

Incentives in Professional Tennis: Tournament Theory and Intangible Factors

Joshua Farrel Silverman

Steven Everett Seidel

Professor Marjorie B. McElroy

Professor Curtis R. Taylor

*Honors Thesis submitted in partial fulfillment of the requirements for Graduation with
Distinction in Economics in Trinity College of Duke University*

Duke University
Durham, North Carolina
2011

Acknowledgements:

We would like to thank Professor Marjorie McElroy, conductor of our thesis seminar, for her endless support and encouragement throughout the thesis-writing process. We would also like to thank Professor Curtis Taylor, our advisor, and our peers, Becky Agostino and Kathryn Li for their continued feedback throughout the past two semesters.

Abstract:

This paper analyzes the incentives of professional tennis players in a tournament setting, as a proxy for workers in a firm. Previous studies have asserted that workers exert more effort when monetary incentives are increased, and that effort is maximized when marginal pay dispersion varies directly with position in the firm. We test these two tenets of tournament theory using a new data set, and also test whether other “intangible factors,” such as firm pride or loyalty, drive labor effort incentives. To do this, we analyze the factors that incentivize tennis players to exert maximal effort in two different settings, tournaments with monetary incentives (Grand Slams) and tournaments without monetary incentives (the Davis Cup), and compare the results. We find that effort exertion increases with greater monetary incentive, and that certain intangible factors can often have an effect on player incentives.

JEL Classification: J31; J33; L83

Keywords: Tournament Theory; Compensation; Sports

I. Introduction

Over the past 30 years, there has been growing interest in the economic community concerning effort maximization and the manner by which agents react to differing payoff matrices. Tournament theory, developed by Sherwin Rosen (1986), asserts that given an ideal pay dispersion scheme, compensation based on position in the firm can be just as effective as compensation based on output. While agents do not see a direct increase in compensation from each extra unit of output, they are driven by the possibility of promotion to a higher position, and, thus, an increase in pay. A new field has emerged in which economists have begun to use individual sporting events to simulate the labor market. As a proxy for workers in a firm, this paper uses ATP tennis players in both Grand Slam and Davis Cup matches. Controlling for ability, we are able to analyze incentives in both settings, which differ due to the presences or absence of monetary reward (tournament prize money). What factors motivate players most, and how do these factors affect players differently in Grand Slam and Davis Cup settings?

In the labor market, firms constantly face a maximization problem in which they attempt to maximize the effectiveness of their human capital, given a fixed compensation purse. The two most common methods of payment include “piece rate” compensation, or compensation in the form of a commission, and “salary” compensation (Lazear and Rosen, 1981). Piece rate compensation relies solely on the productivity of each individual worker to determine total payment figures, while salary-based compensation relies on the relative position of each individual in the firm. Piece rate compensation may appear to be the option that is most advantageous to the firm as it directly promotes effort maximization, but monitoring output can be a costly endeavor (Lazear and Rosen, 1981). Thus, given a fixed human capital purse, firms also face a cost minimization problem that impacts how much of the purse is available for direct

compensation. In reality, most compensation systems utilize a combination of salary and piece rate pay (ie. a base salary plus a yearly productivity-based bonus). Unfortunately, in practice, it is extremely difficult to measure the effort of an employee and thus the efficiency of a firm's pay structure.

Using sporting events to simulate the labor market works surprisingly well. Sporting events are closed system competitive events with distinct payoff matrices. In each event, players compete directly for the top prize. Players are compensated completely based on the final position that they attain in a tournament – there is no attempt to measure each player's level of individual productivity - all that matters is whether or not each player advances to the next round. Thus, by measuring the relative performance of athletes in different events and keeping track of the differing compensation schemes inherently present in these events, we can make conclusions about the amount of effort agents will exert based on different marginal payoffs. These conclusions allow us to better construct ideal pay dispersion schemes in the labor market. Among other factors to be discussed later, the structure of information in tennis tournaments makes tennis a logical choice for this study. The Grand Slam data set will be used to measure the effectiveness of tournament-style pay dispersion schemes in promoting effort maximization.

Contrary to Rosen's tournament theory, Milgrom and Roberts (1984) posed that there are certain social aspects that affect effort, suggesting that compressed pay structures at higher levels of a firm allow executives to work as a team, thus promoting firm productivity. This idea of "equity fairness" contradicts the increased marginal payoffs recommended by tournament theorists. In an attempt to measure the efforts of players that do not receive extra payment from promotion, we look at a situation in which players compete for no monetary reward: the Davis cup. Davis cup is an international team tennis tournament with a similar structure as the

Olympics. The Olympics, however, is somewhat complicated by the fact that for some sports (such as swimming and track), it is considered the ultimate tournament, and can, therefore, lead to considerable future monetary reward. However, because tennis is an inherently international sport, the Davis Cup bears far less weight in the tennis world than international competition bears in most other sports. Using the Davis Cup data set, we measure the amount of effort exerted by players when no monetary compensation is offered and we determine whether intangible factors, such as national pride, affect player performance. Applying this theory to firms, we can say that in the case of a corporation, national pride is analogous to franchise loyalty, which can greatly impact the degree of effort exertion in the workplace.

Finally, our combined data set compares the effect of monetary incentives and intangible factors on overall effort of players in the two different settings. We use this data set to compare whether players react to certain incentivizing factors differently in Grand Slam and Davis Cup settings.

The next section gives background information on the ATP, Grand Slam tournaments, and the Davis Cup. Section III discusses relevant literature on tournament theory and empirical evidence found in firms, tennis, and other sports. Section IV introduces our theoretical framework. Section V presents the data and Section VI discusses empirical specifications. In Section VII we mention our results and analyze their implications. In Section VIII, we draw conclusions and offer our thoughts on future research opportunities in the field.

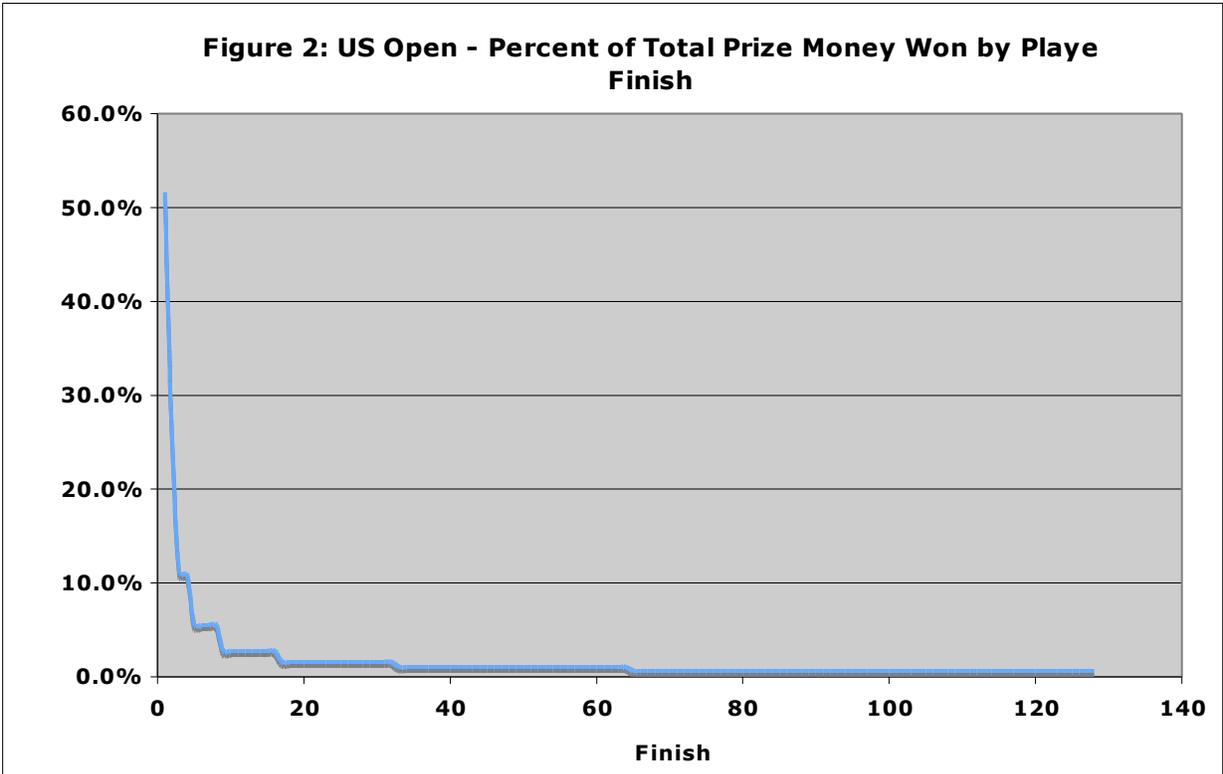
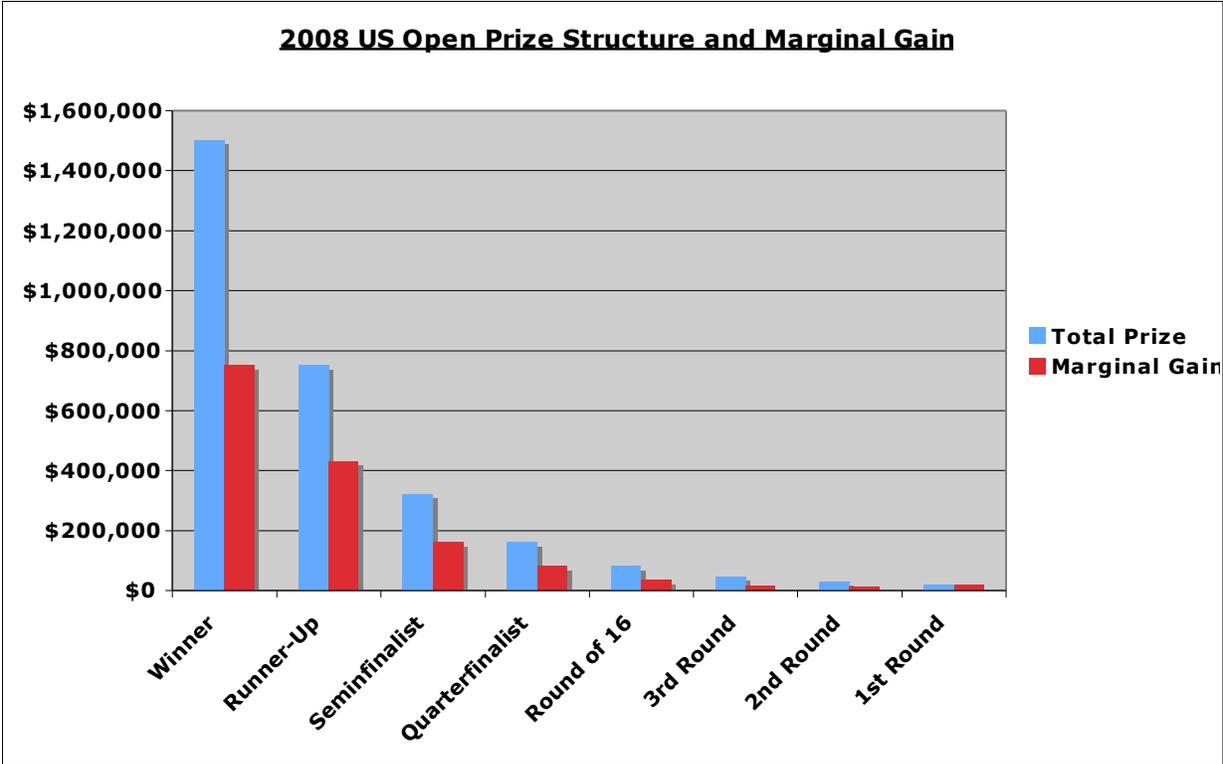
II. Background Information

i.) Grand Slams and the ATP Tour

The Association of Tennis Professionals (ATP), formed in 1972, is the official organizer of the men's worldwide tennis tour. As of 2010, the ATP tour consists of 62 tournaments, in 32 countries, on 6 continents, around the world. Tournaments range in size from 32 to 128 competitors. In each tournament, players compete for both monetary prizes and for ATP points, which determine a player's ATP ranking. Higher ranked players automatically qualify to participate in higher profile (and higher paying) tournaments, and may even be given a seed, which gives them a preferable draw position and, thus, increased opportunities to win more money and points. Lower ranked players must often succeed in a qualifier round if they wish to participate in ATP tournaments.

The four biggest ATP tournaments in terms of field size, total payout, and total points awarded are the grand slams – The Australian Open, Roland Garros (The French Open), Wimbledon, and the U.S. Open. Each grand slam event consists of 128 total players, 32 of which are seeded. The payouts and total points awarded by each tournament are decided on a year-to-year basis. In 2008, the U.S. Open awarded a total of \$2,904,500. Payouts are awarded on a sliding scale, where the prizes (and thus the marginal payouts) roughly double from round to round. Points are similarly awarded on a sliding scale, with marginal payouts increasing in each round¹. These reward schemes align with tournament theory and Rosen's claim that the higher someone's position, the larger his marginal rewards. Figure 1 shows prize structure and marginal gains for the 2008 U.S. Open. Figure 2 shows the distribution of the total purse for the 2008 US Open by ending tournament position.

¹ Marginal ATP point increases do not increase as drastically as marginal \$ by round.



ii.) Davis Cup

The Davis Cup is a men's international team tennis tournament where each country is represented by a national team. The top 16 teams in the world (based on performance in the previous year's Davis Cup) are assigned to the World Group and compete in a one-loss elimination draw. Each "tie", or match-up between two countries consists of 5 total matches – 4 singles and 1 doubles. The country that wins 3 or more matches is considered the winner of the tie, and advances on to the next round. Unlike ATP tournaments, which have set locations, Davis Cup matches are hosted by one of the countries participating in the match on an alternating basis. In addition, each World Group team that loses in the first round must compete in a "play-off" round against a winning team from one of the lower groups to decide which of the two teams will compete in the World Group in the next year. Thus, teams in lower groups are incentivized to do well so that they can move up to the World Group and be given the opportunity to compete for the Davis Cup, while teams in the World Group are incentivized to win so that they do not move down to a lower group (*Davis Cup*, 2011).

Despite their individual match play (within the team setting), participants in the Davis Cup receive no monetary compensation for victories, and only began receiving minimal ATP points in 2009. On top of this, players risk injury and fatigue throughout tournament season, as Davis cup rounds are held sporadically throughout the fall and into the winter months. This element has famously persuaded some major players, including Roger Federer, to stop participating in the Davis cup due to fear that it may negatively impact their performance in tournaments that award money. While this phenomenon would likely only affect top players such as Federer, who is more concerned with breaking world records than winning Davis Cup matches, the choice of players not to participate in Davis Cup at all (due to lack of monetary

incentive) is certainly something that should be considered in our study (*Telegraph*, 2010).

Unfortunately, we have no way of estimating how many other players were asked to participate and declined, and, thus, not enough data to factor in this kind of information.

III. Literature Review

i.) General Theory

The base theoretical framework for this paper comes from two papers, written by Lazear and Rosen (1981), Nalebuff and Stiglitz (1984), and an important expansion by Rosen (1986). In the first paper, Lazear and Rosen established the idea of tournament theory. They asserted that by compensating workers on the basis of their relative position in the firm, one can produce the same incentive structure for risk-neutral workers that the optimal piece rate produces. Due to the costly nature of monitoring outputs (or inputs), they maintained that all things equal, a firm would rather compensate based on relative position than via observation of individual production levels.

Nalebuff and Stiglitz (1984) analyzed the role of competitive compensation schemes on performance and work incentives. They asserted that the use of contests as an incentive device can induce agents to abandon their natural risk aversion and adopt riskier, more profitable production techniques. They concluded that individualistic pay schemes (ie. piece rate) are inferior to schemes that base compensation on relative performance, because people will generally work harder to avoid being a “loser” than they will work to become a “winner”. In a piece rate scheme, everyone can work hard and do well. However, when agents are competing with their peers for a fixed purse, they will do what they must to avoid coming in last place.

Nalebuff and Stiglitz suggested that the use of competitive compensation schemes seems less widespread than their advantages would suggest, as a result of social considerations (ie. work environment) that most labor economists ignore.

Rosen (1986) expanded upon his previous tournament theory model, delving deeper into the structure of tournaments, and claiming that the prizes in a tournament must be disproportionately large in the final rounds. If this were not the case, higher ranked contestants would “rest on their laurels” and exert less effort once they reached a certain level of pay. Rosen contended that the main goals of a tournament are to determine the best contestants via survival of the fittest and to maintain the quality of play throughout the tournament. He also established the idea of “option value” in tournaments, in which players compare the amount they are guaranteed to win at a certain point with the marginal gain from winning the next round. Additionally, he said that players take into account the quality of the pool of participants in which they are competing to determine their level of effort exertion. Through these ideas, he created a model to be outlined in section IV, through which we can understand the creation of efficient tournaments in various contexts.

ii.) Empirical Evidence – Firms

Main, O’Reilly and Wade (1993) applied the concepts above to firm hierarchy in corporate America. By looking at a data set consisting of over 200 firms and over 2,000 corporate executives, over a five-year period, they attempted to rectify two competing claims. The first claim, associated with the idea of “tournament theory,” as evidenced by the literature above, suggests that firms should purposefully differentiate executive pay packages the most at the highest levels so that said executives are incentivized to continue exerting effort. The second claim, associated with the idea of “equity fairness”, argues that a compressed executive salary

structure may be the most efficient, as this promotes teamwork and rids the upper-management of excessive intra-office politics. Ultimately, Main et al. is partial to the former claim, arguing that the best way to promote the exertion of effort is through frequent raises and promotions for productive agents, as opposed to large, one-time-only rewards. They also suggest the idea that there may be other social factors that affect executive motivation, but do not attempt to explore this claim.

Similarly, Lee, Lev and Yeo (2007) tested for the relationship between firm performance and pay dispersion, using a simple linear regression in which Tobin's Q serves as the dependent variable.² Their results emphatically support the idea that increased pay dispersion improves firm performance, and disprove the idea of equity fairness. They noted that firms with higher pay dispersion have significantly higher Tobin's Qs, stock returns, and ROA's.³ They also noted that pay dispersion can be particularly effective in firms with high agency costs and effective corporate governance structures.

iii.) Empirical Evidence- Sports Other than Tennis

Using a data set from the 1987 European Men's PGA Tour, Ehrenberg and Bognanno (1990) attempted to determine whether increased prize money in later rounds and in general, have any effect on the overall score of professional golfers. Ehrenberg and Bognanno constructed a linear model with final score as the dependent variable. They found that players' performance varied directly with both total monetary prizes awarded in the tournament, and the proportion of money awarded in the final rounds of the tournament. This result strongly supports tournament theory's hypothesis that agents will increase effort in a contest when marginal

² Tobin's Q = (Equity Market Value + Liabilities Book Value) / (Equity Book Value + Liabilities Book Value)

³ROA (Return on Assets) = Net Income/Total Assets

payoffs increase in later rounds. It is important to note that while Ehrenberg and Bognanno were able to use final score as their dependent variable, this applies less in tennis. While golf scores are absolute individual measures with obvious meaning, tennis scores are relative measures that incorporate the efforts and abilities of both players, and can be much more difficult to decipher.

Similarly, Becker and Huselid (1992) tested the tournament theory hypothesis on a data set of 44 NASCAR drivers competing in 28 of the 29 races held in 1990. Using driver's finish as their dependent variable, they concluded that higher spreads result in significantly faster times, yet again confirming tournament theory's predictions. Interestingly, Becker and Huselid also found that increased pay dispersion results in increasingly reckless driver behavior. This confirms Nalebuff and Stiglitz's previous theory that agents will adopt riskier techniques as the payoff spread increases.

iv.) Empirical Evidence - Tennis

In one of the first studies to apply professional tennis data to tournament theory, Uwe Sunde (2003) tested that higher levels of heterogeneity (tournament contestants of different abilities) lead to lower effort exertion, and that more tournament prize money leads to higher effort exertion. Tennis tournaments perfectly model the setting of a two-person tournament, and both the incentive and capability effects can be isolated due to the absence of issues such as collusion and sabotage, which are generally present in tournaments with many contestants. The difference between the incentive and capability hypotheses is that according to the capability hypothesis, underdogs perform worse because of weaker ability and not because they are less motivated to put forth increased effort. Sunde used data from 156 male's singles tournaments between 1990 and 2002. For each tournament and year, data was compiled from the semifinals and finals (last two rounds) of each tournament in order to rule out selection issues in seeding

practices and to ensure that there was random variation in relative contestant ability. Using number of games played during the match as a proxy for effort, Sunde utilized a linear specification and concluded that a contestant's ranking before the match, through both capability and incentive effects, influences number of games won in a match. He found that while both effects reinforce each other for underdogs, they work against each other for favorites. He also concluded that monetary incentives had a significant effect on effort, a finding consistent with tournament theory; the incentive effect outweighs the capability effect.

In his 2007 paper, Ivankovic (2007) used data from the ATP Tour to investigate the marginal pay spreads in professional tennis tournaments and their effect on the efforts of players in the tournament. As a proxy for effort, he used a variety of dependent variables, but chose total time of match as the main variable. This means that controlling for the ability of the players and other factors, the longer the match lasts, the harder the players must be trying. He then measured the correlation between time and interranks spread (marginal reward from advancement), controlling for player rankings, the surface, and the format of the match (ie. 2 out of 3 sets or 3 out of 5 sets). Ivankovic found that time was significant and positively correlated with the spread. This suggests that the more monetary reward that players stand to gain from advancing to the next round, the more effort they will put forth in the match.

In 2008, Glisdorf and Sukhatme analyzed a data set of 58 tournaments (2098 matches) held during the 2004 Women's Tennis Association (WTA) Tour. Drawing from Rosen's theoretical model, Glisdorf and Sukhatme utilized a probit model that estimates the probability that the better-ranked player will win, controlling for player ability and other factors. They find that the larger the prize differential, the more likely it is that the higher ranked player wins the

match. This suggests that larger prize differentials motivate stronger players to work harder, despite their believed superior ability prior to the start of the match.

Lallemand, Plasman, and Rycx (2008) examined how players react to prize incentives and heterogeneity in player ability, using a method quite similar to Sunde (2003). Data, though, comes from the final two rounds of all WTA tournaments between 2002 and 2004. Results are consistent with Sunde's study and tournament theory, but lead to the conclusion that the final outcome of a match is more linked to player ability than player incentive. The difference in the number of games won by the favorite and the underdog increases with player ranking differential.

IV. Theoretical Framework

As mentioned earlier, Rosen (1986) developed a sequential elimination tournament model that was used to explain why compensation is highly skewed toward a corporation's upper management. Previous literature indicates that players' effort, particularly in individualistic sports, depends on prize structure and heterogeneity in player ability.

In every tournament, losers are eliminated, while winners move on with the opportunity to continue competing for future reward. Each tournament begins with 2^N players and consists of N stages. Therefore, the player that wins N matches overall is awarded the top prize (W_1) for his efforts. The loser in the finals receives prize W_2 for making it through $N - 1$ matches, while both semifinal losers are awarded prize W_3 . If s is defined as the number of stages remaining, then all players eliminated with s stages remaining are awarded a prize W_{s+1} . The marginal reward for

advancing one round in the tournament is referred to as the interranks spread and is defined as

$$\Delta W_s = W_s - W_{s+1}.$$

The connection between prize structure and incentives can best be studied by specifying how a player's actions affects his probability of winning, $Pr_s(I, J)$. Probability of winning is based on both effort and ability, and can be defined for player I against player J as follows:

$$Pr_s(I, J) = \frac{\gamma_I h(x_{si})}{\gamma_I h(x_{si}) + \gamma_J h(x_{sj})}^4$$

where γ_I and γ_J represent ability levels of player I and J respectively, and x_{si} and x_{sj} represent effort levels of player I and J . Given the ability level of a player's opponent, and that both one's own ability level and the ability level of his opponent are fixed in a given match, a player can increase the probability of winning a match by exerting more effort. The decision concerning how much effort to exert depends on the benefit to greater effort (affiliated with the probability of advancing to the next round of a tournament) and the costs associated with exerting that effort.

Player I must determine the effort level (x_s) that maximizes the value (V_s) of playing in a match with s possible rounds remaining. This depends on the expected value of playing in later rounds of the tournament (EV_{s-1}), the probability of winning the current match (Pr_s), the loser's prize (W_{s+1}), and the player's cost of effort ($c(x_s)$)⁵. The objective function for player I meeting player J can be stated as:

$$V_s(I, J) = \max[\Pr_s(I, J)EV_{s-1}(I) + (1 - \Pr_s(I, J)W_{s+1} - c(x_{si})]$$

Cost of effort per match is assumed to be the same for all players. Differentiating with respect to x_{si} yields a first-order condition which shows that effort in a match depends on ($EV_{s-1}(I) - W_{s+1}$) (Glisdorf and Sukhatme, 2008). EV_{s-1} is a weighted average over J of $V_{s-1}(I, J)$, where

⁴ $h(x)$ is increasing in x and $h(0) \geq 0$.

⁵ $c'(x) > 0$, $c''(x) \geq 0$, $c(0) = 0$

the weights are the probabilities that player I meets and wins a match against players of type J in future stages. Thus, effort depends on both ability and incentives. The question then becomes, which effect is more pronounced?

In our study, we propose that in addition to monetary incentives, certain intangible factors play an important role in determining a player's effort and, thus, his probability of winning a match (Pr_F):

$$Pr_F = f((A_F, A_U, A_{RO}), \Delta W_s, INT)$$

where A_F , A_U , and A_{RO} represent the ability of the favorite, underdog, and remaining opponents in the tournament, and INT represents intangible factors. In section VI, we will discuss more specifically which intangible factors pertain to the ATP tournament model.

Our empirical specification assumes that the underlying model accounts for a tournament consisting of heterogeneous contestants with known ability levels. Survival of the fittest and the elimination of weaker participants lead to increased homogeneity among surviving members. It is implied that stronger players have a larger value of continuation at any stage s , and for any increase in interranks spread, favorites experience a greater value of continuation. As mentioned earlier, two contrasting hypotheses attempt to account for differing effort levels, given varying levels of heterogeneity. The incentive hypothesis says that both players will exert less effort in uneven matches because they have unequal chances of winning. The capability hypothesis says that larger heterogeneity leads the favorite to win more matches than the underdog, strictly due to stronger ability (Glisdorf and Sukhatme, 2008). The difference between the two hypotheses is that according to the incentive hypothesis, underdogs perform worse because they are less motivated by prize, whereas according to the capability hypothesis, they perform worse because of weaker talent (Lallemand et al., 2008).

V. Data and Variables

The data used in this study for the purposes of empirical analysis can be divided into three separate categories – Grand Slam data, Davis Cup data and combined data. The Grand Slam data set contains information and statistics from every match played in each of the four Grand Slam tournaments from 2005 to 2008. The Davis Cup data set contains similar information and statistics from every World Group match played from 2005 to 2010. The combined data set is merely an aggregation of the first two data sets. Tables 2-4 display summary statistics for the three data sets. Each of the observations in each of the three data sets is player-specific. In other words, each unit of observation pertains to a particular player in a given match at a given event (Grand Slam tournament or Davis Cup) in a given year.

The Grand Slam data set is built off of a data set used by Corral and Prieto-Rodriguez (2010). Before creating our player-specific data set, our original set contained 4,318 match-level observations including all men's and women's Grand Slam matches from 2005 to 2008, and matches from the 2009 Australian open.⁶ As women's tennis is beyond the scope of this study, all WTA matches were removed from the data set, reducing it to 2,159 total observations. Similarly, in order to ensure that we could study each year and all four of the grand slam tournaments equally, the matches recorded in 2009 were deleted. From an initial 2032 observations from 2005 to 2008, we removed 86 matches that contained players who retired during the match so as to ensure that this would not skew our final results. Using the data set as our base, we added many of the variables pertinent to our study, including *Countryrank(Diff)*, *Region*, *Home*, *Win*, *Gmswon*, *Games*, *Time*, and all measures of prize incentive. Finally, we took the data set and divided each match into two player-specific observations, resulting in 3,892

⁶ Match-level data consist of units of observation pertaining to an entire match, not just one of the two players in a match

total units of observations. Table 1 contains a summary of the variables presented in the Grand Slam data set.

We compiled the Davis Cup data set from scratch, using information from scorecards provided by the International Tennis Federation (ITF). In full, the original data set contained 460 match-specific observations. We then scrubbed it in a method similar to the Grand Slam data set, removing 7 observations containing players who retired during the match, and 10 observations due to insufficient information. The data was then split into player-specific observations, resulting in 886 total data points. Finally, we aggregated the two data sets to create the combined data set, which contains 4,778 player-specific observations.

There are two main weaknesses of our data sets. The first is that approximately 81% of units of observation in the combined data set are from Grand Slam tournaments (Table 4). This is because only 60 World Group Davis Cup matches are played each year, in addition to 32 World Group playoff matches. Additionally, all of our ATP data is taken from Grand Slam tournaments, which tend to have similar participants, similar payout structures, and similar total purses. This makes it difficult to determine the effect of monetary reward on player incentive.

While Table 1 contains a list of variables relevant to our study, certain variables require further explanation. Past papers have used a variety of variables to simulate the reward incentives that tennis players experience in each round of a tournament. Sunde (2003), for example, used two different measures – the total amount of money in the tournament and the marginal payout, or the prize money gained by a player for winning their current round. We choose not to use total prize money in our study because while Sunde’s analysis incorporated ATP tournaments of differing size and importance and, thus, extremely varied total payouts, we only analyzed the four Grand Slams – whose payouts are typically very similar to one another.

We did, however, choose to incorporate Sunde's second measure, the winner's marginal prize or *PzDiff* as our first gauge of monetary incentive. This is equivalent to the total prize money a player would be awarded by advancing to the next round minus the total prize money he would be awarded if he were to lose in the current round. Expanding upon this measure, we then use a *PzSpread* variable found in Ivankovic (2007), which takes into account not only the most immediate reward, but also future possible rewards from advancement discounted to the present. Ivankovic borrowed from Rosen's theoretical model, by incorporating the probability that a player wins a given match, allowing him to predict the magnitude of a player's monetary incentives in any given round. If M_i were the loser's prize, or the aggregate amount of money made by the player who loses in round s , then player i 's *PzSpread* would be:

$$PzSpread = (M_{s+1}-M_s) + .5(M_{s+2}-M_{s+1}) + .5^2(M_{s+3}-M_{s+2}) + .5^3(M_{s+4}-M_{s+3}) + \dots + .5^{n-1}(M_{n+1}-M_n)$$

where n is the total number of rounds.⁷ Thus, the *PzSpread* for any player currently in the first round of a seven round tournament (ie. Grand Slam) would be $(M_2-M_1) + .5(M_3-M_2) + .5^2(M_4-M_3) + .5^3(M_5-M_4) + .5^4(M_6-M_5) + .5^5(M_7-M_6) + .5^6(M_8-M_7)$ where M_8 is the total prize money won by the victor of the entire tournament. Similarly, the *PzSpread* for a player in the quarterfinals (fifth round) of a seven round tournament would be $(M_6-M_5) + .5(M_7-M_6) + .5^2(M_8-M_7)$. Even though we are dealing with heterogeneous players, Ivankovic used .5 consistently as the probability that a player wins, because he claimed that while the probabilities might vary from match to match, over the course of the tournament they would average out.

We expand upon Ivankovic's *PzSpread* variable to create a new variable, *PzExpec*, using a similar concept of expected future reward, discounted back to the present. However, rather than using a consistent probability of 50%, we use a probability of 70% if the player is expected

⁷ Note that Rosen (1986) uses s to represent number of rounds left in our theoretical model in section IV. Here, s represents current round for simplicity's sake.

to be a favorite in a given round and 30% if they are expected to be an underdog. These probabilities come from both our data sets, which predict that the favored player will win 72% of the time in both Grand Slams and the Davis cup, and from those of Glisdorf and Sukhatme (2008), which predicted that the favored player will win somewhere between 61.9% - 73.9% of the time, depending on the marginal prize of the match. As these are Grand Slams, which typically have larger payouts, we felt that 70% was a fair, round estimate. However, because tournament draws are unpredictable, it is impossible for a player to know exactly who he will be playing in future rounds. Thus, we instead utilize each player's seed (or lack thereof) to determine the round in which he becomes an underdog. For example, assuming that all seeds advance as they are supposed to (which is rarely the case) the 4th seed in any Grand Slam should win ($Pr = .7$) until he reaches the semifinals (sixth round) where he should lose to either the 1 or the 2 seed ($Pr = .3$), depending on the structure of the tournament. Thus, again drawing from Rosen, a general formula for $PzExpec$ would be:

$$PzExpec_s(I) = (M_{s+1} - M_s) + Pr_s(I) * (M_{s+2} - M_{s+1}) + Pr_s(I) * Pr_{s+1}(I) * (M_{s+3} - M_{s+2}) + Pr_s(I) * Pr_{s+1}(I) * Pr_{s+2}(I) * (M_{s+4} - M_{s+3}) + \dots Pr_w(I)^{m-q-1} * Pr_l(I)^{n-m-q} * Pr_e(I)^q * (M_{n+1} - M_n)$$

where $Pr_s(I)$ is the probability that player I wins in round s , Pr_w is the probability that a favored player wins (.7), Pr_l is the probability that an underdog wins (.3), and Pr_e is the probability that a player wins an even match (.5), n is the total number of rounds, m is the number of rounds in which player I is expected to compete based on seed, and q is the number of rounds in which player I is evenly matched. The only time that a player would be evenly matched in a Grand Slam, is when a non-seeded player plays another non-seeded player in the first round, in which case $q = 1$ and we give the player the benefit of the doubt and assume that he will compete in $m = 2$ rounds.

It is important to note that the cumulative probability figure represents the probability that the player will have the opportunity to compete for the prize attached to that round – not the probability that he will win that round. For example, every player has a probability of $Pr = 1$ of competing for the prize awarded to players who win the first round and advance to the second round, but an unseeded player who is playing a seeded player in the first round would only have a $Pr = .3$ chance of competing for the prize awarded to players who advance to the third round, and a $Pr = .3 * .3 = .09$ of competing for the prize awarded to players who advance to the fourth round. To simulate the example used for *PzSpread*, the *PzExpec* of the fifth seeded player in a seven round tournament would be: $(M_2 - M_1) + .7(M_3 - M_2) + .7^2(M_4 - M_3) + .7^3(M_5 - M_4) + .7^4(M_6 - M_5) + .3 * .7^4(M_7 - M_6) + .3^2 * .7^4(M_8 - M_7)$, and the same player's *PzExpec* in the quarterfinals would be $(M_6 - M_5) + .3(M_7 - M_6) + .3^2(M_8 - M_7)$.

This method has some weaknesses. In particular, the 1st and 2nd seeds in every tournament have the exact same *PzSpread* throughout because they both have the opportunity to compete in every round. In actuality, however, this might not be that unreasonable, considering that the top two seeds both have a legitimate shot to win the whole tournament. Similarly, seeds 3-4 are expected to compete for all but the winner's prize, seeds 5-16 up to the runner up's prize and seeds 17-32 up to the semifinalist's prize. Unseeded players are expected to compete for all rewards until the third or fourth round, depending on whether or not they play a seed in the first round. Additionally, because of the way Grand Slam prize schemes are structured, this method indicates that players may have larger overall monetary incentives to win in the quarterfinals and semifinals than in the actual final. Again, because of the option value of future winnings at different stages of the tournament, reflected by the *PzExpec* variable, this might not be completely unreasonable. Nonetheless, this variable provides an improved measure of prize

expectations by incorporating realistic (albeit generalized) probabilities that a player might reach a given round.

The variable *Rankdiff* measures the difference in ATP rank of a player and his opponent.⁸ For Grand Slam matches, this value is measured at the time of the tournament, while for Davis Cup matches, it is measured at the start of the Davis Cup year (or more accurately, the final rankings of the previous year). *Rankdiff* is used as a control variable, in order to separate out the capability effect from the incentive effect that we are trying to measure. It is calculated as a given player's rank minus that of his opponent – thus, it is negative for favorites and positive for underdogs. $Rankdiff^2$ is also included to incorporate the possibility that the effort depends on rank difference quadratically, where the magnitude of rank difference is taken into account, but the direction is not. Rosen argues that both underdogs and favorites try harder when the absolute value of rank difference is minimized, and less when it is maximized. The quadratic term tests the possibility that this relationship is more exaggerated than a simple linear model would suggest.

Our “intangible” variables include *Home*, *Countryrankdiff*, *Region*, and *Country*. *Home* is a simple dummy variable that equals 1 if the player is playing in his home country. *Countryrankdiff* measures the ITF rank of the country from which the player hails, minus the ITF rank of his opponent's country. *Region* is a series of dummy variables for the region from which a player hails. Regions were grouped by geographic and cultural boundaries. *Country* is a fixed effects estimator that specifies a player's home country.

⁸ Player's Rank – Opponent's Rank

VI. Empirical Specifications

The intuition for the empirical model comes from Rosen's theoretical framework concerning two-player elimination tournaments with heterogeneous players, and our expansion into intangible variables as presented previously. Tennis presents a perfect application of this model, as it provides two heterogeneous players with differing capabilities and incentives just as Rosen's framework describes. By including the ATP's estimation of heterogeneity into our model we can separate out the capability effect from the rest of the equation and, thus, analyze what factors most noticeably drive player incentives. This study uses two different empirical specifications: an ordinary least squares specification and a probit specification. Each of these specifications is applied to each of the three data sets (Grand Slam, Davis Cup, combined), ultimately producing six sets of regression analyses. The first iteration of the OLS specification alters Sunde's model intended to measure the effect of increased prize money on a player's effort (2003). Specifically:

$$E_{ijm} = \alpha_0 + \alpha_1 HET_{ijm} + \alpha_2 PRIZE_{ijm} + \alpha_3 X_j + \alpha_4 Y_m + \alpha_5 Z_i + \varepsilon_{ijm}$$

where the dependent variable, E_{ijm} , represents the effort exerted by player i in match m of tournament j , HET_{ijm} is a measurement of the heterogeneity or difference in capability between the two players, $PRIZE_{ijm}$ estimates the monetary incentive of player i in a given match, X_j represents a series of tournament-specific characteristics, Y_m represents a series of match-specific characteristics and Z_i represents a series of player-specific characteristics.

In this model, we estimate heterogeneity using *RankDiff* as provided by the ATP tour. As a measurement of monetary incentive, or prize, we use each of the three prize variables described in section V, specifically *PzDiff*, *PzSpread*, and *PzExpec*. Tournament-specific characteristics include fixed effects estimators for *Year* and *Surface*. We chose not to include a fixed effects

estimator for tournament, as this variable exhibited too much multicollinearity with *Surface* in the Grand Slam setting (4 Grand Slams, 3 Surfaces). Match-specific characteristics are estimated by a fixed effects estimator for *Round*. Finally, we estimate player-specific characteristics using a fixed effects estimator for *Surname*. This takes into account all of the minute differences between different players that might alter an explanatory variable's effect on the dependent variable.

As his dependent variable and proxy for player effort, Sunde (2003) used the total number of games won by a given player. This variable can be somewhat misleading, however, and might not accurately describe a player's overall performance. For example, whereas a top-seeded player might beat a bottom seeded player 6-4 6-4 6-4, exerting little to no effort, he might beat the same player 6-0 6-0 6-0, exerting maximal effort. According to *GamesWon*, however this player would have exerted the same amount of effort in both matches. Thus, instead of *GamesWon*, we use *GamePercent* (*GamesWon*/Total Games). This normalizes the *GamesWon* variable, such that we can analyze player-specific results within the context of a given match. It is our claim that, controlling for the abilities of both players in a match, the more effort a player exerts, the higher percentage of games he will win.

We then incorporate our hypothesis concerning intangible factors into the empirical specification. Specifically:

$$E_{ij} = \alpha_0 + \alpha_1 HET_{ij} + \alpha_2 PRIZE_{ij} + \alpha_3 X_j + \alpha_4 Y_m + \alpha_5 Z_i + INT_{ij} + \varepsilon_{ij}$$

where all variables are the same as above, with the exception of INT_{ij} , which represents a series of intangible variables for a given player playing in a given match of a given tournament. These intangible variables include *Home*, *CountryRankDiff*, *Region* and *Country*. The coefficients on

these variables are treated as explanatory variables, and we analyze how these variables contribute to effort in the Grand Slam and Davis Cup settings.

Our second specification utilizes the same independent variables listed above in a probit regression. Specifically:

$$\Pr_{inj}(win=1) = \phi(\alpha_0 + \alpha_1 HET_{inj} + \alpha_2 PRIZE_{inj} + \alpha_3 X_j + \alpha_4 Y_m + \alpha_5 Z_i + \varepsilon_{inj})$$

where the dependent variable is the probability that a player wins his match. This relates nicely to the Rosen model. Once again, the outcome of a match is based on the two players' relative capability and incentive effects. We separate out the capability effect by controlling for heterogeneity, which then allows us to analyze the factors that increase player incentives, making him more likely to win. Adding intangible factors to this specification, we get:

$$\Pr_{inj}(win=1) = \phi(\alpha_0 + \alpha_1 HET_{inj} + \alpha_2 PRIZE_{inj} + \alpha_3 X_j + \alpha_4 Y_m + \alpha_5 Z_i + INT_{inj} + \varepsilon_{inj})$$

where all variables correspond to their descriptions above.

Once we have completed our regression analysis, we run an F-test on the OLS specification to test the null hypothesis that the coefficients common to both the Grand Slam and Davis Cup regressions are equal in the Grand Slam and Davis Cup settings (McElroy, 2011). This gives us insight into whether players act differently in the two settings. The test is as follows:

i.) Unrestricted Model

The unrestricted model contains two regressions. The first one relates to Grand Slam matches and the second relates to Davis Cup matches.

$$Y_g = a_g + b_c X_c + b_g X_g$$

$$Y_d = a_d + b_c X_c + b_d X_d$$

where Y_g is the dependent variable of an OLS regression run on the Grand Slam data set, a_g is the constant from this regression, X_c is a matrix of the variables common to both Grand Slam matches and Davis Cup matches for each Grand Slam match, b_c is a vector of the coefficients on these variables, X_g is a matrix of variables specific to Grand Slam matches (ie. not present in Davis cup matches, such as prize money) for each Grand Slam match, and b_g is a vector of the coefficients on these variables. Similarly, Y_d is the dependent variable of an OLS regression on the Davis Cup data set, a_d is the constant from this regression, X_c is a matrix of the variables common to both Grand Slam matches and Davis Cup matches for each Grand Slam match, b_c' is a vector of the coefficients on these variables (where the “prime” indicates that the coefficient b_c for Davis Cup may be different to that of Grand Slams), X_d is a matrix of variables specific to Davis Cup matches for each Davis Cup match, and b_d is a vector of the coefficients on these variables.

We take the sum of squared errors from these two regressions and add them together.

This becomes our unrestricted sum of squared errors (SSE_{unres}).

ii.) Restricted Model

The restricted model contains one equation pertaining to the pooled data set. It regresses the dependent variable on all independent variables common to both the Grand Slam data set and the Davis Cup data set, in addition to those variables specific to either one. Specifically:

$$Y_p = a + b_c X_c + b_g X_g + b_d X_d$$

where Y_p is the dependent variable for the pooled data regression, a is the coefficient yielded by this regression, X_c is a partitioned matrix consisting of X_c for each match in the Grand Slam data set on top of X_c for each match in the Davis Cup data set, b_c' is a vector of the coefficients on these variables, X_g is a matrix of variables specific to the Grand Slam data set (that corresponds

to 0 for all Davis Cup matches) for all matches in the pooled data set, b_g is a vector of the coefficients on these variables, X_d is a matrix of variables specific to the Davis Cup data set (that corresponds to 0 for all Grand Slam matches) for all matches in the pooled data set, and b_d is a vector of the coefficients on these variables.

We take the sum of squared errors from this regression and it becomes our restricted sum of squared errors (SSE_{res}).

iii.) F-test

Finally, we test the likelihood that the coefficients on the common variables in Grand Slam and Davis Cup regressions are equal ($b_c = b_{c'}$) using the following:

$$\frac{(SSE_{res} - SSE_{unres}) / q}{SSE_{unres} / d} \sim F(q, d)$$

where SSE_{res} is the sum of the sum of squared errors from the two regressions (Grand Slam, Davis Cup) in the restricted model, SSE_{unres} is the sum of squared errors from the regression in the unrestricted model, $q =$ (total number of coefficients in unrestricted model Grand Slam regression + total number of coefficients in unrestricted model Davis Cup regression) – total number of coefficients in restricted model pooled regression, $d =$ (total observations from unrestricted Grand Slam data set + total observations from unrestricted Davis Cup data set) - (total number of coefficients in unrestricted model Grand Slam regression + total number of coefficients in unrestricted model Davis Cup regression), and F is an F-distribution.

From this test we receive an F-statistic that we convert into a p-Value to test the null hypothesis that the coefficients on the variables common to both the Davis Cup and Grand Slam regressions are the same. We compare the P-value to the standard significance levels (1%, 5%,

10%), and if it is small enough we reject the null hypothesis, meaning that players do, indeed, act differently in the two settings.

VII. Results & Discussion

The results of our regression analysis are displayed in tables 5-10 of the appendix. They are divided into six tables; the first three pertain to the OLS specification of each data set (Grand Slam, Davis Cup, and combined) and the second three pertain to the probit specification of the same three data sets. All standard errors are robust and, thus, have been corrected for heteroskedasticity. In this section, we report our results and discuss their implications, noting particularly significant trends found throughout. Finally, we report findings from the F-test mentioned at the end of section VI.

Using the Grand Slam OLS model, we first replicate the regressions run by Sunde (2003) and Lallemand et al. (2008) to test the relationship between monetary incentive and effort. Tables 5 and 6 display five regression outputs from the OLS and probit specifications that relate only to the Grand Slam data set. The first regression in each table excludes intangible variables but includes player fixed effects. The second regression excludes player fixed effects, and the third uses *PrzSpread* instead of *PzExpec* as the variable that estimates monetary incentives. Each of these regressions attempts to replicate results from Sunde (2003). The final two regressions that utilize just the Grand Slam data set incorporate intangible factors, which effectively expands Sunde's model.

We control for heterogeneity using *RankDiff*. More specifically, *Rankdiff* is used as a control variable to separate out the capability effect from the regression, allowing us to isolate

player incentives. Therefore, while we do not look at the relationship between *RankDiff* and player effort, we expect the coefficient on *RankDiff* to be negative, indicating that the higher ranked player in a given match is expected to win a greater percentage of total games. We find in each of our regressions (OLS and probit) that this relationship always holds true at the 1% significance level. Additionally, we find that $RankDiff^2$ is consistently insignificant, with a coefficient of approximately zero. This implies that the relationship between heterogeneity and player performance fits a linear model better than it does a quadratic model.

Once we control for ability, we are able to analyze the effects of monetary incentives on effort. While previous studies used *GamesWon* as their dependent variable, we use *GamePercent* as an improved measure. In all cases, we find that *PzDiff* and *PzSpread* fail the standard significance tests at every level, and that the coefficients on these two variables tend to be negative and extremely close to zero. In Table 5, the coefficient on *PzSpread* in the third regression is reported as an insignificant -0.0000368. These findings are inconsistent with tournament theory, as we would expect the coefficients on these prize variables to be positive, meaning that players increase their level of effort and, thus, win more games when there is more money on the line. We run the same regression on *GamesWon* to test the possibility that the change in the dependent variable was the cause of this insignificance and unexpected sign, but come up with similar results. When running the same regressions with *PzExpec*, however, our outputs yield results much more consistent with tournament theory. Indeed, we find that in almost every regression, the coefficient on *PzExpec* (using either *GamePercent* or *GamesWon* as our dependent variable) is positive and significant at the 1% level, as tournament theory would suggest. For example, in table 5, the OLS specification on a regression including *PzExpec* and intangible effects yields significant coefficients on *PzExpec* of approximately 0.0002. Based on

these results, we have reason to believe that *PzExpec* provides a more accurate measurement of the manner by which players view the option value of possible future monetary rewards. The coefficient on *PzExpec*, in the Grand Slam OLS specification, ranges from .0002 to .0005, meaning that a *PzExpec* increase of 100 (\$100,000) could provide a player with enough motivation to exert the effort necessary to win as many as 5% more of the total games in a match. This may not seem like much of an effect, but statistical analysis of all three of our data sets suggests that the winner of an average tennis match wins approximately 61% of games played in that match. Given that the margin of victory in terms of games is so small, a 5% swing in either direction can have a sizeable impact on the outcome of the match.

Tables 7 and 8 refer to the Davis Cup data set. Since monetary incentives cannot have an effect on player performance in the Davis Cup setting, we monitor only the effect of intangibles on effort. We find that the coefficient on *Home*, the dummy variable that measures whether or not a player is competing in his home country in a given match, is consistently positive and significant at the 1% level. This value hovers around 0.02 in the Grand Slam OLS specification, and around 0.05 in the Davis Cup OLS specification, suggesting that, on average, players competing at home win 3% more games than they would at a neutral site in Grand Slam events, and 5% more than they would normally in Davis cup matches. This is particularly interesting because it substantiates the idea that home field advantage exists in tennis, a phenomenon more typically associated with popular team sports, such as basketball and football. As expected, the effect of home field advantage is greater in the Davis Cup setting because players compete in a team setting in which fans have the opportunity to support their home country. This fan support, coupled with the fact that players take pride in “defending their home turf,” results in an increase

in effort that is not accounted for, prior to the inclusion of intangible variables in our specifications.

As players competing in Grand Slams and the Davis Cup have drastically different pecuniary incentives, it is difficult to compare the coefficients on intangible incentives from the two settings. In the combined data set, we set any prize variables relating to Davis Cup matches equal to zero, allowing us to analyze monetary and intangible incentives within the same set of regressions. These results are shown in tables 9 and 10. The coefficient on *PzExpec* continues to hover around 0.0002, and the coefficient on *Money*, a dummy variable that indicates the presence of monetary incentives, fluctuates, occasionally exhibiting a positive relationship with effort, and occasionally relating negatively. These results suggest that players might not exert effort differently in the two settings; the F-test presented at the end of this section tests this claim. The coefficient on *Home* remains generally positive, as we expected, while the coefficient on *CountryRankDiff* is generally negative.

The coefficient on *CountryRankDiff*, measured as the difference between a player's ITF country rank and that of his opponent, is consistently negative and significant at the 1% level. Assuming that we have already controlled for heterogeneity using *RankDiff*, the coefficients on *CountryRankDiff* indicate that players from top ranked countries exert more effort, possibly to preserve the prestigious reputation of those countries. However, it is likely that *CountryRankDiff* is highly correlated with *RankDiff*, as players with lower rankings (better players) are more likely to play for countries with lower rankings. Nonetheless, we can still compare coefficients on *CountryRankDiff* in similar regressions in the Grand Slam and Davis Cup settings. In Grand Slams, the coefficient on *CountryRankDiff* from the OLS model hovers around -0.0002, while the same coefficient in the Davis Cup regressions hovers around -0.001. This indicates that

players from better ranked countries try harder to preserve their country’s reputation when they are explicitly competing on behalf of their country, as in the Davis Cup setting.

In order to measure whether certain countries consistently exhibit significantly higher or lower incentives than other countries, we add *Country* fixed effects to our regressions. Results from the inclusion of these fixed effects are largely inconclusive. In most cases, coefficients on the estimators are either insignificant or fluctuate greatly in both direction and magnitude. After observing *Country* fixed effects, we group the countries together by geographic and cultural boundaries creating nine *Region* dummy variables (Table 12). Certain regions exhibit notable characteristics. *Eastern European* countries, for example, seem to perform significantly worse in the Davis Cup setting than in the Grand Slam setting (coefficients of -0.166 and -0.049 respectively, both significant at the 10% level). This might suggest that players from Eastern Europe exert less effort in the Davis Cup setting, indicating that Eastern European countries do a poor job of motivating players to succeed in international team competitions with no monetary rewards. Alternately, this decline in effort could result from a player’s lack of pride in his country or a lack of desire to represent his country in international competition. As such, a player might value Davis Cup matches less than he values ATP matches.

The results of the F-test on the OLS specification can be found in Table 11 below:

TABLE 11: F-test that $b_c = b_{c'}$			
$(q, d) = (11, 4193)$	<i>Restricted Model</i>	<i>Unrestricted Model</i>	
	<i>Pooled</i>	<i>Grand Slam</i>	<i>Davis Cup</i>
# of Coefficients	538	333	216
# of Observations	4742	3888	854
Sum of Squared Errors	60.024	51.087	8.738
Sum of Squared Errors	60.024	59.825	
F-Statistic	1.267		
P-Value	0.273		

The test yields an F-statistic of 1.267 with (11, 4193) degrees of freedom, which yields a P-value of 0.237. From this, we cannot reject the null hypothesis that the coefficients on the variables common to both Grand Slam and Davis Cup regressions are equal in both settings. While we cannot definitively conclude that players exhibit equal effort in the two settings, we can conclude that players do not exhibit noticeably more effort either when playing for their country in the Davis Cup or when playing for monetary incentives in Grand Slams.

VIII. Conclusions and Further Research

This study analyzes the factors that incentivize tennis players to exert effort in two very different settings: Grand Slam tournaments and the Davis Cup. In the first setting, the best tennis players in the world are given the opportunity to compete for sizeable monetary rewards in four separate 128-person elimination draws each year. In the second setting, players represent their countries and compete for no monetary reward in a team setting. The aim of our study is to determine what factors motivate players most, in general, and whether or not these factors differ in the two settings.

As predicted by Rosen (1986), the results of our study confirm that monetary incentives and prize structure are important factors in encouraging increased levels of effort in the four Grand Slam tennis tournaments. Players take into account not only their immediate rewards, but also the potential for even greater future earnings as they progress in a given tournament. However, our results indicate that the presence of monetary incentive is not the only factor that motivates male professional tennis players. In particular, factors such as pride, simulated in our study by variables such as *CountryRank* and *Home*, may indeed have a noticeable effect on

player performance. While our F-Test indicates that players may not act differently in the presence or absence of monetary reward, our regressions suggest that “intangibles” can have a significant effect on effort in both settings.

To apply our findings to the corporate world, we believe that agents in the marketplace would respond to both monetary and intangible incentives in the same way that tennis players react in our study. Thus, while a salaried payment scheme that incorporates increasing marginal payoffs is certainly a valuable tool in maximizing worker effort, companies and organizations with a fixed purse (like that of a tournament) might utilize other non-pecuniary incentives to ensure that workers are reaching their full potential. These techniques should be designed to give workers a greater stake in the company and increase their pride in the organization as a whole. Noting most significantly the effect of *Home*, our study suggests that developing these intangible incentives is most definitely a valuable proposition. A good example of a company that uses these kinds of techniques to emphasize strong corporate culture and boost morale is Google, which allows its workers to spend 20% of their time at the office working on any project they please (Hayes, 2008). This not only gives workers a favorable view of their employer, but it allows them to maximize their own creativity and human capital, thus giving them a larger stake in the company as a whole.

Ultimately, despite our generally significant results, it is difficult to extrapolate from the world of sports into the corporate world. In order to truly link tournament theory to the corporate setting, this topic requires an increase in empirical research that studies worker incentives and corporate success as related to payout schemes. Economists and psychologists alike must study the effect that intangible factors (e.g. franchise loyalty) have on general effort in the workplace.

Only then, will we truly begin to grasp the reasons why workers react the way they do to effort-inducing factors in the workplace.

Works Cited

- Atp world tour. (n.d.). Retrieved from <http://www.atpworldtour.com/>
- Becker, B.E. and Huselid, M.A. (1992). The incentive effects of tournament compensation systems, *Administrative Science Quarterly*, 37, 336-50.
- Corral, J.D. & Prieto-Rodriguez, J. (2010). Are differences in ranks good predictors for Grand Slam tennis matches? *International Journal of Forecasting*, 26, 551-563.
- Davis cup. (n.d.). Retrieved from <http://www.daviscup.com/en/home.aspx>
- Ehrenberg, R.G. and Bognanno, M.L. (1990b). The incentive effects of tournaments revisited: evidence from the European PGA Tour, *Industrial and Labor Relations Review*, 43, 745-885
- Glisdorf, K, & Sukhatme, V. (2008). Testing Rosen's Sequential Elimination Tournament Model: Incentives and Player Performance in Professional Tennis. *Journal of Sports Economics*, 9(3), 287-303.
- Glisdorf, K, & Sukhatme, V. (2008). Tournament incentives and match outcomes in women's professional tennis. *Applied Economics*, 40, 2405-2412.
- Hayes, Erin. (2008). Google's 20 percent factor. ABC News, Retrieved from <http://abcnews.go.com/Technology/story?id=4839327&page=1>
- Ivankovic, M. (2007). The tournament model: an empirical investigation of the ATP Tour. *Zb Rad Ekon Fak Rij*, 25, 83-111.
- Lallemand, T, Plasman, R, & Rycx, F. (2008). Women and competition in elimination tournaments. *Journal of Sports Economics*, 9(1), 03-19.
- Lazear, P.E. and Rosen, S. (1981). Rank-Order Tournaments as Optimum Labor Contracts. *Journal of Political Economy*, 89(5), 841-864.
- Lee, K.W., Lev, B. and Yeo, G.H.H. (2007). Executive pay dispersion, corporate governance, and firm performance. *Rev Quant Finan Acc*, 30, 315-338.
- Lynch, J.G. (2005). The effort effects of prizes in the second half of tournaments. *Journal of Economic Behavior & Organization*, 57, 115-129.
- Main, B.G., O'Reilly, C.A. and Wade, J. (1993). Top executive pay: tournament or teamwork? *Journal of Labor Economics*, 11, 606-28.
- McElroy, M. (2010). Personal communication.

- Milgrom, P. and Roberts, J. (1988). An economic approach to influence activities in organizations. *American Journal of Sociology*, 94, S154-S179.
- Nalebuff, B.J. and Stiglitz, J.E. (1984). Prizes and Incentives: Toward a General Theory of Compensation and Competition. *Bell Journal of Economics*, 2, 27-56.
- Roger federer opts out of davis cup duty for switzerland. (2010). The Telegraph, Retrieved from <http://www.telegraph.co.uk/sport/tennis/rogerfederer/8004214/Roger-Federer-opts-out-of-Davis-Cup-duty-for-Switzerland.html>
- Rosen, S. (1986) Prizes and incentives in elimination tournaments, *American Economic Review*, 76, 701-15.
- Sunde, U. (2003). Potential, prizes, and performance: testing tournament theory with professional tennis data. *IZA Discussion Paper Series*, 01-39.
- Sunde, U. (2009). Heterogeneity and performance in tournaments: a test for incentive effects using professional tennis data. *Applied Economics*, 41, 3199-3208.

Appendix

Table 1. Variable Definitions

Variable	Definition
rankdiff	<i>The difference in rank between player and his opponent</i>
pzexpect (\$1000)	<i>Prize Expectation (Monetary Reward)</i>
pzspread (\$1000)	<i>Prize Spread (Measure of monetary reward used by Ivankovich (2007))</i>
pzdif (\$1000)	<i>Marginal monetary reward for advancing one round</i>
ptexpect	<i>ATP Point Expectation</i>
ptspspread	<i>ATP Point Spread</i>
ptdif	<i>Marginal ATP Points rewarded for advancing one round</i>
money	<i>Dummy variable representing the presence of monetary reward (1 if present, 0 if absent)</i>
countryrankdiff	<i>The difference in country rank between player and his opponent</i>
home	<i>Dummy variable that is 1 if player competes at home, 0 if not</i>
gmswon	<i>Games won by player in match</i>
games	<i>Total number of games played in match</i>
gamepercent	<i>Games won out of total number of games played</i>
ptswon	<i>Points won by player in match</i>
points	<i>Total number of points played in match</i>
setswon	<i>Sets won by player in match</i>
sets	<i>Total number of sets in match</i>
time (min)	<i>Time of Match</i>
format	<i>Dummy variable that is 1 if 5 set match, 0 if 3 set match</i>
surface	<i>Surface on which match is played (1=hard, 2=clay, 3=grass, 4=carpet)</i>
tournam	<i>For Grand Slam Data Set, 1=Aus, 2=French, 3=Wimb, 4=US</i>
round	<i>Tournament rounds 1-7 for Grand Slam, 1-4 and -1 for Davis Cup</i>
year	<i>Year in which tournament takes place</i>
height (cm)	<i>Height of player (cm)</i>
weight (kg)	<i>Weight of player (kg)</i>
win	<i>Dummy variable that is 1 if player wins, 0 if not</i>

Table 2. Grand Slam Summary Statistics

	Observations	Mean	Std. Dev.	Min	Max
rankdiff	3892	0.00	118.13	-1122	1122
pzexpect (\$1000)	3892	102.40	132.54	16.731	955
pzspread (\$1000)	3892	132.98	120.23	47.583	805
pzdifff (\$1000)	3892	33.46	70.78	7.463	750
ptexpect	3892	134.89	96.31	54	522
ptspread	3892	160.75	78.38	106	400
ptdifff	3892	53.71	47.94	30	300
countryrankdiff	3892	0.00	19.27	-105	105
home	3892	0.10	0.29	0	1
gmswon	3888	17.90	6.14	1	40
games	3888	35.81	9.43	19	72
ptswon	3884	112.65	33.24	27	256
points	3884	225.29	62.41	105	490
setswon	3892	1.84	1.29	0	3
sets	3892	3.67	0.77	3	5
time (min)	3872	146.31	45.65	63	312
height (cm)	3892	184.28	6.39	165	208
weight (kg)	3892	78.86	6.77	58	107
round	3892	1.95	1.27	1	7
win	3892	0.50	0.50	0	1

Table 3. Davis Cup Summary Statistics

	Observations	Mean	Std. Dev.	Min	Max
rankdiff	854	0.00	241.77	-1249	1249
countryrankdiff	886	0.00	13.00	-54	54
home	886	0.50	0.50	0	1
gmswon	886	16.38	6.60	1	42
games	886	32.76	11.13	13	82
ptswon	842	102.79	37.66	19	251
pts	842	205.58	72.28	72	494
setswon	886	1.67	1.23	0	3
sets	886	3.33	0.97	2	5
time (min)	874	145.62	58.51	44	359
format	886	4.46	0.88	3	5
win	886	0.50	0.50	0	1

Table 4. Combined Summary Statistics

	Observations	Mean	Std. Dev.	Min	Max
rankdiff	4746	0.00	148.16	-1249	1249
pzexpect (\$1000)	4778	83.41	126.07	0	955
pzspread (\$1000)	4778	108.32	120.19	0	805
pzdif (\$1000)	4778	27.25	65.19	0	750
ptexpect	3892	134.89	96.31	54	522
ptspread	3892	160.75	78.38	106	400
ptdif	3892	53.71	47.94	30	300
money	4778	0.81	0.39	0	1
countryrankdiff	4778	0.00	18.33	-105	105
home	4778	0.17	0.38	0	1
gmswon	4774	17.62	6.26	1	42
games	4774	35.24	9.84	13	82
ptswon	4726	110.89	34.27	19	256
points	4726	221.78	64.72	72	494
setswon	4778	1.80	1.28	0	3
sets	4778	3.61	0.82	2	5
time (min)	4746	146.19	48.27	44	359
format	4778	0.95	0.22	0	1
win	4778	0.50	0.50	0	1

TABLE 5: Grand Slam OLS Regression Results

	<i>OLS (GamePercent)</i>				
	<i>(1)</i>	<i>(2)</i>	<i>(3)</i>	<i>(4)</i>	<i>(5)</i>
RankDiff	-0.00028 [3.79E-05]***	-0.0003 [2.87E-05]***	-2.99E-05 [3.86E-06]***	-0.0003 [3.8E-05]***	-0.0003 [3.82E-05]***
RankDiff ²	-7.36E-08 [7.12E-08]	-5.21E-09 [6.91E-08]	-7.80E-08 [7.34E-08]	-7.49E-08 [7.11E-08]	-7.67E-08 [7.13E-08]
PzExpec (\$1000)	0.0002 [4.15E-05]***	0.0005 [2.69E-05]***		0.0002 [0.4.15E-05]***	0.0002 [4.16E-05]***
PzSpread (\$1000)			-3.68E-05 [9.04E-05]		
Money ^a					
CountryRanDiff				-0.00027 [0.0001]*	-0.0003 [0.0001]*
Home ^a				0.01652 [0.0088]*	0.016 [0.0089]*
Australia ^{ad}				-0.0537 [0.0517]	
Eastern Europe ^{ad}				-0.0493 [0.0253]*	
Great Britain ^{ad}					0.0998938 0.0552384
France ^{ad}					-0.1372261 0.0245976
Constant	0.4656 [0.0242]***	0.4872 [0.0053]***	0.4694 [0.0245]***	0.4927 [0.0334]***	0.4639 [0.0243]***
Player Fixed Effects ^b	Yes	No	Yes	Yes	Yes
Tournament/Match Fe ^c	Yes	Yes	Yes	Yes	Yes
N	3888	3888	3888	3888	3888
F	-	59.15	-	-	-
R ²	0.3201	0.1934	0.3152	0.3221	0.3221

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

a) Dummy variable

b) Includes player by last name

c) Includes year, surface, format, round

d) Countries/regions present in results are notable examples

TABLE 6: Grand Slam Probit Regression Results

	<i>Probit (Pr(win=1))</i>				
	(1)	(2)	(3)	(4)	(5)
RankDiff	-0.0036 [0.0006]***	-0.0038 [0.0005]***	-0.0049 [0.0006]***	-0.0036 [0.0006]***	-0.0037 0.0005667
RankDiff ²	-4.73E-07 [1.44E-06]	6.10E-08 [1.81E-06]	-1.07E-20 [2.29E-06]	-5.14E-07 [1.43E-06]43	-5.40E-07 [1.44E-06]
PzExpec (\$1000)	0.0025 [0.0006]***	0.0057 [0.0005]***		0.0025 [0.0006]***	0.0024 [0.0006]
PzSpread (\$1000)			5.72E-17 [0.0009]		
Money ^a					
CountryRanDiff				-0.002 [0.0017]	-0.0018 [0.0017]
Home ^a				0.3048 [0.1004]***	0.2899 [0.1010]
Australia ^{ad}				0.3055 [0.5293]	
Eastern Europe ^{ad}				-0.1175 [0.2952]	
Great Britain ^{ad}					-5.6092 [1.1097]***
France ^{ad}					1.4564 [0.44]***
Constant	-0.3038 [0.3003]	-0.1465 [0.0556]***	-3.76E-15 [0.0644]***	-0.2015 0.4018	-0.3113 [0.302]
Player Fixed Effects ^b	Yes	No	No	Yes	Yes
Tournament/Match Fe ^c	Yes	Yes	Yes	Yes	Yes
N	3717	3892	3892	3717	3716
Wald Chi ²	820.08	343.91	66.29	834.62	1780.85
Pseudo R ²	0.2136	0.1452	0.0991	0.2162	0.2163

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

a) Dummy variable

b) Includes player by last name

c) Includes year, surface, format, round

d) Countries/regions present in results are notable examples

TABLE 7: Davis Cup OLS Regression Results

	<i>OLS (GamePercent)</i>			
	(1)	(2)	(3)	(4)
RankDiff	-0.0025 [0.0005]***	-0.0002 [3.39E-05]***	-0.0002 [1.72E-05]***	-0.0002 [3.39E-05]***
RankDiff ²	5.07E-07 [9.41E-07]	1.43E-09 [3.84E-08]	-4.33E-09 [2.12E-08]	1.43E-09 [3.84E-08]
PzExpec (\$1000)				
PzSpread (\$1000)				
Money ^a				
CountryRanDiff		-0.001 [0.0006]	-0.0019 [0.0004]***	-0.001 [0.0006]
Home ^a		0.0526 [0.0105]***	0.0515 [0.0086]***	0.0526 [0.0105]***
Australia ^{ad}		-0.1377 [0.0499]***	-0.0259 [0.0251]	
Eastern Europe ^{ad}		-0.1664 [0.0969]*	-0.0073 [0.0155]	
India ^{ad}				-0.2049 [0.0944]**
Romania ^{ad}				-0.2198 [0.0784]*
Constant	0.6427 [0.0848]***	0.5235 [0.0421]***	0.4794 [0.03112]***	
Player Fixed Effects ^b	Yes	Yes	No	Yes
Tournament/Match Fe ^c	Yes	Yes	Yes	Yes
N	854	854	854	854
F	-	-	14.13	-
R ²	0.4473	0.4762	0.2527	0.4762

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

a) Dummy variable

b) Includes player by last name

c) Includes year, surface, format, round

d) Countries/regions present in results are notable examples

TABLE 8: Davis Cup Probit Regression Results

	<i>Probit (Pr(win=1))</i>			
	(1)	(2)	(3)	(4)
RankDiff	-0.0025 [0.0005]***	-0.0024 [0.0005]***	-0.0026 [0.0004]***	-0.0024 [.0005]***
RankDiff ²	5.07E-07 [9.41E-07]	6.91E-07 [9.41E-07]	5.03E-07 [7.11E-07]	6.91E-07 [9.41E-07]
PzExpec (\$1000)				
PzSpread (\$1000)				
Money ^a				
CountryRanDiff		0.0019 [0.007]	-0.0093 [0.004]**	0.0019 [0.007]
Home ^a		0.564 [0.1194]***	0.4879 [0.094]***	0.5640 [0.1194]***
Australia ^{ad}		-1.6469 [0.765]**	-0.2882 [0.3339]	
Eastern Europe ^{ad}		-5.383 [0.8245]***	-0.0111 [0.2088]	
Ecuador ^{ad}				4.5561 [0.8974]***
Sweden ^{ad}				-4.3490 [1.081]***
Constant	1.1894 [0.582]**	1.2239 [0.5603]**	-0.2208 [0.3550]	0.8578 [0.6]
Player Fixed Effects ^b	Yes	Yes	No	Yes
Tournament/Match Fe ^c	Yes	Yes	Yes	Yes
N	693	693	846	693
Wald Chi ²	149.88	1095.23	115.9	1095.14
Pseudo R ²	0.182	0.2084	0.143	0.2084

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

a) Dummy variable

b) Includes player by last name

c) Includes year, surface, format, round

d) Countries/regions present in results are notable examples

TABLE 9: Combined OLS Regression Results

	<i>OLS (GamePercent)</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
RankDiff	-0.0003 [2.64E-05]***	-0.0003 [2.64E-05]***	-0.0003 [2.65E-05]***	-0.0003 [2.69E-05]***	-0.0003 [2.65E-05]***	-0.0003 [2.67E-05]***
RankDiff ²	-5.87E-08 [4.28E-8]	-5.72E-08 [4.28E-08]	-5.88E-08 [4.32E-05]	-6.33E-08 [4.39E-08]	-5.88E-08 [4.32E-08]	-6.17E-08 [4.34E-08]
PzExpec (\$1000)	0.0002	0.1112	0.0002		0.0002	
PzSpread (\$1000)	[4.19E-5]***	[0.0767]	[4.18E-05]***		[4.18E-05]***	
Money ^a	-0.1291 [0.0552]**	0.0002 [4.18E-05]***		-0.0114 [0.0403]		0.1196 [0.0772]
CountryRanDiff	-0.0003995 [0.0001]***	-0.0004 [0.0001]***				-0.0004 [0.0001]***
Home ^a	-0.0004 [0.0065]***	0.03 [0.0065]***				0.0292 [0.0065]***
Eastern Europe ^{ad}		-0.0531 [0.0258]**				
Western Europe ^{ad}		-0.0531 [0.0214]**				
Great Britain ^{ad}	-0.2944 [0.1089]***					
Sweden ^{ad}	-0.1473 [0.0281]***					
Ecuador ^{ad}	0.1878 [0.0541]***					
Constant	0.6092 [0.0586]***	0.3936 [0.0745]***	0.4823 [0.0277]***	0.496 [0.0351]***	0.4823 [0.0277]***	0.3902 [0.0750]***
Player Fixed Effects ^b	Yes	Yes	Yes	Yes	Yes	Yes
Tournament/Match Fe ^c	Yes	Yes	Yes	Yes	Yes	Yes
N	4742	4742	4742	4742	4742	
F	-	-	-	-	-	-
R ²	0.3486	0.3491	0.3427	0.3385	0.3427	

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

a) Dummy variable

b) Includes player by last name

c) Includes year, surface, format, round

d) Countries/regions present in results are notable examples

TABLE 10: Combined Probit Regression Results

	<i>Probit (Pr(win=1))</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
RankDiff	-0.0035 [0.0004]***	-0.0035 [0.0004]	-0.0033 [0.0004]***	-0.0033 [0.0004]***	-0.0033 [0.0004]***	-0.0033405 [0.0004]***
RankDiff ²	-3.59E-07 [1.17E-06]	-3.99E-07 [1.15E-06]	-3.63E-07 [1.09E-06]	-3.73E-07 [1.1E-06]	-3.63E-07 [1.09E-06]	-3.23E-07 [1.11E-06]
PzExpec (\$1000)			0.0026 [0.0006]***	0.0026 [0.0006]***	0.0026 [0.0005]***	0.003 [0.0005]***
PzSpread (\$1000)						
Money ^a	-0.3745 [0.5526]	-0.191 [0.5924]**	-0.3233 [0.5925]	0.4023 [0.0774]	-0.3233 [0.5925]	
CountryRanDiff		-0.0037 [0.0016]***	-0.0035 [0.0016]**	-0.0032 [0.0016]**	-0.0035 [0.0016]**	
Home ^a		0.3988 [0.0767]	0.406 [0.0766]***	0.4023 [0.0773]***	0.4059 [0.0766]	
Eastern Europe ^{ad}		-0.1267 [0.2983]	-0.1409 [0.2953]		-0.1409 [0.2953]	
Western Europe ^{ad}		-0.2072 [0.2418]	-0.1955 [0.2397]		-0.1955 [0.2397]	
Great Britain ^{ad}				-5.5347 [1.0677]***		
Sweden ^{ad}				-3.32842 [1.1006]***		
Ecuador ^{ad}				5.4733 [0.9342]***		
Constant	0.3794 [0.4936]	-0.8472 [0.6044]	0.2798 [0.57]	-0.8472 [0.6043]	-0.2545 [0.4035]	-0.0307 [0.3469]
Player Fixed Effects ^b	Yes	Yes	Yes	Yes	Yes	No
Tournament/Match Fe ^c	Yes	Yes	Yes	Yes	Yes	Yes
N	4410	4410	4410	4409	4410	4410
Wald Chi ²	947.69	987.75	1005.45	3079.23	1005.45	966.14
Pseudo R ²	0.2044	0.2101	0.2136	0.2139	0.2136	0.2078

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

a) Dummy variable

b) Includes player by last name

c) Includes year, surface, format, round

d) Countries/regions present in results are notable examples

Table 12. Breakdown of Regions by Country

1. USA and Canada		5. Northern Europe	
Canada		Denmark	
United States		Finland	
		Sweden	
2. Latin America		6. Asia	
Argentina	Ecuador	India	Pakistan
Brazil	Mexico	Japan	Thailand
Chile	Paraguay	Kazakhstan	Taipei
Colombia	Peru	Korea	Uzbekistan
Costa Rica	Uruguay	Latvia	
3. Eastern Europe		7. Australia	
Austria	Poland	Australia	
Belarus	Romania		
Croatia	Serbia		
Czech Republic	Slovak Republic	8. Middle East	
Greece	Ukraine	Armenia	
		Cyprus	
		Georgia	
		Israel	
4. Western Europe		9. Africa	
Belgium	Luxembourg	Morocco	
France	Netherlands	South Africa	
Germany	Portugal		
Great Britain	Spain		
Italy	Switzerland		