	0.884	0.895	0.884	0.895
Year FE	Yes	Yes	Yes	Yes
Team FE	No	No	No	No
Opponent FE	No	No	No	No
Team Year FE	Yes	Yes	Yes	Yes
Team Opponent FE	Yes	Yes	Yes	Yes

Note: The dependent variable is the amount of gold collected by a team.

Knockout stage only. Robust standard errors in parentheses,

*** p<0.01, ** p<0.05, * p<0.10

Table 16: Results for the Teams that (post factum) Proceeded to Knockout Stage

	Coefficient of Variation		1st Prize as Pool %	
	(1)	(2)	(3)	(4)
Measure of Skewness	1.000	3.097	2.949	5.110
	(2.188)	(2.915)	(2.991)	(4.972)
Pool (1000s)	-0.0004	-0.0005**	-0.0005	-0.0010***
	(0.0005)	(0.0002)	(0.0005)	(0.0003)
Game Minutes	1.898***	1.900***	1.898***	1.900***
	(0.019)	(0.020)	(0.019)	(0.021)
Prize Places	-0.047	-0.609	0.091	0.365
	(0.266)	(0.309)	(0.192)	(0.175)
Teams	0.091	0.232	0.066	-0.059
	(0.196)	(0.205)	(0.165)	(0.172)
RedKills	-0.556***	-0.565***	-0.556***	-0.564***
	(0.012)	(0.013)	(0.013)	(0.013)
Year FE	Yes	Yes	Yes	Yes
Team FE	Yes	No	Yes	No
Opponent FE	Yes	No	Yes	No
Team-Year FE	No	Yes	No	Yes
Opponent-Year FE	No	Yes	No	Yes
Observations	3,119	3,119	3,119	3,119
R-squared	0.871	0.878	0.871	0.878

Note: The dependent variable is the amount of gold collected by a team.

Group stage only. Robust standard errors in parentheses,

*** p<0.01, ** p<0.05, * p<0.10

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