Gender Differences in Response to Setbacks: Evidence from Professional Tennis

by

Lauren Banko
Department of Economics
Temple University

Eva Marikova Leeds
Department of Economics and Business
Moravian College

Michael A. Leeds
Department of Economics
Temple University

Department of Economics
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Lauren Banko
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Abstract

A large experimental literature has arisen that shows significant differences in how men and women respond to economic contests. Non-experimental studies, however, frequently contradict the experimental findings. We use data from the ATP and WTA professional tennis tours (in which all contests are best-of-three matches) to test one prediction of the experimental literature: that women react more negatively to setbacks than men do. Ordered probits show that women who lose the first set are no more likely to lose the match in either straight sets or three sets than men are. Similarly, binomial probits show that women who win the first set but lose the second are no more likely to lose the third than men are. However, we do find that women who do lose in straight sets generally lose by larger margins than men do.

I. Introduction

The continued failure of women to reach the top of the corporate ladder has often been attributed to a "glass ceiling," a form of discrimination that limits women's access to leading positions in firms. Recent research suggests, however, that the barriers facing women may depend less on outright discrimination than on how women respond to the economic settings they face. If women respond less positively to competitive situations than men do, they could face significant limits on their ability to rise in corporate or political spheres even in the absence of outright prejudice. As a result, gender differences in preferences have become the subject of a large and growing literature.

This literature has arisen in two different areas of economics. In experimental economics, researchers have sought to isolate gender differences in highly controlled settings. In sports economics, the ready availability of data on performance and pay in sports has allowed economists to analyze gender differences in non-experimental settings. Interestingly, the two literatures have come to different conclusions, with the experimental literature finding a large disparity in how men and women respond to competitive settings and the sports literature finding little or no disparity.

In this paper, we use data on performance by professional tennis players on the men's and women's tours to test one aspect of the gender gap in responses to competitive settings. We test if women respond worse than men to setbacks. The first set of regressions tests whether, as the experimental literature suggests, women are more likely than men to lose matches in straight sets. Our results clearly indicate that this is not the case.

The second set of regressions moderates this finding somewhat. These regressions examine the determinants of the score in the second set. We find that, women who lose the first set perform worse in the second set than men do. Thus, women are no more likely than men to lose in straight sets, but those who do so lose by larger margins than men. Second, men appear to respond more to prize incentives, as the size of the purse affects match-outcomes for men but not for women.

Finally, we look at the outcome of matches that go to three sets. Consistent with our initial finding, women who lose the first set are no more or less likely than men to win in three sets. However, we again find a difference between men and women. This time, we find that a woman who retires in the third set is much more likely to have lost the second set, while a man is no more likely to have done so. This outcome suggests greater discouragement by women who lost the second set.

In the next section of this paper, we review the literature on gender-based preferences and economic contests, with specific attention to the different conclusions reached by the experimental and sports literatures. In Section III, we derive an empirical model from the standard Rank Order Tournament framework and describe the data we use to test it. Section IV discusses the results and Section V concludes.

II. Literature Review

The notion of a rank-order tournament (ROT) as an optimal labor contract was first proposed by Lazear and Rosen (1981). They show that, under specific conditions, employers do not have to pay workers their marginal revenue products to generate the efficient amount of effort. Instead, they can offer a reward structure with discrete drops in pay based on the rank order of an employee's performance. Because the employer does not have to measure a worker's precise contribution, such a compensation system is much cheaper for the firm to implement.

ROTs pay the "winners" of the contest a reward that exceeds their marginal revenue product and pay the "losers" less than their marginal revenue product. By increasing or reducing the difference in pay between winners and losers, the firm can increase or reduce the degree of effort contestants put forth to win the contest. The efficiency of ROTs has led to their wide application in settings ranging from executive compensation (see, for example, Bognanno, 2001) to compensation in professional sports.

Ehrenberg and Bognanno's (1990a and 1990b) analyses of reward and performance on the PGA and European golf tours were the first application of ROTs to sports. Because the prize gradient in golf is non-linear, the reward to improving one's position by one spot in the last round of a tournament increases as one moves up in the standings. In addition, because the prize gradient is fixed across tournaments, the reward to improving one's position also increases with the total purse offered by a given tournament. Ehrenberg and Bognanno find that golfers respond to greater monetary incentives by improving their scores in the final round when they have more to gain

Lynch and Zax (2000) apply a similar model to professional road racing. They find that times are lower in races with larger purses. However, they attribute the improvement to the impact of the purse on the field of competitors rather than on the incentives present for a given set of competitors.

Gilsdorf and Sukhatme (2008a and 2008b) use data from women's and men's professional tennis to test Rosen's (1986) extension of ROT to elimination tournaments. They confirm Rosen's hypothesis that greater mismatches result in lower effort for both men and women. They also find that larger purses, and hence larger monetary differences in prize money for the winner and loser, increase the probability that the favored player wins at each stage of the tournament.

Frick et al. (2003) test Lazear's (1989) hypothesis that teamwork limits the power of pay differentials to stimulate performance. They specify team performance for the four major North American sports leagues (MLB, NBA, NFL, and NHL) and find that salary differentials among teammates, as measured by the Gini coefficient, have an uneven impact on team performance. They find that pay differentials have a positive impact on performance in the National Basketball Association, a statistically insignificant impact on performance in the National Football League and National Hockey League, and a negative impact on performance in Major League Baseball.

ROTs present at least two problems. First, ROT can have perverse incentives. For example, Lazear (1989) shows that ROTs can undermine teamwork by causing workers to focus on their own performances rather than on the team's overall output. In extreme circumstances, ROT can even cause competitors to sabotage each other's efforts. Second, the ROT model assumes that all workers are equally talented. O'Keeffe, Viscusi, and Zeckhauser (1984) relax this assumption by analyzing contests involving heterogeneous workers. They conclude that, if the difference in expected productivity is great enough, less-talented workers expect to lose no matter how hard they try. Workers are therefore better off letting the superstar win and putting forth the minimal acceptable level of effort.

Brown (2011) applies this negative "superstar" effect to golf. She analyzes the impact of Tiger Woods on the performance of competing golfers from 1999 to early 2010 and that competing players' scores rose in tournaments in which Woods participated. Moreover, this negative impact on performance was greatest for Woods's closest competitors.

Experimental studies show that the gender difference in the response to ROT holds for very different age groups and for very different activities. Gneezy, Niederle, and Rustichini (2003) asked students at the Technion, an engineering university in Israel, to solve mazes. Some students were told that they would receive a fixed payment for each maze they solved. Others were told that the person who solved the most mazes in their group would receive one large prize. They found no difference in the number of mazes men and women solved in the piece rate setting but that men outperformed women in the tournament setting.

Gneezy and Rustichini (2004) had Israeli fourth graders run timed, individual sprints as well as head-to-head competitions. Boys ran faster in the competitive settings than in the non-competitive settings, while girls ran slower. The results were robust to the gender make-up of the competitive race and the relative abilities of the runners.

Booth and Nolen (2012) find that women show a greater aversion to tournament settings than men do. They randomly sorted a sample of English high school students into single-sex and mixed groups and had the students solve mazes subject to a piece rate reward system in the first round and a tournament system in the second round. In the third round, students could choose either reward system. Girls were more likely than boys to choose the piece rate setting.

Most important for this study, Gill and Prowse (2010) find that women take discouraging news worse than men do. In their experiment, men and women were randomly assigned to groups of two, though the identity of the partner was kept secret. Each participant positioned a "slider" on a computer screen using a mouse and was graded based on how many sliders he or she placed at exactly 50 on a scale of 0 to 100 in two minutes. The prize for the round was then awarded to a single winner, based on a lottery. The likelihood of winning the lottery rose with the participant's performance of the task. Performance was thus not the sole determinant of who won the prize. Gill and Prowse found that women respond to not winning as a result of bad luck by reducing their effort in later rounds of the experiment. The gender difference in the response to bad luck was so pronounced that the "differential responses to luck account for about half of the gender performance gap that we observe in our experiment." (Gill and Prowse, 2010: 1)

Recent non-experimental studies from the economics of sports are less uniformly supportive of the hypothesis of gender differences in contest performance. Several papers have found that women's tennis matches are far more likely to end in blowouts than are men's matches. Magnus and Klaassen (1999) found that women's matches at Wimbledon lasted fewer games than did men's matches. Krumer et al. (2014) found the same result for the men's and women's tours in general. Neither of these studies, however, linked their findings to gender preferences. In fact, Krumer et al. claim that gender distinctions disappear when one adds the physical characteristics of the participants.

Other studies do specifically examine the response to the incentives created by tournament settings. Gilsdorf and Sukhatme (2008a and 2008b), for example, find no difference in how men and women respond to incentives in elimination tennis tournaments. Che and Humphreys (2013) find mixed evidence regarding how female skiers respond to incentives, though they have no baseline results for men to which they can compare their findings. Finally, Leeds and Leeds (2013) find that female figure skaters respond more to incentives than their male counterparts.

The contradictory findings of the experimental and sports literature probably reflects the presence of selection bias. Normally, economists regard selection bias as a problem to be overcome. By carefully selecting a random sample of subjects, the experimental literature would seem to have resolved this problem. In the real world, however, individuals self-select into particular occupations. When individuals follow a specific career path – be it athletic or corporate – they choose the arena in which they feel most prepared to compete. Our findings could thus be more readily generalized than randomized experiments to the labor market, where people tend to self-select into specific occupations.

III. Model and Data

In their model of ROT, Lazear and Rosen (1981) assume that a risk neutral worker (*i*) faces a contest with worker j that has the prize structure (W_1, W_2), where W_1 is the prize awarded to the winner of the contest, W_2 is the prize awarded to the loser, and $W_1 >> W_2$. Each worker expends some level of effort, μ_k ($k=i, j$), which imposes the cost $C(\mu_k)$, where $C' > 0$ and $C'' > 0$. The employer observes the output by each worker, $q_k = \mu_k + \varepsilon_k$, where ε_k is a random error term attributable to luck or to measurement error by the employer. The probability that worker *i* wins the contest is

$$\Pr(q_i > q_j) = \Pr(\mu_i + \varepsilon_i > \mu_j + \varepsilon_j) = G(\mu_i - \mu_j), \quad (1)$$

where G is the cumulative distribution function. Lazear and Rosen show that the optimal degree of effort by worker i is given by the condition

$$(W_1 - W_2)*g(\mu_i - \mu_j) - C'(\mu_i) = 0, \qquad (2)$$

where g is the density function, which can be interpreted as $\partial[Pr(q_i > q_j)]/\partial\mu_i$. The first term on the left-hand side of Equation (2) can be interpreted as the marginal benefit of effort (MB_E), while the second term is the marginal cost of effort (MC_E). Assuming for simplicity that the marginal benefit of effort is decreasing, the equilibrium level of effort is given by the intersection of MB_E and MC_E, as shown in Figure 1.

This simple framework, when combined with the experimental work of Gill and Prowse (2010) and of Booth and Nolen (2012), allows us to show how differing attitudes toward contests might lead to different behavior by men and women. The most important insight that theory provides to this context is that the impact of effort on the probability of winning helps determine the marginal benefit of effort and hence the optimal degree of effort. For example, the optimal degree of effort declines over the course of a given competition, as the chances of winning diminish. Beyond some point in the contest, the impact of greater effort diminishes to zero, and the marginal benefit of effort shifts down from MB_E to MB'_E, as seen in Figure 1. Thus, a football team that is losing by 10 points might still try very hard with 10 minutes remaining in the game, but it is unlikely to compete with the same intensity with 10 seconds left, when there is little chance that effort will alter the game's outcome.

As noted earlier, the experimental literature has found that girls and women respond more negatively to bad news than boys and men do and that "women report more intense nervousness and fear than men in anticipation of negative outcomes." (Croson and Gneezy, 2009: 452) In terms of our model, women have a lower subjective probability that added effort will positively affect the contest outcome at any given point in the contest than men do. This, in turn, implies that marginal benefit of effort and the optimal level of effort are also lower for women than for men ($MB_E' < MB_E$ in Figure 1).

If women have less confidence in the impact of their effort on contest outcomes, then they are less likely to put in the effort needed to overcome obstacles that appear in their path. In a corporate context, this reasoning implies that female executives will become more quickly discouraged by the failure of a new product or sales initiative. Such behavior, however, is difficult or impossible to quantify. As a result, most studies of such behavior take place in experimental settings.

The ready availability of performance data in sports allows us to determine whether women become more easily discouraged in a non-experimental setting. In particular, many sporting contests take place in discrete units, such as halves, sets, or innings. An athlete or team that is trailing in a contest must exert extra effort to win the contest. If women systematically have less faith in the impact of their effort on the contest's outcome, they will rationally apply less effort in the wake of the early deficit and will be less likely to come back to win.

Professional tennis is a particularly appropriate setting for testing whether men and women differ in their ability to recover from adversity. First, the structure of the contest is uniform across the sexes. Aside from men's Grand Slam events, almost all tennis tournaments are decided on a best-of-three-set basis.[1] The player who loses the first set must therefore win the next two sets to win the match. The discrete outcomes of such a match are best modeled by the ordered probit technique. The observed dependent variable, y_{ijk}, the outcome of a match between Player i and Player j in contest k given that Player i has lost the first set, can take on three different values:

$y_{ijk} = 0$: Player i loses in straight sets

$y_{ijk} = 1$: Player i loses the first and third sets

$y_{ijk} = 2$: Player i loses the first set but wins the match

The discreet outcome actually reflects a continuous, unobserved variable, y^*_{ijk}. In this case, y^*_{ijk} could be interpreted as a measure of the relative effort of the two players. This latent variable is in turn a function of observable characteristics of the players and the contest setting, which we define below.

$$y^*_{ijk} = \beta_0 + \beta_1 FEM_{ij} + \gamma' X_i + \delta' X_j + \theta' Z_k + \varepsilon_{ijk} \tag{3}$$

The observable value takes on specific values as the random error term crosses particular thresholds. In this case:

$$y_{ijk} = 0 \text{ if } \varepsilon_{ijk} \le \theta_1 \tag{4a}$$

$$y_{ijk} = 1 \text{ if } \theta_1 < \varepsilon_{ijk} \le \theta_2 \tag{4b}$$

$$y_{ijk} = 2 \text{ if } \varepsilon_{ijk} > \theta_2 \tag{4c}$$

[1] The Grand Slam consists of the Australian Open, the French Open, Wimbledon, and the US Open.

where the μ_i are cutpoints that are defined by the ordered probit algorithm. The ordered probit is more appropriate than a standard multinomial probit precisely because we can order the outcomes. That is, a random factor that acts in favor of player *i*'s winning the second set after losing the first will also make Player *i* more likely to win the third set. Because the ordered probit makes use of this information, it is a more efficient estimator than a multinomial probit in which the order of the outcomes is arbitrary.

Equation (3) has three components. X_i is a vector of characteristics of player *i*, X_j is a vector of characteristics of player *j*, Z_k is a vector of characteristics of the match in which they play, and FEM_{ij} is a dummy variable indicating whether players *i* and *j* are women. To gain greater insights into the impact of gender on the response to setbacks, we also run separate versions of Equation (3) for the men's and women's tours without the dummy variable FEM_{ij}.

In practice, we define the vector X_i as the characteristics of the player who loses the first set (Player i). Hence, X_j contains the characteristics of the player who wins the first set (Player j). The most important characteristic of a player is his or her ranking. Much of the theoretical literature on ROT assumes that the contestants are "symmetric" in that they have the same underlying ability. However, most contests are between unevenly talented players, and better players lose less frequently. Thus, Player *i* should lose less frequently in straight sets as his or her ranking improves. Conversely, Player *i* is more likely to lose in straight sets as the ranking of Player *j* improves. We include the individual rankings of Player *i* and Player *j* as well as the ratio of the rank of Player *j* to the rank of Player *i* (winner to loser of the first set).

The setting of a specific match – and the overall tournament in which it takes place – can make a comeback more or less likely. The variables reflecting the setting are contained in the vector Z_k. One of the most important such variables is the number of games that Player i wins in the first set. (Player j invariably wins six or seven games.) Although losing a set 6-0 does not count any more than losing that set 7-6 in a tiebreak, the precise score of the first set can affect the outcome of the match because, as indicated by the theory outlined above, a player who loses the first set badly might enter the second set more discouraged than a player who takes his or her opponent to a tiebreak.

The financial incentives facing the players change with the purse and round of a tournament. The reward a player gets for winning a given match and advancing to a later round (or, ultimately, winning the tournament) could, in turn, affect the likelihood of a straight-set loss. Rosen (1986) theorized and Gilsdorf and Sukhatme (2008a and 2008b) have shown empirically that elimination tournaments with higher purses elicit greater effort by both players and result in fewer upsets. Thus, a tournament's purse should increase the likelihood that an underdog loses in straight sets and reduce the likelihood that a favorite loses in straight sets.

We also control for whether a player retired (withdrew) from the match. While a player could retire for a number of exogenous reasons, such as an injury sustained or aggravated during a match, it is also possible that a player's ability to continue playing is affected by his or her state of mind. The coefficient of this variable allows us to determine whether players who lose the first or second set are more likely to withdraw from a match.

Finally, we include control variables for the surface on which the match is played. We do not have any *a priori* beliefs in whether the surface has a different impact in the performance of men and women, but it is possible that different surfaces could affect players' ability to collect themselves and to play through adversity.

To estimate the ordered probit, we use 2011 tournament data from the ATP and WTA Tour websites ("Results Archive," *ATP World* Tour, 2013, and "WTA Tournament Archive," *WTA,* 2013). In addition to 2011 match outcome, the websites also provide data on player rank in 2010. The websites provided the ranks of only the top 100 men and women. Omitting matches involving an unranked player would greatly reduce the size of our data set. We therefore set the ranking of all unranked players equal to 100 and then include a dummy variable that indicates whether the player is unranked.

The data from the two tours allow us to test our hypotheses, but they present one possible problem. Men compete only against other men on the ATP tour, while women compete only against women on the WTA tour. It is possible that men and women would behave differently in the presence of the opposite sex.

While the probability of losing a match in straight sets (outcome 4a, above) tells us something about a player's response to adversity, it does not provide a complete picture. A player who loses in straight sets but who loses the second set in a 7-6 tiebreak, has clearly played a more competitive match than a player who loses the second set 6-0. We therefore include a set of OLS regressions that ask whether women play less competitive second sets.

$$DIF2_{ijk} = \beta_0 + \beta_1 FEM_{ij} + \beta_2 DIF1_{ijk} + \gamma' X_i + \delta' X_j + \theta' Z_k + \varepsilon_{ijk} \qquad (5)$$

where $DIF2_{ijk}$ is the game differential (games won by Player *j* minus games won by Player *i)* in the second set, and $DIF1_{ijk}$ is the game differential (games won by Player *j* minus games won by Player *i)* in the first set. Again, we use both a combined sample with the dummy variable FEM_{ij}. followed by separate samples for men and women.

Finally, the player who loses the first set is not the only one who faces adversity during a match. The player who won the first set might feel discouraged (and his/her opponent might feel more confident) if s/he fails to win the second set. Our final set of regressions thus tests whether there is a gender difference in the outcome of a three-set match. That is, whether a man who won the first set but lost the second is more or less likely than a woman to win the third. We therefore estimate the binomial probit

$$\Pr\left(z_{ijk} = 1\right) = \beta_0 + \beta_1 FEM_i + \gamma' X_i + \delta' X_j + \theta' Z_k + \varepsilon_{ijk} \qquad (6)$$

where z_{ijk} is a dummy variable that equals 1 when player *i* wins the third set of a match and equals 0 when player *j* wins the third set. The possible outcomes are that Player *i* wins the second set but loses the third (z_{ijk}=0) and that Player *i* goes on to win the match (z_{ijk}=1). The sample for this regression is smaller than for the first two sets of regressions, as we do not include matches that resulted in a straight set victor for Player *j*. As before, we run a combined regression with the dummy variable FEM_{ij} and separate regressions for men and women.

The means of relevant variables appear in Table I. As expected, the winner of the first set (who wins over 80% of all matches for both men and women) is better-ranked than the loser of the first set. (Recall that a better ranking corresponds to a lower number.) On average, a woman who loses the first set wins about 3 games, while a losing man wins about 3.5 games. Men and women play on very similar surfaces. A little over half the matches are played on hardcourt surfaces, and about one-third are played on clay. The remaining men's matches are played on grass, while the remaining women's matches are played on either grass or carpet, a surface that was not mentioned in any of the men's tournaments in our sample. The difference in prize money between men's and women's tournaments was surprisingly large, with men's tournaments offering over twice the purses of women's tournaments. The means confirm a loss of momentum for players who win the first set but lose the second set, as fewer than half the players who lose the second set go on to win the third. This result is slightly more exaggerated for women than for men.[2]

IV. Results

The last three rows of Table I present the outcomes of the matches. They show that over 69 percent of men and over 71 percent of women who lose the first set go on to lose in straight sets. However, both men and women who are able to force a third set are slightly more likely to win the match than to lose it – though the difference is not statistically significant. More importantly, none of the entries in the last three rows differ significantly by sex. These results, however, are unconditional, so, while suggestive, they are not conclusive.

Ordered probit results for the inequalities (4a)-(4c) appear in Table II. Because probit results have no natural interpretation other than size and sign, we also present the marginal effects for selected variables in Table III. The marginal effects for an ordered probit show the impact of a small change in the independent variable on the likelihood of any one outcome. Because an increase in the likelihood of observing any one outcome of the dependent variable must come at the expense of another value, the sum of the marginal effects of any given variable must equal zero.

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[2] These percentages are computed by taking the percent of the time Player A wins in 3 sets and dividing by the sum of the percent of the time either player wins in 3 sets. For men: 0.144/(0.144 + 0.166) = 0.465.

A χ^2 test of the likelihood ratio indicates that all three ordered probit regressions do a good job of explaining the data. The dummy variable indicating the sex of the participants in the first column of Table II is the key variable for the combined sample. Its coefficient is statistically insignificant, which shows that, all else equal, women are no more likely to lose in straight sets than men are.

The next two columns of Table II present separate results for men and women. We find that far more variables have a significant impact on the outcomes of men's matches than is the case for women's matches. Only one variable has a statistically significant impact in both the men's and women's equations: the number of games won in the first set by Player *i*. In addition to this variable, the rank of Player *j*, the ratio of the players' ranks, the size of the purse, the interaction of purse and round, and the dummy variable indicating whether the match was contested on a clay court are all significant in the men's equation. For women, the only other statistically significant variable was the rank of Player *i*.

Because the coefficients in an ordered probit are so difficult to interpret, we refer now to the results in Table III, which shows the marginal effects of the regression. For men, we see that an increase in the rank number of Player *j* (meaning a decrease in Player *j*'s quality) reduces the likelihood that *j* will win in straight sets and increases the likelihood of the other two outcomes, that he will win in three sets and that he will lose in three sets. Similarly, an increase in the ratio of rankings (Player *j* worsens relative to Player *i*) negatively impacts a straight-set win and positively impacts both three-set outcomes. The only ranking variable to affect women's outcomes is the ranking of Player *i*. This, too, has the expected effect, increasing the likelihood of a straight-set loss by *i* and reducing the probability of both three-set outcomes.

The number of games won by Player *i* in the first set has a statistically indistinguishable impact on match outcomes for men and women. For both sexes, as *i* wins more games, the likelihood that *i* loses the match in straight sets falls. Analogously, the likelihood of both three-set outcomes rises.

The results in Table III also indicate that men respond to the incentives provided by the reward system, while women do not. The likelihood of a straight-set victory rises with the purse. This impact is offset in the first round by the interaction between the purse and round of the tournament.[3] In later rounds the interaction effect dominates, so that player *i* is more likely to win the second set or win the match outright as the purse rises. Finally, the likelihood of a straight-set outcome was lower when the match was played on a clay surface.

Table IV shows the results of equation (5) where we regress the difference between Player *j*'s points and Player *i*'s points in the second set on a series of explanatory variables. A positive coefficient means that a variable increases the advantage (reduces the disadvantage) of Player *j* over Player *i* in the second set. While we display the results for the combined sample and both subsets, a Chow test fails to reject the null hypothesis that the coefficients are identical for both subsets. As a result, we confine our discussion to the results for the full sample, in column one.

Our most important result in this set of equations is the coefficient on the dummy variable indicating that the match is between women. The coefficient shows that the game differential in the second set is over a quarter of a game greater for women than for men. This

[3] We also tried interacting purse with player rank, but the results were uniformly statistically insignificant. We do not show those regressions here.

result adds nuance to the conclusions we can draw from the first set of regressions, which show that women who lost the first set are no more likely to lose the second set than otherwise equivalent men. While our ordered probit results indicate that the outcome of the match does not vary by sex, a woman who loses in straight sets loses the second set by larger margins than a man who also loses in straight sets. Thus, women are no more likely to be discouraged than men are, but those who are discouraged are more deeply affected than men are.

As expected, players who lose the first set by a larger margin also do worse in the second set. One added point in the difference in the scores of Player *j* and Player *i* in the first set increases the game differential in the second set by almost one-third of a game in the second set. Thus, the more soundly player *j* defeats player *i* in the first set, the more soundly s/he is likely to beat player *i* in the second set as well. Also as expected, the better the rank of Player *j* (the lower the number), the greater the game differential in the second set.

As was the case for gender, the impact of ranking at first appears inconsistent. The results from Table III show that a higher-ranked player who loses the first set is less likely to lose in straight sets than a lower-ranked player. However, Table IV shows that the point differential in the second set rises as the ranking of the player who lost the first set improves. Thus, as was the case for women, a better player who loses the first set is not more likely to lose the second set, but if he does lose, it will be by a larger margin.

Table V shows the results of equation (6), the probit estimation for a dependent variable indicating whether Player *i* came back to win the match. This equation uses a subset of our data, which consists of matches that go the full three sets. Consistent with our ordered probit results, women who come back to win the second set are just as likely as men to win the third set. This reinforces our earlier finding that women are no more or less likely than men to come back from adversity.

As expected, better players tended to win third-set matches, though the results differed for men and women. In the combined sample, a worse ranking for Player *j* (a higher number) increases the likelihood of a three-set victory for Player *i.* All else equal, a player whose ranking is 10 below another player has a 2.2 percent greater chance of losing the third set if s/he had won the first set but lost the second. Similarly, a worse ranking for Player *i* reduces the likelihood of such a victory by approximately the same percentage. These results are confirmed in the subsamples, but the results differ by sex. For men, a drop in rankings hurts player *j* (who won the first set) but not player *i* (who won the second set). Precisely the opposite holds for women.

While our data do not specifically state which player withdrew from the match, a positive coefficient implies that a "retirement" increases the likelihood of a victory for Player *i.* This match outcome, in turn, implies that Player *j* was more likely to be the one who retired, while a negative coefficient implies that Player *i* was more likely to retire. The positive coefficient in column 1 shows that Player *j* – who had won the first set but lost the second – was more likely to have retired. However, this result is completely driven by the women's subset. A women's match that goes three sets and ends with one player's retiring is 35 percent more likely to result in a victory for player *i.* It is possible that this result could simply reflect the fact that player *j* had been injured in the second set, which caused her to lost that set before withdrawing. That conclusion is made less plausible by the fact that the coefficient is statistically insignificant in the men's sample. The result thus suggests that Player *j* becomes particularly discouraged after losing the second set if she is a woman.

Men again appear more responsive to the incentives provided by the size of the reward. The size of the purse reduces the probability that Player *j* wins the match among men, but it has no effect for women. For men, a $100,000 increase in the size of the purse reduces the probability that Player *j* comes back from losing the second set by 2.23 percent. A larger purse thus appears to tighten men's matches but not women's matches. Finally, the type of surface appears to affect the outcome of the match, as Player *i* is more likely to win on a hard surface in the combined and men's sample. The same is true for men when the match is on clay.

V. Conclusion

This paper presents a model of how individuals respond to a multi-stage contest. The standard rank-order tournament model assumes a single competition with a winner and a loser. However, many competitions are structured so that the participants receive information about the likely outcome at each stage of the contest. If, as is often concluded in the experimental literature, women are more easily discouraged in a tournament setting, we would expect them to be less likely to come back in the face of adversity. Sports provide a natural setting for identifying both adversity and a competitor's response to it.

Tennis on the ATP and WTA tours is particularly well suited to our theoretical framework, as its outcome is determined in distinct stages. The player who loses the first set must come back to win the second to avoid losing the match. If s/he comes back to force a third set, then the winner of the first set must regroup to win the third set. After each set, one player or the other must respond to a disappointing outcome. The experimental literature implies that a woman who loses the first set is more likely than a man to become discouraged and lose the second set as well. If she does come back to win the second set, then her opponent, in turn, should be less likely than a man to come back and win the third set.

Using data from the 2011 ATP (men's) and WTA (women's) tennis tours, we find no evidence to support the hypothesis that women are less likely to come back than men are. This result holds both for the players' responses to the outcome of the first set and for their responses to the outcome of the second set. In both cases, women are just as likely to come back and win the following set as men are. Moreover, we find that the factors that affect a player's ability to come back from losing the first set are indistinguishable for men and women. This evidence strongly indicates that women and men respond identically to initial setbacks.

Women who lose a set are no more likely than men to lose the following one, but there are several differences between men's and women's behavior in the ensuing set. While women who lose the first set are no more likely than men to lose the second set, they win fewer games relative to their opponent than men do. This means that a woman who loses in straight sets is more likely to "collapse" in the second set than a man is.

We also find that, when the third set of a women's match ends in withdrawal, the outcome strongly favors the player who won the second set. While this could simply reflect the impact of an injury on performance, we find no such evidence for men's matches. We therefore suspect that retiring in the third set also reflects emotional as well as physical distress.

These results strongly contradict those of the experimental literature. One standard explanation for such a difference is the presence of self-selection in the non-experimental sample. To be sure, our results hold for a highly self-selected group. No one would claim that professional tennis players resemble the typical players on the court. Rather than discredit our results, however, we believe that the presence of self-selection makes our findings more relevant than those of a carefully randomized study. Participants in economic contests, be it on the tennis court or in the corporate world, are not randomly chosen individuals. They are participating in the contest of their choosing. Our results, while subject to selection bias, more accurately reflect the reality that competitive settings attract competitive people. Just as individuals with unusual drive and physical gifts compete in the tennis tournament, the corporate boardroom contains unusually motivated people with a talent for business.

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Figure 1

The Optimal Level of Effort Fall beyond Some Point in A Game

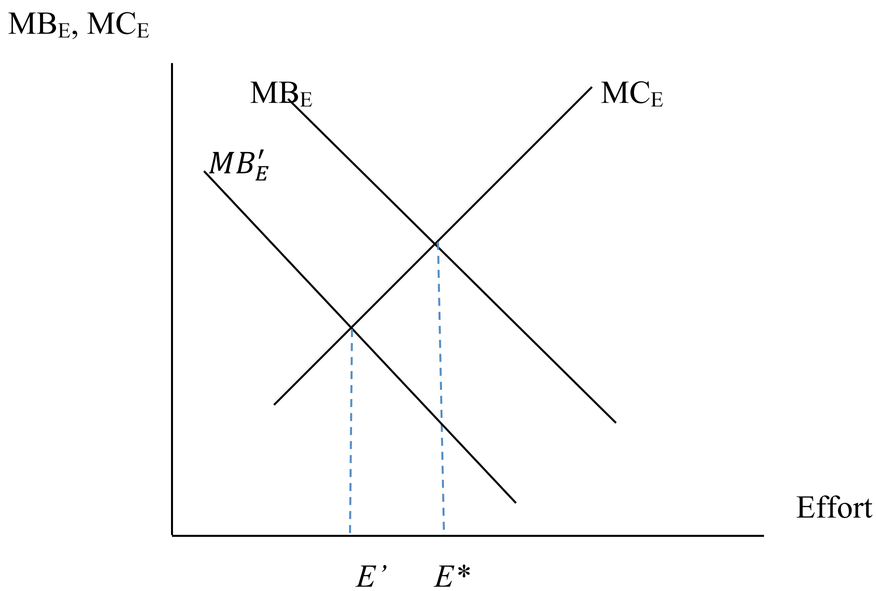

Table I: Means of Relevant Variables for the ATP and WTA Tours		
	Men	**Women**
Tournaments	46	39
Matches	1426	1209
Players	282	282
Rank of Player i[a]	50.84	52.63
Rank of Player j	41.78	45.45
First-set Games Won by Player i	3.49	3.05
Grass Court	8.70%	5.13%
Hard Court	56.52%	58.97%
Clay Court	34.78%	33.33%
Carpet Court	N/A	2.56%
Average Purse	$740,452	$322,410
One Player Retired from the Match	3.09%	3.97%
Straight-set Matches	985 69.1%	860 71.1%
Player i Wins in 3 Sets	236 16.6%	198 16.4%
Player j Wins in 3 Sets	205 14.4%	151 12.5%

[a] *Conditional on Player i or j being ranked in the top 100.*

Table II: Determinants of Match Outcomes: Ordered Probit			
Variable	**Combined**	**Men**	**Women**
Rank of Player j	0.0047*** (3.82)	0.0061*** (3.34)	0.0025 (1.40)
Player j Unranked	0.0009 (0.01)	-0.1837 (1.57)	0.1861 (1.58)
Rank of Player i	-0.0047*** (3.32)	-0.0034 (1.57)	-0.0044* (2.10)
Player i Unranked	-0.0202 (0.25)	-0.0310 (0.27)	-0.0389 (0.33)
Ratio of Rankings (j to i)	0.0143 (1.34)	0.0514* (1.91)	0.0096 (0.82)
Games Won by j in the First Set	0.0920*** (5.85)	0.1012*** (4.68)	0.0818*** (3.55)
One Player Retired	-0.2101 (1.31)	-0.2921 (1.25)	-0.1440 (0.65)
Round of Tournament	-0.0059 (0.15)	0.1063* (1.64)	0.0521 (0.75)
Total Purse (000s)	-0.0002 (1.52)	-0.0004** (2.15)	-0.0002 (0.43)
Purse Interacted with Round (000s)	0.0001 (1.17)	0.0002** (2.23)	0.0000 (0.03)
Hard Court Tournament	0.1053 (1.13)	0.1851 (1.46)	0.0045 (0.03)
Clay Court Tournament	0.1128 (1.17)	0.2254* (1.72)	-0.0134 (0.09)
Women's Tournament	-0.0846 (1.34)	N/A	N/A
χ^2	135.40	90.60	56.83
Observations	2502	1326	1176

t-statistics in parentheses
**Significant at the 10-percent level*
***Significant at the 5-percent level*
****Significant at the 1-percent level*

Table III: Marginal Effects for Selected Variables		
Variable	**Men**	**Women**
Rank of Player j (Straight Sets)	-0.0022*** (3.34)	N/A[a]
Rank of Player j (j wins in 3)	0.0007*** (3.22)	N/A
Rank of Player j (i wins in 3)	0.0015*** (3.34)	N/A
Player j Unranked (Straight Sets)	0.0646 (1.61)	-0.0650 (1.55)
Player j Unranked (j wins in 3)	-0.0210 (1.53)	0.0181 (1.61)
Player j Unranked (i wins in 3)	-0.0436* (1.64)	0.0469 (1.52)
Rank of Player i (Straight Sets)	0.0012 (1.57)	0.0015** (2.10)
Rank of Player i(j wins in 3)	-0.0004 (1.56)	-0.0004** (2.06)
Rank of Player i (i wins in 3)	-0.0008 (1.57)	-0.0011** (2.09)
Ratio of Rankings (Straight Sets)	-0.0185* (1.90)	N/A
Ratio of Rankings (j wins in 3)	0.0058* (1.89)	N/A
Ratio of Rankings (i wins in 3)	0.0127* (1.90)	N/A
Games Won by i in the First Set (Straight Sets)	-0.0364*** (4.68)	-0.0280*** (3.56)
Games Won by i in the First Set (j wins in 3)	0.0113*** (4.37)	0.0082*** (3.38)
Games Won by i in the First Set (i wins in 3)	0.0250*** (4.66)	0.0198*** (3.55)
Tournament Round (Straight Sets)	0.0382* (1.64)	N/A
Tournament Round (j wins in 3)	-0.0119 (1.63)	N/A
Tournament Round (i wins in 3)	-0.0263* (1.64)	N/A
Tournament Purse (000s) (Straight Sets)	0.0001** (2.15)	N/A
Tournament Purse (000s) (j wins in 3)	-0.00004** (2.11)	N/A
Tournament Purse (000s) (i wins in 3)	-0.0001** (2.15)	N/A
Purse Interacted with Round (000s); (Straight Sets)	-0.0001** (2.24)	N/A

Purse Interacted with Round (000s); (j wins in 3)	0.00002** (2.20)	N/A
Purse Interacted with Round (000s); (i wins in 3)	0.00004** (2.23)	N/A
Clay Court Tournament (Straight Sets)	-0.0821* (1.70)	N/A
Clay Court Tournament (j Wins in 3)	0.0244* (1.77)	N/A
Clay Court Tournament (i Wins in 3)	0.0577* (1.67)	N/A

t-statistics in parentheses
**Significant at the 10-percent level*
***Significant at the 5-percent level*
****Significant at the 1-percent level*
[a] *Variable was insignificant at the 10-percent level*

Table IV: Determinants of Game Differentials in the Second Set			
Variable	**Combined Sample**	**Men**	**Women**
Difference in First Set	0.2851*** (6.46)	0.2722*** (4.54)	0.2952*** (4.52)
Rank of Player j	-0.0104*** (3.73)	-0.0110*** (2.72)	-0.0080* (1.90)
Player j Unranked	-0.1442 (0.74)	0.1086 (0.41)	-0.4104 (1.45)
Rank of Player i	0.0085*** (2.57)	0.0059 (1.19)	0.0075 (1.48)
Player i Unranked	0.1875 (1.00)	0.3087 (1.21)	0.1212 (0.43)
Ratio of Ranking (j to i)	-0.0284 (1.14)	-0.1086* (1.70)	-0.0206 (0.71)
Round of Tournament	-0.0634 (0.68)	0.1453 (0.99)	-0.2757 (1.64)
Total Purse (000s)	-0.0001 (0.34)	0.0003 (0.90)	-0.0011 (1.09)
Purse Interacted with Round (000s)	-0.00001 (0.54)	-0.0003* (1.67)	0.0004 (0.82)
Hard Court Tournament	-0.1495 (0.69)	-0.3231 (1.15)	0.0716 (0.21)
Clay Court Tournament	-0.1290 (0.57)	-0.2157 (0.74)	0.0072 (0.02)
Women's Tournament	0.2710* (1.85)	N/A	N/A
Adjusted R^2	0.0559	0.0554	0.0445
Number of Observations	2474	1311	1163

t-statistics in parentheses
**Significant at the 10-percent level*
***Significant at the 5-percent level*
****Significant at the 1-percent level*

Table V: The Probability that Player *i* Wins in a 3-Set Match			
Variable	**Combined**	**Men**	**Women**
Rank of Player j	0.0054** (2.28)	0.0062* (1.81)	0.0029 (0.82)
Player j Unranked	-0.1308 (0.88)	-0.4003* (1.95)	0.1714 (0.78)
Rank of Player i	-0.0054** (2.03)	-0.0012 (0.29)	-0.0087** (2.21)
Player i Unranked	0.1173 (0.78)	0.1224 (0.58)	0.0086 (0.40)
Ratio of Rankings (j to i)	0.0307 (1.14)	0.0843 (1.64)	0.0192 (0.85)
Games Won by i in the First Set	0.0262 (0.92)	0.0440 (1.16)	0.0022 (0.05)
Games Won by j in the Second Set	-0.0305 (1.05)	-0.0508 (1.30)	-0.0137 (0.30)
One Player Retired	0.6293* (1.81)	0.1930 (0.41)	1.2194** (2.04)
Round of Tournament	0.0006 (0.01)	-0.1382 (1.24)	0.1289 (0.98)
Total Purse (000s)	-0.0003 (1.14)	-0.0006* (1.80)	-0.0002 (0.17)
Purse Interacted with Round (000s)	-0.0001 (0.78)	0.0001 (0.53)	-0.0004 (1.030
Hard Court Tournament	0.3916** (2.34)	0.6377*** (2.75)	0.1596 (0.63)
Clay Court Tournament	0.2623 (1.51)	0.4512* (1.88)	0.1066 (0.40)
Women's Tournament	-0.01086 (0.95)	N/A	N/A
χ^2	47.67	35.21	26.93
Observations	788	439	349

t-statistics in parentheses
**Significant at the 10-percent level*
***Significant at the 5-percent level*
****Significant at the 1-percent level*