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Employment Relationships Over Time: Retention and Promotion

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Employment Relationships Over Time: Retention and Promotion

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For Rev. Msgr. Michael J. Gilleece (7/29/31 - 8/2/79)

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Employment Relationships Over Time: Retention and Promotion

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In this dissertation, I examine how available information affects promotion and turnover decisions in internal labor markets. In the first essay, I use data on all Major League Baseball managers from 1950 to 1996 to consider multiple evaluation measures and their role in actual firings of managers. The results indicate that firms use all of the distinct measures of managerial performance in termination and rehire decisions. However, the results also suggest that teams, in making termination decisions, use information that is unlikely to reflect managerial ability. That is, talent *at the time of hire* affects the risk of termination, even after conditioning on team performance relative to expectations after the date of hire. In the second essay, I use the 1979 National Longitudinal Survey of Youth data to explore the factors that are important determinants of an individual's promotion. One issue that arises in estimating the probability of promotion from longitudinal work history data is that researchers only observe promotion for individuals who remain at a job between interviews. I improve upon earlier studies by using a bivariate probit analysis to correct the bias from partial observability and provide more informative estimates of the promotion process. These new estimates allow differences in promotion rates across demographic groups to be decomposed into differences in the probability of promotion conditional on staying and differences in the probability of staying. In the third essay, we explore the differential patterns of job attachment between men and women by examining how men and women respond to promotion expectations. Using the 1979 National Longitudinal Survey of Youth, we find that early in their career women with low promotion expectations are more likely to stay on a job than corresponding men. We also find that this difference diminishes with experience.

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Chapter 1

Introduction

Employment relationships develop and change over time. As workers gain experience in the labor market and tenure at a firm, they gain and reveal information. This new information affects the subsequent decisions of both the workers and the firms, specifically turnover and promotion decisions. In the following dissertation, I study how available information affects both turnover and promotion.

Turnover decisions are important in any employment relationship and they are assumed to reflect the productivity of the relationship. That is, if a worker's cost or wage exceeds the benefit to the firm then the firm will end the relationship. Similarly, if a worker's value in alternative employment exceeds the current firm's willingness to pay the worker then the worker will end the relationship. However, in the case of workers, non-wage benefits are also important determinants of the decision to leave a firm. Factors that the worker may consider are the loss of any firm specific skills or knowledge, or the presence of a job ladder within the firm. The latter consideration is of particular interest. Workers who are likely to receive a promotion and its benefits have a higher reservation wage and therefore are less likely to leave a firm. As such, firms have an incentive to offer promotions to workers that are more productive to encourage remaining with firm. The turnover and promotion decisions are more difficult when information regarding productivity and worker-firm match quality is either unobserved or noisy.

In chapter 2, I examine the case of high-level management. The productivity of high-level managers is hard to observe directly since these managers often do not have a direct task in production. Compensation schemes and termination decisions must take the scarcity of information into account. Firms must induce the desired actions by designing a compensation scheme that gives the managers an incentive to perform the desired actions. However, in these situations, any determinants of firm performance that can be observed or inferred and are unrelated to the manager's actions should be filtered out of the performance measure. Therefore, compensation and termination decisions should not respond to movements in firm performance due to inferable factors not attributable to the agent.

I use Major League Baseball field manager to examine two specific aspects of the market for high-level management. First, I test whether termination and rehire decisions depend on a measure of performance that does not contain information on manager actions or ability. Second, I test whether termination and rehire decisions depend on multiple measures of managerial performance, each of which plausibly contains different information regarding manager actions and ability. The data has advantages over data used in previous studies. The data I use has detailed information regarding the industry, the production process, and the competitors in the industry. As such, I am able to analyze the effects of multiple measures of manager performance as well as a measure related to team performance but independent of a manager's actions- namely, team quality prior to a manager's hire. Furthermore, the data has a much higher frequency of performance realizations and contains information about managers from the start of their career. The results indicate that firms use all of the distinct measures of managerial performance in termination and rehire decisions. However, the results also suggest that teams, in making termination decisions, use information that is unlikely to reflect managerial ability. That is, player talent *at the time of hire* affects the manager's risk of termination, even after conditioning on team performance relative to expectations after the date of hire.

In chapter 3, I examine the determinants of promotion. Specifically, I address the role of gender in the promotion decision. It is a commonly held belief that women face a 'glass ceiling' with regard to internal upward mobility. Discrimination in the market for promotions may explain observed wage differences between men and women since promotions are a significant source of wage growth. I improve upon previous studies on gender differences in promotion by addressing a particular selection issue that is present in any estimation of promotion probability that relies on longitudinal work histories to observe promotions. Namely, previous studies neither address the issue that for an individual to receive a promotion that individual must stay on the job nor the issue that an individual may turn down a promotion and leave the firm or leave when not offered a promotion. I use the 1990 round of the National Longitudinal Survey of Youth (NLSY) to estimate a bivariate probit model of promotion. The primary equation is an equation for promotion and mirrors equations presented in previous literature. The secondary equation is an equation for 'staying on a job.' The stay equation addresses the selection issue present in the observed promotions. Allowing correlation in the error terms across the equations and estimating the bivariate probit refines the estimates and yields more informative results. The significance of the estimated correlation in the bivariate probit model suggests the univariate estimates for promotion conditional on staying on a job are biased.

Specifically, the results suggest that the univariate estimates of promotion for women are not biased while the univariate estimates of promotion for men are biased. The bivariate probit model also allows the probability of an observed promotion (i.e. the joint probability of staying and receiving a promotion offer) to be decomposed in the probability of promotion conditional on staying on a job and the probability of staying on a job. These estimates suggest that women are less likely to receive a promotion *a priori* than men all else equal. The estimates also suggest that women are more likely to remain on a job than men all else equal. Furthermore, there is evidence that women stay on jobs in order to signal attachment to the labor market.

Chapter 4 explores this result. We study how the expectation of promotion affects men's and women's decision to stay on a job and whether this relative pattern varies with the amount of labor market experience. Since training workers is a costly activity, firms are only willing to invest in those workers from whom they expect to recoup the costs of training. Given that the expected time horizon to recover these costs is shorter for women, firms may be unwilling to train their women workers. And since training is invariably a prerequisite for promotion, promotion rates for women may tend to be smaller than those for men. However, if women are staying in careers and on jobs longer then we would expect firms to treat these women - the 'stayers' - no differently from men. A problem that arises is that women are a heterogenous group comprising both 'stayers' and 'quitters.' If firms cannot distinguish between the two types of women workers based on observables, statistical discrimination would still result in lower promotion rates for women and a persistence of the wage gap. If, on the other hand, the stayers could successfully signal their intentions to stay in the labor force and separate themselves from the quitters, they could overcome internal labor market discrimination.

It is our view that women who are concerned about their careers are using job attachment as a signal to indicate their attachment to the labor force. We expect women with little or no job market experience to have lower job turnover rates compared to men of similar experience, all else equal. Therefore, during this period, we expect women's turnover decisions to exhibit less sensitivity to expectations of promotion, relative to men. This rationale also suggests that once women have gained adequate labor market experience and revealed themselves as stayers, their job attachment patterns should respond more strongly to their expectations of promotions. We use NLSY data to examine how promotion expectations affect men's and women's decision to stay on a job and whether this relative pattern varies with the amount of labor market experience. We find evidence that women are more likely than men to stay on a job all else equal and that women with low promotion expectations are more likely than comparable men to stay on a job. Furthermore, this difference is more pronounced early in careers. The fact that the difference diminishes with experience supports the signalling explanation.

Chapter 2

Performance Evaluation and Turnover: Field Managers in Major League Baseball

2.1 Introduction

Managerial effort and ability are crucial determinants of firm performance but are often hard to observe directly because of the nature of high-level management jobs. High-level managers often do not have a direct task in production but rather perform hard to measure tasks such as organizing, delegating, and motivating. Therefore, firm owners must structure compensation and make subsequent termination decisions in such a way as to encourage high effort and attract high ability individuals to the job.

When profits are affected by the actions of an agent and are observable to the principal, an efficient contract clearly states the actions to be taken and the compensation for those actions. When an agent's actions are not directly observable to the principal, the principal must induce the desired actions by designing a compensation scheme that gives the agent an incentive to perform the desired actions. However, in these situations, any determinants of firm performance that can be observed or inferred and are unrelated to the manager's actions should be filtered out of the performance measure.[1] Thus,

[1]It is possible that agents are rewarded for outcomes that may or may not be related to the manager's actions.

managerial wages and termination outcomes should not respond to movements in observed performance due to inferable factors not attributable to the agent.[2]

Previous empirical studies have examined the relationship between the performance of high-level managers and compensation. Early studies [Antle and Smith (1986), Gibbons and Murphy (1990)] find support for the notion that firms attempt to distinguish between changes in measured performance due to manager input and changes in measured performance not attributable to manager performance. Both papers present the concept of *relative performance evaluation* where firms evaluate managers in relation to managers that face the same common risk. Garen (1994) finds that, while the executive compensation has aspects of the principal-agent problem, there is little evidence to support the notion of relative performance evaluations. Hall and Leibman (1998) show that while CEO pay responds significantly to changes in firm performance relative performance evaluations are not a significant determinant of compensation. Garvey and Milbourn (2003) also find little support for relative performance evaluations, in general, but do find evidence that firms use relative performance evaluations when executives face high costs of shielding themselves from market fluctuations.

Other studies have extended the idea of efficient compensation to include the retention decision firms make regarding managers. A number of empirical studies [Weisbach (1988), Warner et al (1988), Gibbons and Murphy (1990), Blackwell et al (1994), Geddes and Vinod(1997)] examine the relationship between observable manager performance and termination. The results

[2] As an example, Holmstrom(1979) shows how the optimal wage contract changes when an additional signal is added to the information set. The wage will depend on this additional signal only if this signal provides incremental information about the agent's action.

from these studies support the notion that relative performance evaluations are used to determine manager performance and that the performance evaluations are used in retention decisions. However, DeFond and Park (1999) find that the use of relative performance evaluation in turnover decisions depends on the competitiveness of the industry. The more competitive the industry the more important relative performance evaluations are in the turnover decision. Extensions of these studies [Khorana (1996), Chevalier and Ellison (1999)] examine how the relationship between termination and observed performance changes as firms acquire information regarding manager performance. The results from these studies suggest that as more information about a manager's performance is acquired the retention decision is less responsive to single performance realizations.

In this paper, I examine termination and rehire decisions firms make regarding high-level managers. Specifically, I examine whether termination and rehire decisions depend on a measure of performance that does not contain information on manager actions or ability. I also examine whether termination and rehire decisions depend on multiple measures of managerial performance, each of which plausibly contains different information regarding manager actions and ability. In order to answer these questions, I need a significant amount of information regarding the industry involved, the production process, and the competitors in the industry. The Major League Baseball manager data I use has the necessary information and has some advantages relative to the data used in previous studies. First, most prior studies simply relate managerial wages and/or turnover to firm profit (in some cases relative to other firms). These analyses are informative but are also limited because some of the variation in firm profits may be due to factors beyond the manager's control that are observable to shareholders but not the econometrician. In contrast, the present data allow me to analyze the effects of multiple measures of manager performance as well as a measure related to team performance but independent of a manager's actions- namely, team quality prior to a manager's hire.[3] Lastly, the data has a much higher frequency of performance realizations than previous studies and contains information about managers from the start of their career.

The structure of the rest of the paper is as follows. Section 2.2 presents the econometric methodology. This section is divided into three parts. The first part addresses the construction of expected performance levels for teams aggregated from expected player performance; the second part addresses the estimation of expected win probabilities for individual teams; and the third part addresses the termination and rehire decisions made by teams regarding managers. Section 2.3 concludes.

2.2 Econometric Methodology

In this paper, there are multiple components in the econometric model. Each component builds toward the estimation of manager termination and rehire equations, which I assume are dependent upon manager performance and, possibly, other factors. Isolating a manager's performance (i.e. contribution to wins) requires controlling for the quality of the players at his disposal. In order to do so, it is necessary to estimate a model for team wins as a function of the quality of players on both the manager's own team and the opposing team.

[3] Bertrand and Mullainathan (2001) account for a random shock to performance and find that CEO compensation responds equally to performance attributable in part to manager performance and performance not attributable to manager performance.

Each player's quality, in turn, depends on his age and individual-specific talent level. To account for this relationship, I estimate models that relate individual performance to age and individual fixed effects. The results from each of the estimations are then used to construct measures of 'excess performance' due to manager input, which are the key explanatory variables in the models of managerial termination and rehire. Below, I first estimate individual-player-level equations and use the results to construct aggregate player quality variables for each team in each year. Next, I relate player quality levels of teams to wins by estimating a probit equation for games won and I use the probit estimates to generate expected win probabilities for each team in each game. Finally, I use actual winning percentage as well as the expected winning percentage in the termination and rehire equations to isolate manager performance. Consider each component in turn.

2.2.1 Individual Player Performance

2.2.1.1 Model Specification

In order to establish an expected level of team performance, I need to establish expected player performance. I generate expected player performance levels by estimating a fixed effect regression for player performance. The specification of the fixed effect equation is as follows:

$$y_{it} = X_{it}\beta + \gamma_i + \varepsilon_{it} \tag{2.1}$$

where γ_i represents an individual-specific effect. For the equations I estimate, y_{it} is either a measure of hitting or pitching performance while X_{it} includes both age and year dummy variables. There is a fixed effect for each individuals in the sample. Estimating this equation establishes an age profile for all players while allowing the fixed effect to account for individual ability. The year dummy variables account for any differences that may occur across years and affect all of the players' performances.[4] Including a series of age dummy variables allows flexibility in the age profile. The dummy groups are defined as 19 or less, 42 and older, and each year of age in between.[5]

2.2.1.2 Player Data

The player data are in two parts: hitters and pitchers.[6] The hitter data include the standard hitting statistics: at-bats, hits, singles, doubles, triples, home runs, base-on-balls, hit-by-pitches, sacrifices, stolen bases and the number of times caught stealing. The pitcher data include the standard pitching statistics: wins, losses, strikeouts, earned runs allowed, innings pitched, hits allowed, home runs allowed, and base-on-balls allowed. I use these data in the fixed effects regressions for individual performance. The hitter regressions include any player who had a plate appearance or who made an appearance as a pinch runner between the years 1901 and 1996.[7] The pitcher regressions include any player that threw a pitch in a game between 1901 and 1996.[8]

The measure of performance I use in the hitter regressions accounts for each opportunity a player has to achieve a base and each time a player costs

[4] An example is 1968, often referred to as 'the year of the pitcher.' Pitchers were so dominant that rules were subsequently changed to benefit hitters.

[5] I use the 'baseball age' of each player, defined as age on July 1 of each year.

[6] Both parts of the data were compiled from two sources: *Total Baseball* (sixth ed.) and from the website 'The Baseball Archive' (www.baseball1.com).

[7] I limit the sample to post-1901 because this is the first year that the American and the National League coexisted.

[8] Seven players are not included in the sample because they have no reported age. Each player played during 1901 or 1902 with only three of the players having a career of any length.

his team a base. I call this metric bases-per-chance (BPC).[9] It is defined in the following way:

$$BPC = \frac{TB + BB + HBP + SF + SH + SB - CS}{AB + BB + HBP + SF + SH + SB + CS} \tag{2.2}$$

The numerator accounts for the total number of bases a player achieves for his team. It includes the base value acquired for each hit (TB), each base-on-balls (BB), each hit-by-pitch (HBP), each sacrifice fly (SF) and hit (SH), and each stolen base (SB). The measure also takes a base away for each time a player is caught stealing (CS). The denominator accounts for each opportunity the player has to achieve a base. It includes each plate appearance (AB plus BB plus HBP plus SF plus SH) as well as any time a player on a base attempts to advance another base (SB plus CS). BPC is average bases advanced per opportunity to advance bases.[10]

The measure of performance I use in the pitcher regression relates the bases a pitcher allows to the opportunity hitters have to achieve bases at the expense of the pitcher. Put simply, the metric is bases allowed per batter faced.[11] It is defined as follows:

$$BPBF = \frac{(HA - HRA) * (\mathit{1B\%} + 2 * \mathit{2B\%} + 3 * \mathit{3B\%}) + 4 * HRA + BB}{3 * IP + HA + BB}. \tag{2.3}$$

[9]See Appendix A for a discussion of the process of choosing this measure over standard measures of hitter performance.

[10]In some years, not all of the variables are available. SF were not recorded before 1954. For the years pre-1954, I omit SF from the equation. Similarly, CS was not recorded pre-1920 in the American League and was not recorded pre-1951 in the National League. In these years, I omit both CS and SB to avoid crediting players with bases for stolen bases without counting the bases lost through being caught stealing.

[11]See Appendix B for a discussion of the process of choosing this measure over standard measures of pitcher performance.

The pitching data do not include the base value for each hit allowed (HA). It only includes the total number of hits allowed and the total number of home runs allowed (HRA). In order to approximate the total bases allowed, I calculated single, double, and triple rates for each year in the data set using the hitter data (*1B%*, *2B%*, *3B%*, respectively). I used these rates to approximate the base value of each hit allowed by a pitcher. The addition of base-on-balls to this number mimics the corresponding numerator in hitter productivity measure. The denominator approximates batters faced by the pitcher. Innings pitched (IP) multiplied by three accounts for the fact that a pitcher at a minimum must face three batters per inning. Each hit allowed and base-on-balls increases the number of batters by one.[12] This metric is the pitching equivalent of the hitter productivity measure. The summary statistics for bases earned, chances, BPC, bases allowed, batters faced, and BPBF are in Table 2.1.

2.2.1.3 Player Regression Results

The hitter regression contains 59,020 observations from 11,425 different individuals while the pitcher regression contains 28,152 observations with 5,889 different individuals. The overall R^2 is .0206 for the hitter regression and .0287 for the pitcher regression. In both regressions, the effects of interest are best shown using graphs. As such, I present Figures 2.1, 2.2, and 2.3 in lieu of a table of coefficients.

In both the hitter and pitcher equations, I include dummy variables

[12]It is possible that a pitcher will not face more than three batters even if he allows a hit or a base-on-balls because hitters sometimes hit into double (or triple) plays. However, the pitching data do not include this information. It is in this sense that the denominator is an approximation.

for each age between 19 and 42. I include these variables in order to capture the relationship between player production and age in an unrestrictive way. In the hitter regression, I also include interaction terms between age and a pitcher dummy variable. These interactions allow the age-hitter productivity profile to differ for position players and pitchers. As can be seen in Figure 2.1, the age-hitting productivity profile has an inverse U-shape for position players but not for pitchers.[13] The position player graph increases early in the career, remains relatively flat from ages 26 to 32,[14] and then declines gradually after 32.[15] The pitcher graph has a sharp increase early in the career but then remains relatively flat after age 24. This flatness could be to the fact that pitchers do not specialize in hitting and therefore, experience no mid-career decrease in hitting production.

The pitching productivity regression does not suggest a quadratic relationship between age and pitching productivity. The graph is relatively flat with a slight decline in performance with age, which is indicated by an increase in the graph. The minimum of the age-productivity schedule occurs at age 20 with a slight non-monotonic increase, which indicates a performance decline, through age 42. An F-test for joint significance of the age dummy variables is not significant at any meaningful significance level.[16] This result suggests that there is not a relationship between age and pitching production. There is a possible explanation for the difference between the age profile for pitching

[13] F(23, 47358) = 25.24 (p-value = 0.000) for joint significance of the age dummy variables. F(23, 47358) = 5.39 (p-value = 0.000) for joint significance of interaction terms. F(46, 47358) = 14.78 (p-value = 0.000) for joint significance of age dummy variables and interaction terms.

[14] A test of the hypothesis that the coefficients on ages 26 through 32 are equal cannot be rejected; F(6, 47358) = 0.65 p-value = 0.6903.

[15] The peak age of production for position players is 29.

[16] F(23, 22048) = 1.23. (p-value = 0.2042)

skills and the age profile for hitting skills. Pitchers may develop skills over their careers that compensate for any loss in physical ability. These skills may include pitch control, pitch repertoire, and general 'game management.' In contrast, hitting relies more upon strength and reflexes, which peak in early years. This explanation suggests that effective pitching is more of a learned skill than a physical talent.

In both the hitter and the pitcher equations, I include a series of dummy variables that account for the differences between the American and National League. I include a full set of league-year interaction terms. The interactions allow the differences across the leagues to differ across years. The reason I include the interaction terms is to account for the Designated Hitter rule. In 1973, the American League established a rule that allows one player to hit in place of the pitcher without playing in the field. This rule allows American League pitchers to focus on pitching alone while certain American League players can focus on hitting alone. The introduction of this rule should affect any difference between the leagues. The direction of the effect depends on the relative impact of improved hitting and improved pitching. The American League post-1972 should have stronger pitchers since they can focus on pitching alone, which suggests that in the American League hitters would produce less while pitchers produce more. However, the pitchers must face a lineup of 9 hitters, which suggests pitchers will produce less.[17] The league dummy variables and the interactions account for any fundamental difference in pitcher and hitter production across leagues and eras. However, I expect the leagues to differ the most in the Designated Hitter era.[18]

[17] National League pitchers face 9 hitters but one of the hitters is the opposing pitcher. As a general rule, pitchers are not strong hitters and as such, are easier to retire.

[18] In the hitter regression, I omit any pitchers who appeared as hitters or baserunners

The year effects are plotted in Figures 2.2 and 2.3. The year dummy variables are jointly significant at the one percent level.[19] Similarly, the American League dummy variable and American League-Year interaction terms are jointly significant at the one percent level.[20] Also, the year dummy variables, the American League dummy variable, and the American league-year interaction terms are jointly significant.[21] However, the graphs suggest that qualitatively there is little difference across the leagues.[22] The largest difference across the leagues should be in the designated hitter era (post-1972). However, the null hypothesis that the post-1972 year-league interactions are jointly equal to zero cannot be rejected in the pitcher regression and are only significant at the 7% level in the hitter regression.[23] The only notable difference between the leagues in the pitcher productivity graphs is the 1950s. During this time, the National League exhibits a sharp decrease in productivity not evident in the corresponding American League graph. The only notable difference between the leagues in the hitter productivity graph is in the 1930s and late 1940s. During this time, the American League exhibits a slight increase while the National league exhibits a decrease. The American League does decrease but much later in the 1930s. This difference may be a residual effect of World War

post-1972 since there are less than 7 chances per year by pitchers.

[19] $F(95,47358) = 3.37$ (p-value $= 0.000$) for the hitter regression and $F(95, 22048) = 3.63$ (p-value $= 0.000$) for the pitcher regression.

[20] $F(96, 47358) = 1.81$ (p-value $= 0.000$) for the hitter regression and $F(96, 22048) = 1.94$ (p-value $= 0.000$) for the pitcher regression.

[21] $F(191, 47358) = 3.45$ (p-value $= 0.000$) for the hitter regression and $F(191, 22048) = 3.81$ (p-value $= 0.000$) for the pitcher regression.

[22] The mean of the difference between the year effects for hitter productivity is -.00692 with a standard deviation of .01995. Similarly, the mean of the difference between the year effects for pitcher productivity is .0009 with a standard deviation of .0223.

[23] $F(24, 22048) = 1.04$ (p-value $= 0.4082$) for the pitcher regression and $F(24, 47358) = 1.45$ (p-value $= 0.0726$) for the hitter regression.

II.

An important determinant of production in the equations described above is the individual fixed effect of the players. The mean fixed effect in the hitter equation is -.0444 with a standard deviation of .1778 while in the pitcher equation the mean is .0196 with a standard deviation of .1201. In both equations, the fixed effects pass an F-test for joint significance. This result suggests that a portion of the variation in performance is due to individual specific abilities. This result is intuitive. It is reasonable to expect different players to produce at different levels throughout their careers.

I use the estimates from the player regressions to obtain predicted values of both hitter and pitcher productivity for each player. I then aggregate the predicted values to obtain team expected performance levels. In order to account for playing time, I weight each player's predicted individual hitting productivity by the number of chances and I weight each player's predicted individual pitching productivity by the number of batters faced. Thus, team predicted hitting productivity is

$$\widehat{BPC}_{team} = \frac{\sum_{i=1}^{N_t} \widehat{BPC}_{it} * C_{it}}{\sum_{i=1}^{N_t} C_{it}} \tag{2.4}$$

and team predicted pitching productivity is

$$\widehat{BPBF}_{team} = \frac{\sum_{i=1}^{N_t} \widehat{BPBF}_{it} * BF_{it}}{\sum_{i=1}^{N_t} BF_{it}}. \tag{2.5}$$

Each of the predicted individual productivity levels reflect expected productivity conditional on age, year, league, and the player's individual effect. These values aggregated to the team level represent the offensive and pitching production a team could expect at the beginning of a year given the players on its roster.

I also construct the actual hitter and pitcher productivity of a team in a year from the individual productivity levels of the players on the team during that year as follows:[24]

$$BPC_{team} = \frac{\sum_{i=1}^{N_t} BPC_{it} * C_{it}}{\sum_{i=1}^{N_t} C_{it}} \tag{2.6}$$

$$BPBF_{team} = \frac{\sum_{i=1}^{N_t} BPBF_{it} * BF_{it}}{\sum_{i=1}^{N_t} BF_{it}} \tag{2.7}$$

The performance levels are constant for a team within a year, which implicitly assumes that player composition is constant within a year. The aggregation provides an opportunity to relate the probability team i beats team j to their respective run-producing and run-preventing abilities in that year. The summary statistics for actual *BPC* and *BPBF* are in Table 2.2.

2.2.2 Team Win Probabilities

2.2.2.1 Model Specification

The second part of the econometric model is estimating how team hitting and pitching productivity relate to wins. In doing this, I estimate a probit equation for win on the actual productivity levels of teams in a given year. The probit equation for whether a team wins is specified in the following way for any pair of opponents in a game:

$$Pr(w_H = 1) = \Phi[\alpha_0 + \beta_1 * X_H + \beta_2 * Y_H + \beta_3 * X_V + \beta_4 * Y_V] \tag{2.8}$$

$$\begin{aligned} Pr(w_V = 1) &= \Phi[-\alpha_0 + \beta_1 * X_V + \beta_2 * Y_V + \beta_3 * X_H + \beta_4 * Y_H] \\ &= 1 - \Phi[\alpha_0 - \beta_1 * X_V - \beta_2 * Y_V - \beta_3 * X_H - \beta_4 * Y_H] \end{aligned} \tag{2.9}$$

[24]In the case of players who play for multiple teams during a year, only the production recorded with the specific team counts in the aggregate team performance levels.

where Φ represents the cumulative standard normal distribution function. X and Y represent team productivity levels of hitting and pitching, respectively, and the subscripts H and V represent the home and visiting teams, respectively. β_1 through β_4 is the set of parameters to be estimated. α_0 is a constant term to be estimated and reflects the possible presence of a home team advantage. I impose the following restriction in the estimation to ensure that $Pr(w_H = 1) + Pr(w_V = 1) = 1$:

$$
\begin{aligned}
-\beta_1 &= \beta_3 \\
-\beta_2 &= \beta_4
\end{aligned}
\tag{2.10}
$$

This restriction yields:

$$Pr(w_H = 1) = \Phi[\alpha_0 + \beta_1 * (X_H - X_V) + \beta_2 * (Y_H - Y_V)] \tag{2.11}$$

$$Pr(w_V = 1) = \Phi[-\alpha_0 + \beta_1 * (X_V - X_H) + \beta_2 * (Y_V - Y_H)] \tag{2.12}$$

Equation [2.11] and equation [2.12] imply that the probability of winning depends on the differences in the teams' hitting and pitching productivity and any home field effects. I estimate these equations below.

2.2.2.2 Win Probit Results

In estimating win probabilities, I use a simple account of 115,728 regular season MLB games between 1923 and 1996 and the constructed actual hitting and pitching productivity described in the previous section.[25] The summary statistics for the difference variables used in the team probit equations are presented in Table 2.2. The results of the estimation are presented in Table

[25] The individual game data was obtained free of charge from and is copyrighted by *Retrosheet*. Interested parties may contact *Retrosheet* at 20 Sunset Rd., Newark, DE 19711.

2.3. The significance and positive sign of the constant term suggest a home team advantage. A home team that is playing an equally talented team such that the hitting productivity and the pitching productivity differentials both equal zero has just over a .54 probability of winning. A home team that has a one standard deviation advantage in hitting productivity but is otherwise equally talented as the visitor has just under a .62 probability of winning. Similarly, a home team that has a one standard deviation advantage in pitching productivity but is otherwise equally talented as the visitor has just over a .59 probability of winning. If the visitor has a one standard deviation advantage in hitting productivity and the teams are otherwise equally talented then the home team has just under a .47 probability of winning. Finally, a home team that is at a one standard deviation disadvantage in pitching productivity but is otherwise equally talented has just over a .49 probability of winning. The estimated model passes a simple F-test for joint significance and supports the conjecture that team levels of hitting and pitching productivity affect the probability of winning.[26]

I use the coefficients on BPC, $BPBF$, and the constant term to construct expected win probabilities for a team in each game in each year. These win probabilities are constant across games between teams within a year and with the same home team but will differ by year, team pair, and home team. I use the win probabilities to construct three expected winning percentages. These expected winning percentages are then used in the termination equation to isolate manager input to production.

[26]I also estimated the model with an interaction term. The interaction term took the form $BPC_i * BPBF_j - BPC_j * BPBF_i$ and accounted for any effect the relative levels of hitting productivity and pitching productivity had on the probability of winning. The coefficient on the term was insignificant.

The first expected win probability for game g, $\widehat{WIN}_{1,g}$, takes the following form:

$$\widehat{WIN}_{1,g} = \Phi[\widehat{\alpha} + \widehat{\beta}_1(BPC_{i,t} - BPC_{j,t}) + \widehat{\beta}_2(BPBF_{i,t} - BPBF_{j,t})] \tag{2.13}$$

where Φ represents the standard normal distribution function, BPC and $BPBF$ are *actual* current year performance levels of both the home team (i) and its opponents (j) in year t, and $\widehat{\alpha}$, $\widehat{\beta}_1$, and $\widehat{\beta}_2$ are obtained from the estimation of equation [2.11]. This win probability represents the predicted game outcome given the actual productivity levels of the teams in year t.

The second expected win probability for game g, $\widehat{WIN}_2$, takes the following form:

$$\widehat{WIN}_{2,g} = \Phi[\widehat{\alpha} + \widehat{\beta}_1(\widehat{BPC}_{i,t} - \widehat{BPC}_{j,t}) + \widehat{\beta}_2(\widehat{BPBF}_{i,t} - \widehat{BPBF}_{j,t})] \tag{2.14}$$

where Φ, $\widehat{\alpha}$, $\widehat{\beta}_1$, and $\widehat{\beta}_2$ are again obtained from equation [2.11] and $\widehat{BPC}$ and $\widehat{BPBF}$ are the *expected* team productivity in equations [2.4] and [2.5], respectively. This win probability reflects the expected game outcome if all members of each team performed at their predicted levels in year t as derived from the individual player regressions. The distinction between $\widehat{WIN}_1$ and $\widehat{WIN}_2$ is important. The latter is the win probability for the home team if all players on both teams performed at their expected levels in year t. The former is the win probability for the home team given the actual performance level of all players on both teams in year t.

The third expected win probability for game g, $\widehat{WIN}_{IS}$, takes the following form:

$$\widehat{WIN}_{IS,g} = \Phi[\widehat{\alpha} + \widehat{\beta}_1(\widehat{BPC}_{i,t-k} - \widehat{BPC}_{j,t}) + \widehat{\beta}_2(\widehat{BPBF}_{i,t-k} - \widehat{BPBF}_{j,t}) \tag{2.15}$$

where Φ, $\widehat{\alpha}$, $\widehat{\beta}_1$, and $\widehat{\beta}_2$ are defined as before, $\widehat{BPC}_t$ and $\widehat{BPBF}_t$ are defined as before, and $\widehat{BPC}_{t-k}$ and $\widehat{BPBF}_{t-k}$ are expected team productivity levels given the players on the home team (i), k periods ago.[27] This win probability represents the predicted game outcome for the home team given the expected performance levels of the players on the home team t-k periods ago. Each of the expected win probabilities presented above can be used to construct cumulative expected winning percentages in the following way:

$$\widehat{WPCT}_z = (\frac{1}{G}) \sum_{g=1}^{G} \widehat{WIN}_{z,g} \tag{2.16}$$

where G is the number of games managed and z is either *1*, *2*, or *IS*.

2.2.3 Manager Regression

2.2.3.1 Model Specification

The final step in the estimation is the hazard for manager termination. The hazard specified here follows the proportional hazard suggested by Cox (1972). It is factored as follows:

$$\lambda(t, x, \beta, \lambda_0) = \lambda_0(t)\lambda_1(x, \beta) \tag{2.17}$$

where λ_0 is the baseline hazard, x is a vector of possibly time-varying explanatory variables, and β is a vector of coefficients. Specifying the hazard in this way, allows for flexibility in the form of the baseline hazard by allowing for non-monotonic changes in the function. The partial log-likelihood function is:

$$L = \sum_{i=1}^{N} \{ln\lambda_1(x_i, \beta) - ln[\sum_{j=i}^{N} \lambda_1(x_j, \beta)]\} \tag{2.18}$$

[27] In the hazard estimation, k is chosen so that the team is composed of the existing players just prior to the beginning of a manager's spell. The variable is described in further detail in the next section.

where N is the set of ordered failures, i is the individual whose spell is completed at time t, and j represents the individuals at risk at time t. This form allows for parametric estimation of λ_1 without direct specification of λ_0. I specify $\lambda_1(x,\beta) = \exp^{x_i\beta}$, which implies that

$$\frac{\partial \ln \lambda(t, x, \beta, \lambda_0)}{\partial x} = \frac{\partial \ln \exp^{x_i\beta}}{\partial x} = \beta \tag{2.19}$$

and therefore β can be interpreted as the constant proportional effect of a unit change in x on the conditional probability of ending a spell.

A simple specification of the covariate vector includes variables such as manager experience, dummy variables for the occurrences of the all-star break and the end of the season, and the manager's actual winning percentage to date .[28] However, this specification is naive; it does not account for the fact that different managers control teams of different aggregate quality. In order to account for the differences in team quality across managers, I prefer a specification that replaces actual winning percentage with expected winning percentage given team quality at time of hire and several measures of the manager's 'excess winning percentage.' In particular, note that cumulative winning percentage through game G can be written in the following form:

[28]The all-star break and end-of-season dummy variables account for periods of time when the costs associated with manager turnover are lowest. As such, teams should be more willing to fire a manager during these portions of the season.

$$
\begin{aligned}
(\frac{1}{G})\sum_{g=1}^{G} WIN_g =& (\frac{1}{G})\sum_{g=1}^{G}(WIN_g - \widehat{WIN_{1}}_{,g}) + (\frac{1}{G})\sum_{g=1}^{G}(\widehat{WIN_{1}}_{,g} - \widehat{WIN_{2}}_{,g}) \qquad (2.20)\\
&+ (\frac{1}{G})\sum_{g=1}^{G}(\widehat{WIN_{2}}_{,g} - \widehat{WIN}_{IS,g}) + (\frac{1}{G})\sum_{g=1}^{G}(\widehat{WIN}_{IS,g})\\
OR&\\
WPCT =& (WPCT - \widehat{WPCT}_1) + (\widehat{WPCT}_1 - \widehat{WPCT}_2) \qquad (2.21)\\
&+ (\widehat{WPCT}_2 - \widehat{WPCT}_{IS}) + (\widehat{WPCT}_{IS})
\end{aligned}
$$

Each of the individual terms on the right hand side of equation [2.20] are winning percentages as defined in equation [2.16] and correspond to the terms in [2.21]. The first term on the right hand side represents the cumulated difference between the manager's *actual* winning percentage and the manager's *expected* winning percentage given the actual performance of the players on his team. The second term represents the cumulated difference between the manager's expected winning percentage given the *actual performance* of the players on his team and the manager's expected winning percentage given the *ex ante expected performance* of the players on his team. The third term represents the cumulated difference between the manager's expected winning percentage given the ex ante expected performance of the players on his team and the manager's expected winning percentage given ex ante expected performance of the players present on the team *prior to the beginning* of a manager's spell with that team. The last term represents the manager's expected winning percentage given ex ante expected performance of the players present on the team prior to the beginning of a manager's spell with that team. Consider each of the measures in turn.

$WPCT$ is the manager's actual cumulative winning percentage. $\widehat{WPCT}_1$ is the expected cumulative winning percentage given the actual performance level of players across seasons. The difference between these two variables arguably reflects both managerial ability and purely random events. The managerial ability present in this variable is likely due to in-game decisions while the random events include randomness in the distribution of runs scored and runs allowed across games.[29] $\widehat{WPCT}_2$ is the expected winning percentage given the ex ante expected performance of players. It represents the team's productivity if all players performed at their expected levels.[30] This will differ from expected winning percentage given *actual* player productivity if many players perform better (or worse) than expected in a given season, which could be due to either manager ability or random fluctuation. Here, manager ability likely takes the form of any training effect a manager has on player performance, including activities such as a player's off-season workout program (or lack thereof), as well as diagnosing and correcting any loss of form. $\widehat{WPCT}_{IS}$ is the expected winning percentage for a team in year t given player composition just prior to the manager's arrival. Therefore, the final difference $(\widehat{WPCT}_2 - \widehat{WPCT}_{IS})$ reflects any effect a manager has on input composition. The manager has no control over the initial stock of talent of a team but subsequent roster decisions likely include the manager's input. Including the initial stock of talent separately as an explanatory variable accounts for a factor that is unrelated to the manager's performance and presumably can be filtered out. If this variable has a role in the retention decision it will suggest that firms hold managers accountable for measured performance that does not reflect a manager's ability or effort.

[29]An in-game decision that may have zero net effect on runs allowed and runs scored over the course of the season but may redistribute both advantageously is the removal of star pitchers and star hitters in a game that is lopsided.

[30]The expected levels are based on the player's age and estimated age-productivity profile. See section 2.2.1.1 for a complete description of the estimation.

It is important to note two points about the specification presented above. First, there is no reason to expect each of the variables to contain the same amount of information about managerial ability. Consequently, there is no reason to expect that a unit change in the variables has the same effect on the termination hazard. In particular, since $\widehat{WPCT}_{IS}$ depends on the team composition prior to the manager's arrival one might expect the coefficient on this variable to equal zero whereas the coefficients on the other variables should presumably be negative since they contain information about the manager's ability. Second, the performance measures are cumulative across all prior spells. Cumulating the measures in this way gives equal weight to each game managed and implicitly assumes that information regarding manager performance is publicly observable and that managerial ability is time-invariant.

2.2.3.2 Manager Data

The manager data contains work histories of MLB managers from 1950 to 1996.[31] For each manager-team-year observation, the data includes the number of wins, losses, and total games managed within the year. It also includes the cumulative number of games managed over the manager-team spell (tenure) and the cumulative games managed over the manager's career (experience). An attractive piece of information in the data is the information regarding spell endings; each spell ending is identified as either a fire or a quit. I obtained this information from the manager files available at the A. Bartlett Giamatti Research Center located at the Baseball Hall of Fame.[32]

[31] The manager work histories are from *Total Baseball* through 1992 and updated through 1996 from the website 'Baseball Reference' (www.baseballreference.com).

[32] I am grateful to Claudette Burke and Rachael Kepner of the A. Bartlett Giamatti Research Center at the Baseball Hall of Fame for providing me access to the data.

Each of the files contains newspaper clippings that report events in the career of the manager that allow quits to be distinguished from firings. Since I am interested in estimating the determinants of firing, distinguishing quits from fires is useful.[33]

The manager data contain 252 different managers involved in 447 different manager-team spells. Of these 447 spells, 339 end by a fire. Of the remaining 108, 86 end by a quit with 22 censored observations in 1996. Table 2.4 presents the time pattern of spell endings.

2.2.3.3 Manager Hazard Results

Table 2.5 presents the summary statistics for each of the excess performance measures as well as the initial stock of talent. As presented, each of the 818 observations are single complete seasons and represent the typical year. I use the stadard deviations from this table to illustrate the relative magnitudes of the effects of interest. Table 2.6 presents the results of the proportional hazard estimation. Kiefer (1988) offers that the interpretation of the coefficients depends significantly on the functional form. However, the specification of $\lambda_1 = \exp^{x_{it}\beta}$ allows an interpretation of the coefficients analogous to the interpretation of the linear model. A negative (positive) sign on a coefficient suggests that an increase in the variable increases (decreases) the expected duration of a spell. Furthermore, it is important to note that the explanatory variables are measured in levels. This convention allows the hazard

[33] Some discretion was necessary in the assignment of fires and quits. There are nine situations where a manager is refused a new contract. These situations are classified as fires since the team chose not to renew the contract and the manager subsequently quit. The four managerial trades are also classified as fires. The three managerial deaths are classified as quits, as are the four situations where the manager is also the general manager and replaces himself with a new manager.

where $\lambda_1(\cdot) = 1$ to be interpreted as the case where a team is performing at expected levels, random effects are zero, and the manager has not contributed to production.

The first column of Table 2.6 presents the results of the hazard estimation that assumes firms weight information about a manager's performance equally regardless of when that information was acquired. The results suggest that the time in the season is an important determinant of termination. The coefficients on the all-star break and end-of-season dummy variables are significant at the 1% level. Other things equal, the hazard ratio rises by a factor of 5.1 at the all-star break and rises by a factor of 132 at the end of the season. This result suggests that firms take advantage of the situations when the cost of manager turnover is lowest. The presumption is that search costs and production losses are at a minimum during all-star breaks and at the end of seasons.

Each of the coefficients on the excess performance measures are significant at the 5% significance level. These measures each carry negative signs. This result is expected since better performance should reduce the likelihood of termination. The results indicate that, in making retention decisions, firms consider not only factors attributable to the manager but also a factor not attributable to the manager (inherited team quality) that could be filtered out. Since the excess performance measures are partly influenced by a manager's contribution to production, the significance of the coefficients suggests that firms make retention decisions based in part on manager performance. However, I constructed the variable $\widehat{WPCT}_{IS}$ to represent the expected winning percentage of a team given the player composition *prior* to a manager's hire. This variable is a measure of performance that is unrelated to a manager's performance and should be filtered out of the performance measure used to make the retention decision. An alternative interpretation of the significance of this coefficient is that managers with high unobserved ability are matched with high quality teams.

Figures 2.4-2.7 illustrate the relative magnitudes of the effects of the managerial performance variables and how they change with prior experience. In particular, I consider the effect of managerial performance in the current year that is at the sample mean, that is one standard deviation above the sample mean, and that is one standard deviation below the sample mean, assuming that managerial performance in all prior years was exactly at the sample mean. The four figures correspond to the four different performance measures.[34] Each graph in each figure shows the risk of termination relative to a manager with no prior experience who performed at the sample mean in his first year. The solid line represents the relative termination hazard at each experience level given average current year performance. The dashed line gives the relative termination hazard at each experience level for a manager who performs one standard deviation above the mean level in the current year. The dotted line gives the relative termination hazard at each experience level for a manager who performs one standard deviation below the mean level in

[34]The predicted values are each $\exp^{X\beta}$ and are calculated using the following formula:

$$\frac{exp\{[(\frac{t}{t+1}) * \overline{X} + (\frac{1}{t+1})(\overline{X} \pm \text{s.d.}(x))] * \widehat{\beta_1} + (t) * \widehat{\beta_2}\}}{exp\{\overline{X} * \widehat{\beta_1}\}} \tag{2.22}$$

where t is years of prior experience, $\overline{X}$ is mean performance level, according to one of the performance measures, s.d.(x) is the standard deviation of the performance measure, over a season, $\widehat{\beta_1}$ is the estimated coefficient for the performance measure, and $\widehat{\beta_2}$ is the estimated coefficient on prior experience. For simplicity in the calculations, I assume that in each prior year the manager performs at the mean level for a 162 game season and that it is neither the all-star break nor the end of the season.

the current year.

Figure 2.4 presents the effect of the difference between the actual winning percentage of the team and the expected winning percentage given the actual performance of its players. The solid line represents a 'pure' experience effect. The negative slope suggests that as managers gain experience the likelihood of termination decreases. The standard deviation of experience is 722 games. For a manager that lasts one standard deviation longer (roughly 4 years), the likelihood of firing decreases by 12.3%. The coefficient on experience is not significant at conventional significance levels but does suggest that managers acquire skills through work and as a result are less likely to be fired. The insignificance of the coefficient mirrors the result in Audas et al (1999). The authors find that in a sample of English Soccer coaches experience does not play a role in the firing of managers.[35] This effect is depicted in each of the figures. The coefficient on the difference between the actual winning percentage of the team and the expected winning percentage given the actual performance of its players is roughly -1.3. If a manager with no prior experience increases this first measure of excess winning percentage by one standard deviation (.0399, 6.5 games) the hazard ratio shifts down by 5.05%.[36] A corresponding one standard deviation decrease in this measure of excess winning percentage results in a 5.32% increase in the hazard. The magnitude of this effect decreases as experience increases. A manager with

[35]The authors do find a significant effect of experience on voluntary turnover and suggest that experienced managers are desirable in the market. A significant effect of experience on voluntary turnover also seems to suggest that experienced managers retire of their own volition rather than by involuntary termination.

[36]The means and standard deviations used in these calculations are constructed using outcomes from single, complete years. There are 818 incidences of a manager starting a year and managing all of a team's games within that year. The summary statistics are presented in table 2.5.

3 years of prior experience that increases this measure of excess winning percentage by one standard deviation decreases the hazard by only 1.28%. This effect diminishes to a .7% decrease in the hazard for a manager with 6 years of experience. The corresponding standard deviation decreases in this measure of excess winning percentage result in a 1.3% and .7% increase in the hazard for a manager with 3 and 6 years of experience, respectively. These results suggest that firms decide to retain managers based on what can be attributed to either managerial in-game ability or luck over the entire career and that the hazard is less sensitive to performance realizations at higher experience levels. If this variable reflects more managerial ability than randomness we would expect firms to use this measure to make retention decisions. If the opposite is true we would expect firms to be less sensitive to this measure of performance. Relative to the other measures of excess winning percentage, termination is insensitive to deviations in this measure. This result indicates that it contains the most noise of any of the measures.

Figure 2.5 presents the effect of players over-performing their expected levels through manager led training (or other training).[37] The sign on this coefficient indicates that an increase in the variable shifts the hazard down. An increase of one standard deviation (.0422, 6.8 games) in the second measure of excess winning percentage shifts the hazard ratio down by 26.8%. A decrease of one standard deviation in this measure increases the hazard ratio by 36.6%. As a manager's experience increases the effect of this measure diminishes as well. At 3 years of experience, a one standard deviation increase in this measure shifts the hazard down by only 7.5% while a one standard deviation decrease

[37] Other training may include such things as independent off-season workouts or the absence of the same.

in this measure increases the hazard by only 8.1%. At 6 years of experience, a one standard deviation increase in this measure shifts the hazard down by only 4.3% while a one standard deviation decrease in this measure increases the hazard by 4.6%.

The third measure of excess winning percentage reflects the cumulative effect a manager has on player performance levels as well as any managerial decisions regarding input composition. The coefficient on this variable is roughly -6.2. Figure 2.6 presents the relative magnitude of this effect. Increasing this measure by one standard deviation (.0615, 10 games) shifts the hazard down by a factor of 31.7% while decreasing it by one standard deviation increases the hazard by 46.4%. At 3 years of experience, a one standard deviation increase in this measure shifts the hazard down by only 9.1% while a one standard deviation decrease in this measure increases the hazard by only 10%. At 6 years of experience, a one standard deviation increase in this measure shifts the hazard down by only 5.3% while a one standard deviation decrease in this measure increases the hazard by 5.6%. At low experience levels, this measure exhibits the largest difference in the likelihood of termination between managers that perform one standard deviation above the mean and managers that perform one standard deviation below the mean. This measure reflects the cumulative effect a manager has on input composition. The result indicates that this measure has the least noise. This is reasonable since teams know whether or not they used a manager's suggestion when adding or subtracting a player from the roster.

It is reasonable to assume that a manager has no effect on team composition prior to the date of hire. As such, one might expect the risk of termination to be independent of the team's talent level at the time of hire.

By including the expected winning percentage given expected performance of the players present on the team prior to the beginning of a manager's spell with that team ($\widehat{WPCT}_{IS}$), I can test whether termination decisions are partly based on factors that do not reflect manager ability and should be filtered out of the decision process. The significance of the coefficient on this variable suggests that the risk of termination is partly based on a performance measure that is not attributable to manager ability, namely the initial expected performance of inputs prior to the manager's arrival. The coefficient suggests that a one standard deviation (.0612, 10 games) increase in inherited team quality shifts the hazard down by a factor of 19.2% (Figure 2.7) while a decrease in inherited team quality shifts the hazard up by 23.7%. Managers that begin spells with teams that have high levels of talent are less likely to be fired than those who do not.

2.2.3.4 Alternative Specification

The results in the first column of table 2.6 are suggestive but the model is restrictive. It assumes that firms do not distinguish between information acquired from different points in a manager's career. An alternative specification would allow firms to treat information from different points in a manager's career differently. Consider the following identity:

$$\begin{aligned}(WPCT - \widehat{WPCT}_1)_{\text{career}} = {} & (\frac{\text{pre-spell games}}{\text{total games}}) * (WPCT - \widehat{WPCT}_1)_{\text{pre-spell}} \\ & + (\frac{\text{current games}}{\text{total games}}) * (WPCT - \widehat{WPCT}_1)_{\text{within spell}}.\end{aligned} \tag{2.23}$$

Equation [2.23] splits the information contained in the career form of the first excess winning percentage ($WPCT - \widehat{WPCT}_1$) into a pre-spell portion and a current spell portion. This decomposition applies for each of the performance variables. A specification that enters the two terms on the right hand side of equation [2.23] as separate explanatory variables allows the possibility that a firm's use of information about manager performance depends on whether the information was acquired while the manager was with the team or while the manager was with another team. If there is a significant privately observed component in the performance variables, firms will weight information acquired during the current spell more heavily than information acquired in prior spells with other teams.[38] The simple specification in column 1 of table 2.6 can be tested by a simple test of equality of the coefficients on each of the two terms.[39] In this case, the null hypothesis that the coefficients are equal maintains that the cumulative career values of the performance variables are what is relevant in the retention decision.

The second column of table 2.6 presents the results of the alternative specification (2). This specification includes each of the 'excess performance' variables included in specification (1) decomposed as described in equation [2.23]. Each of the coefficients on the within spell variations of the excess performance variables are significant at the 5% level. The coefficients are all

[38]The private component of the information may include work habits of the manager or the manager's interaction with players. Presumably, this information may also help the firm distinguish between the manager's effect on player performance levels and the effects of individual player's work habits.

[39]As a practical matter, some managers are in their first spell in the data. In these cases, I impute the values of the pre-spell differences to be zero. This restriction emphasizes that firms know very little (in fact nothing) about a manager's ability before the manager is actually working. This restriction follows from Jovanovic (1979). In this paper, the author posited that labor is an experience good. In this sense, neither the worker nor the firm knows the yield of the relationship at the outset. Over time both acquire the necessary information. It is possible that firms observe a manager's ability prior to the manager's appearance in the data set by observing a manager's performance realizations from another baseball league (Japanese, College, or Minor League Baseball).

negative implying that better performance according to each measure lowers the termination hazard, as does inheriting a more talented team. The results also indicate that firms consider pre-spell information. The null hypothesis that the coefficients on the pre-spell versions of the variables are jointly equal to zero can be rejected ($\chi^2_{(4)} = 11.90$, p-value $= 0.0181$). These estimated coefficients are also negative although only two of the individual coefficients on the pre-spell versions of the performance variables are significant.

An important aspect of specification (2) is that it allows a simple test of whether or not firms treat information from prior spells and current spells equally. Equality of the coefficients within a variable pair suggests that firms weight current and prior spell information equally. The joint hypothesis that the coefficients on the current spell performance variable and prior spell performance variable are equal for each of the four performance measures cannot be rejected.[40] This result is consistent with the notion that firms weight information regarding manager performance equally regardless of what firm the manager was with at the time of the performance realization.[41] Thus, one cannot reject the specification of the hazard presented in column one of table 2.6.

2.2.3.5 Manager Rehire Results

The results presented in table 2.6 suggest that managers are terminated partly on factors beyond their control. A simple examination of the robustness of this result is to consider the factors that affect the hiring decision firms

[40]The χ^2_4 statistic for this test is 2.93 with a p-value $= 0.5699$.

[41]I also tested the equality of each pair independently. I could not reject the null hypothesis that the coefficients were equal except for the pair of initial stock of talent variables ($\widehat{WPCT}_{IS}$) but the standard errors are relatively large.

face. For this estimation, I consider the same sample of managers used in the retention estimation. The only difference in the sample is that the 22 managers who have jobs at the end of the 1996 season and the three managers whose last spells were ended by their death are not considered as possible new hires. This restriction limits the sample to 422 endings with 206 rehires.[42] The model I estimate is the hazard model presented and utilized in the previous sections. In this case, the estimation considers the length of 'unemployment' a manager endures after a job ending.[43] I consider the length of unemployment spell as the number of games played between the end of a manager's last spell and the beginning of a new spell.

Table 2.8 presents the results of the estimation using the career specification of the variables. The results suggest that firms consider only some of the measures of excess winning percentage in the rehire decision. The coefficient on the first measure of excess winning percentage is 1.297. A one standard deviation increase (0.112) over a career results in a 15.6% increase in the likelihood of rehire.[44] This coefficient indicates that firms use information about manager performance that is attributable to in-game decisions or randomness. The coefficient on the second measure of excess winning percentage is 8.43. A one standard deviation (0.031) increase in this measure of excess winning percentage over a career results in an 30% increase in the likelihood of rehire. The coefficient on the third measure of excess performance is 4.56. A one stan-

[42] The 206 rehires include managers who were rehired more than once. In these cases, each 'unemployment' spell is considered independently.

[43] All managers who are alive at the time of a job opportunity are considered as a possible rehire. Managers who are not rehired by the time of their death are considered censored. Similarly, managers who have not been rehired by the end of the 1996 season are considered censored.

[44] The summary statistics for the set of regressors in the rehire estimation are presented in table 2.7.

dard deviation increase in this measure (.0385) over a career results in a 19.2% increase in the likelihood of rehire. These results indicate that firms consider excess winning percentage that is attributable to both players over-performing due to training and the effect a manager has on input composition.

I found that the initial stock of talent had a significant effect on the likelihood of being fired. This result suggests that firms do not filter a measure of performance that is unrelated to manager performance. The same result is not evident in the estimation of the likelihood of being rehired. The coefficient is 1.985. It suggests that a one standard deviation (.053) increase in this measure increases the likelihood of rehire by 11.2%. However, the coefficient is estimated imprecisely and I cannot reject the null hypothesis of no effect.

The results also suggest that experience has an important role in determining whether a manager gets rehired. An increase of one standard deviation (841) in experience increases the likelihood of rehire by almost 65.7%. This result supports the idea that managers acquire human capital over their careers. However, the likelihood of rehire decreases by 45.2% if a manager is one standard deviation (7.5) older at the time of of last job separation. The coefficient on FIRE suggests that managers who were fired from their last job are more likely to get rehired. However, this coefficient is not significant at an acceptable significance level. The last explanatory variable is a dummy variable that equals one if an off-season has passed since the manager has last managed. The coefficient on this variable is -2.27 and suggests that having an off-season pass without a new job decreases the likelihood of rehire by almost 90%.[45]

[45] There are 23 incidents of managers who do not have an off-season pass. 10 of these are managers who were fired during 1996, the last year of the sample. The remaining 13

It is useful to address the similarities and differences in the results of the termination and rehire estimations. The estimations indicate that more experienced managers are both less likely to be fired and more likely to be rehired. This result supports the notion that managers acquire human capital throughout their careers. The first measure of excess performance appears to have a role in both the termination decision and the rehire decision. Since this excess performance measure is attributable to in-game decisions and randomness, this result is not surprising. It is reasonable that this measure includes a significant amount of information about manager ability. However, this measure contains a significant amount of randomness. As such, teams may discount this information. The results from both estimations suggest that teams put the least weight on this information and is consistent with theory. Both estimations also agree in the role of the second and third measure of excess performance. The estimations suggest that excess performance due to either manager-led training or input composition decreases the likelihood of termination and increases the likelihood of rehire. The results of the estimation disagree on the role of the initial stock of talent on a team prior to the manager's hire. The termination estimation suggests that undertaking a job with a poor performing team is costly since the likelihood of termination is higher, all else equal. However, the rehire estimation suggests this cost does not carry over to the likelihood of rehire. One potential interpretation of the coefficient on the expected winning percentage given expected performance of the players present on the team prior to the beginning of the manager's spell ($\widehat{WPCT}_{IS}$) is that it accounts for unobserved ability. That is, managers who undertake jobs with poor teams are less able in ways not accounted for by

managers were rehired within the season of their last spell ending.

the excess performance measures. But if so, this variable should also reduce the rehire likelihood of managers that ended spells with poor quality teams. However, the rehire estimation suggests that it does not have an effect on the likelihood of rehire. The disparity in the results suggest that the 'unobserved ability' explanation of the inherited team quality variable may not be valid. Therefore, rehire decisions appear to be rational in the sense that teams filter out information that is unrelated to manager performance. In contrast, termination decisions appear not to be rational in the sense that teams do not filter out information unrelated to manager performance.

2.3 Conclusion

In this paper, I examined the retention and rehire decisions firms make regarding field managers in Major League Baseball. The evidence from both estimations indicate that teams use multiple measures of performance in termination and rehire decisions. Each measure of performance presented plausibly contains information on manager ability. The estimated coefficients on the variables have expected signs and substantial magnitudes. Furthermore, the estimated coefficients support the notion that the informational content differs across the performance variables. However, the results of the termination estimation also suggest that teams use information that is unlikely to reflect managerial ability. That is, talent *at the time of hire* affects the risk of termination, even after conditioning on team performance relative to expectations after the date of hire. Since the rehire estimation does not support this result, it appears that rehire decisions are rational while termination decisions are not. The estimates from the termination equation suggest managers with no prior experience face a likelihood of termination that is reduced by 19.2% if they begin spells with teams that are more talented than the average by one standard deviation. This result suggests managers should receive a premium for beginning spells with low talent teams since the likelihood of fire is higher and raises questions about whether baseball teams make rational termination decisions. Garen (1994) and Hall and Leibman (1998) found that firms do not use relative performance evaluation to shield CEOs from common risk while Bertrand and Mullainathan (2001) found that firms reward CEOs for observable 'luck.' The results presented in this paper are comparable to both Hall and Leibman (1998) and Bertrand and Mullainathan (2001) since the observable measure of team performance unrelated to manager performance was not filtered out of the termination decision.

It should be noted that the analysis presented here relies upon information that is not available for most CEOs or high-level managers. Given the availability of the information, one would expect firms to shield managers from performance measures that are not attributable to the manager. I found, in termination decisions, that firms do not. Finding this result in the presence of the available information suggests that contracts for high-level managers are more complicated than standard contract theory allows for. One complication not considered by the standard model is the importance of 'public perception.' In situations where agents are recognizable to the public (CEOs, fund managers, etc) and principals rely upon the public for revenue (investment decisions for a fund, etc), it may be optimal for principals to act as if the agent is responsible for a poor outcome if the public perceives it to be true. This complication may play an important role in the findings presented in this paper.

Furthermore, the results presented here are for a specific labor market relationship. This relationship carries aspects that are unlikely to be found in other relationships. As such, the results should be cautiously applied to other labor market relationships. Despite this caveat, this paper does have significant contributions to the literature. The nature of the job of Major League Baseball manager shares many things in common with CEOs and other high-level and high-profile managers and the analysis provides valuable information regarding the turnover of the same. The similarities include the difficulty in determining the input and the performance of the manager since observable output is highly correlated with subordinate performance. Understanding firms action under these conditions is valuable in the study of the market for high-level managers. I exploited the high-frequency data available regarding Major League Baseball managers to isolate a manager's contribution to production. In doing so, this paper provides a clear evaluation of hypotheses suggested by theory.

Table 2.1: Descriptive Statistics
Player Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
BASES EARNED	82.3452	106.5812	-2	610	59020
CHANCES	187.159	217.5234	0	874	59020
BPC	0.3545	0.1825	-1	4	59020
BASES ALLOWED	130.2667	115.777	0	552.0728	28152
BATTERS FACED	394.6304	357.1044	1	1802	28152
BPBF	0.3474	0.1129	0	4	28152

The data in this table is the set of all Major League Baseball players from 1901-1996. $BPC = \frac{BASES\ EARNED}{CHANCES} = \frac{TB+BB+HBP+SF+SH+SB-CS}{AB+BB+HBP+SF+SH+SB+CS}$ where TB is the total base value of all hits accrued, BB is base on balls, HBP is hit-by-pitches, SF is sacrifice flies, SH is sacrifice hits, SB is stolen bases, CS is caught stealing, and AB is at-bats. $BPBF = \frac{BASES\ ALLOWED}{BATTERS\ FACED} = \frac{(HA-HRA)*(1B\%+2*2B\%+3*3B\%)+4*HRA+BB}{3*IP+HA+BB}$ where HA is hits allowed, HRA is home runs allowed, BB is base on balls, IP is innings pitched, and *1B%*, *2B%*, *3B%* represent the percentage of hits within that are singles, doubles and triples, respectively.

Table 2.2: Descriptive Statistics
Team Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
BPC	0.4471	0.0302	0.3575	0.5488	115728
$BPBF$	0.3372	0.0239	0.2666	0.4453	115728
$BPC_i - BPC_j$	0	0.0345	-0.1311	0.1311	115728
$BPBF_i - BPBF_j$	0	0.0242	-0.1017	0.1017	115728

The sample represents the 115,728 regular season Major League Baseball games that occurred between 1923 and 1996. In this table, BPC and $BPBF$ represent the team levels of BPC and $BPBF$. The variables are aggregated from individual levels in the following way: $BPC_{team} = \frac{\sum_{i=1}^{N_t} BPC_{it} * C_{it}}{\sum_{i=1}^{N_t} C_{it}}$ and $BPBF_{team} = \frac{\sum_{i=1}^{N_t} BPBF_{it} * BF_{it}}{\sum_{i=1}^{N_t} BF_{it}}$.

Table 2.3: Win Probit Estimation

	WIN
	(1)
$BPC_i - BPC_j$	5.3817***
	(.11)
$BPBF_i - BPBF_j$	-5.3938***
	(.156)
Constant	.107***
	(.0037)
Observation	115728
Log-Likelihood	-77821.96
χ^2 statistic	3992.891

Standard errors are in parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The estimation includes all games between 1923 and 1996. However, only home teams are used. As such, the constant is interpretable as a home team advantage. BPC and $BPBF$ are measures of team hitting and pitching, respectively. $BPC_{team} = \frac{\sum_{i=1}^{N_t} BPC_{it} * C_{it}}{\sum_{i=1}^{N_t} C_{it}}$ and $BPBF_{team} = \frac{\sum_{i=1}^{N_t} BPBF_{it} * BF_{it}}{\sum_{i=1}^{N_t} BF_{it}}$

Table 2.4: Empirical Hazard of Job Ending, by Type of Job Ending

Year of Spell	**Risk Set**	**Quit** during	**Quit** end of	**Fire** during	**Fire** end of	**Censor**
1	447	4	13	61	72	8
2	289	6	10	52	22	5
3	194	8	12	43	21	0
4	110	5	10	21	10	3
5	61	2	1	13	5	2
6	38	2	1	2	3	1
7	29	2	0	4	1	1
8	21	0	2	3	1	1
9	14	0	1	2	2	0
10	9	1	1	0	0	0
11	7	0	1	0	0	1
12	5	0	0	0	1	0
15	4	0	1	0	0	0
17	3	0	1	0	0	0
21	2	1	0	0	0	0
23	1	1	0	0	0	0
TOTAL	0	32	54	201	138	22

This table presents the nature and timing of spell endings for Major League Baseball managers between 1950 and 1996. The data was constructed from the manager files available at the A. Bartlett Giamatti Research Center located at the Baseball Hall of Fame. Some discretion was necessary in the assignment of fires and quits. There are nine situations where a manager is refused a new contract. These situations are classified fires since the team chose not to renew the contract and the manager subsequently quit. The four managerial trades are also classified as fires. The three managerial deaths are classified as quits, as are the four situations where the manager is also general manager and replaces himself with a new manager.

Table 2.5: Descriptive Statistics - Hazard Regression Single Year Outcomes

Variable	Mean	Std. Dev.	Min.	Max.	N
$WPCT - \widehat{WPCT}_1$	0.0037	0.0399	-0.1241	0.103	818
$\widehat{WPCT}_1 - \widehat{WPCT}_2$	0.0034	0.0422	-0.1422	0.1381	818
$\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$	0.0022	0.0615	-0.1925	0.2334	818
$\widehat{WPCT}_{IS}$	0.4989	0.0612	0.2844	0.6919	818

The 818 observations are single complete seasons by managers between 1950 and 1996. A complete season is defined by the total games a team played within a year. Each of the variables is a measure of excess winning percentage. $WPCT - \widehat{WPCT}_1$ is the difference between the actual winning percentage and the expected winning percentage given the actual performance of the players on the team; $\widehat{WPCT}_1 - \widehat{WPCT}_2$ is the difference between the expected winning percentage given the actual performance of the players on the team and the expected winning percentage given the ex ante expected performance of the players on the team; $\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$ is the difference between the expected winning percentage given the ex ante expected performance of the players on the team and the expected winning percentage given the expected performance of the players present on the team prior to the beginning of a manager's spell; $\widehat{WPCT}_{IS}$ is the expected winning percentage given the expected performance of the players present on the team prior to the beginning of a manager's spell.

Table 2.6: Hazard Estimation

	FIRE (1)	FIRE (2)
WPCT - $\widehat{WPCT}_1$	-1.2972** (.6032)	.
$\widehat{WPCT}_1 - \widehat{WPCT}_2$	-7.3924*** (1.8957)	.
$\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$	-6.1946*** (1.6056)	.
$\widehat{WPCT}_{IS}$	-3.4749** (1.3992)	.
$(\frac{\text{current games}}{\text{total games}})$*(WPCT - $\widehat{WPCT}_1$) *within spell*	.	-1.3149** (.5851)
$(\frac{\text{current games}}{\text{total games}})$*($\widehat{WPCT}_1 - \widehat{WPCT}_2$) *within spell*	.	-7.4629*** (1.8905)
$(\frac{\text{current games}}{\text{total games}})$*($\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$) *within spell*	.	-5.155*** (1.6354)
$(\frac{\text{current games}}{\text{total games}})$*($\widehat{WPCT}_{IS}$) *within spell*	.	-3.2798** (1.3894)
$(\frac{\text{pre-spell games}}{\text{total games}})$*(WPCT - $\widehat{WPCT}_1$) *prior to spell*	.	-.2123 (3.586)
$(\frac{\text{pre-spell games}}{\text{total games}})$*($\widehat{WPCT}_1 - \widehat{WPCT}_2$) *prior to spell*	.	-5.8094 (5.2312)
$(\frac{\text{pre-spell games}}{\text{total games}})$*($\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$) *prior to spell*	.	-8.5215*** (2.875)
$(\frac{\text{pre-spell games}}{\text{total games}})$*($\widehat{WPCT}_{IS}$) *prior to spell*	.	-3.758*** (1.4327)
EXPERIENCE prior to the start of spell	-.0001818 (.00012)	-.00007 (.0002)
ALL-STAR BREAK	1.803*** (.354)	1.7974*** (.3541)
END OF SEASON	4.8904*** (.1406)	4.8995*** (.1413)
Observations	159607	159607
Log-Likelihood	-1350.811	-1349.5844
χ^2 statistic	1354.544	1362.03
Fires	339	339
Subjects	447	447

Standard errors are in the parentheses and are calculated using the method described by Lin and Wei (1989). *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The table presents estimates of the likelihood of fire for Major League Baseball managers between 1950 and 1996. The measures of excess winning percentage are constructed using data on all Major League Baseball players between 1901 and 1996 and all games played between 1923 and 1996. Experience is measured as prior to the current spell. The estimates are obtained using the proportional hazards model suggested by Cox (1972) and given by the following equation: $L = \sum_{i=1}^{N}\{ln\lambda_1(x_i,\beta) - ln[\sum_{j=i}^{N}\lambda_1(x_j,\beta)]\}$.

Table 2.7: Descriptive Statistics - Rehire

Variable	Mean	Std. Dev.	Min.	Max.	N
WPCT - $\widehat{WPCT}_1$	-0.0033	0.1119	-0.5101	0.6778	422
$\widehat{WPCT}_1 - \widehat{WPCT}_2$	-0.0034	0.0309	-0.1095	0.1498	422
$\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$	0.0032	0.0385	-0.1658	0.1535	422
$\widehat{WPCT}_{IS}$	0.4902	0.0534	0.311	0.6633	422
EXPERIENCE	774.9005	841.8346	1	4377	422
AGE	49.7639	7.5092	33.8521	75.0329	422

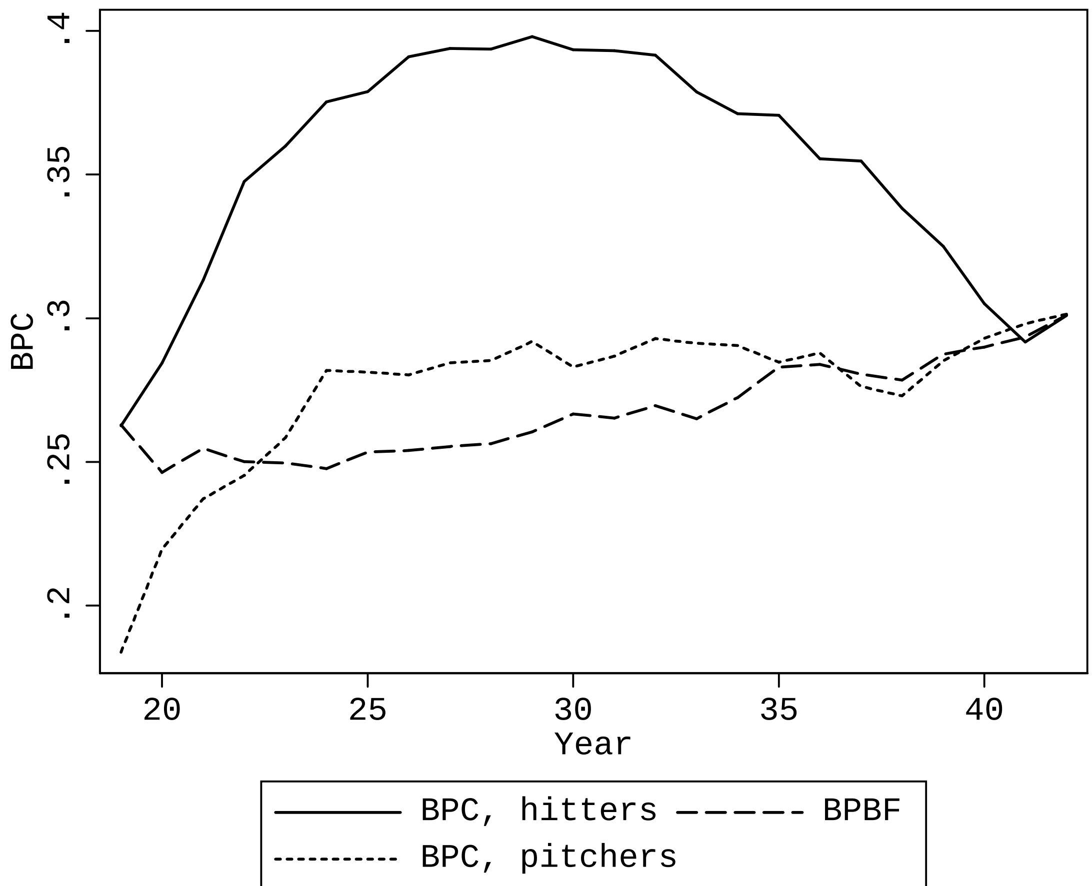
The 422 observations are the sample of Major League Baseball managers who had a spell begin and end between 1950 and 1996. The values of the variables are career levels up to the employment spell end. Each of the variables is a measure of excess winning percentage. $WPCT - \widehat{WPCT}_1$ is the difference between the actual winning percentage and the expected winning percentage given the actual performance of the players on the team; $\widehat{WPCT}_1 - \widehat{WPCT}_2$ is the difference between the expected winning percentage given the actual performance of the players on the team and the expected winning percentage given the ex ante expected performance of the players on the team; $\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$ is the difference between the expected winning percentage given the ex ante expected performance of the players on the team and the expected winning percentage given the expected performance of the players present on the team prior to the beginning of a manager's spell; $\widehat{WPCT}_{IS}$ is the expected winning percentage given the expected performance of the players present on the team prior to the beginning of a manager's spell.

Table 2.8: Rehire Estimation

	(1)
WPCT - $\widehat{WPCT}_1$	1.297** (.6206)
$\widehat{WPCT}_1 - \widehat{WPCT}_2$	8.413*** (2.0464)
$\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$	4.5584** (2.2281)
$\widehat{WPCT}_{IS}$	1.9853 (1.6776)
EXPERIENCE	.0006*** (.00009)
FIRE	.1812 (.2237)
AGE	-.0801*** (.0109)
OFF	-2.2728*** (.2346)
Observations	422
Log-Likelihood	-1111.082
χ^2 statistic	196.6476
Rehires	206
Subjects	422

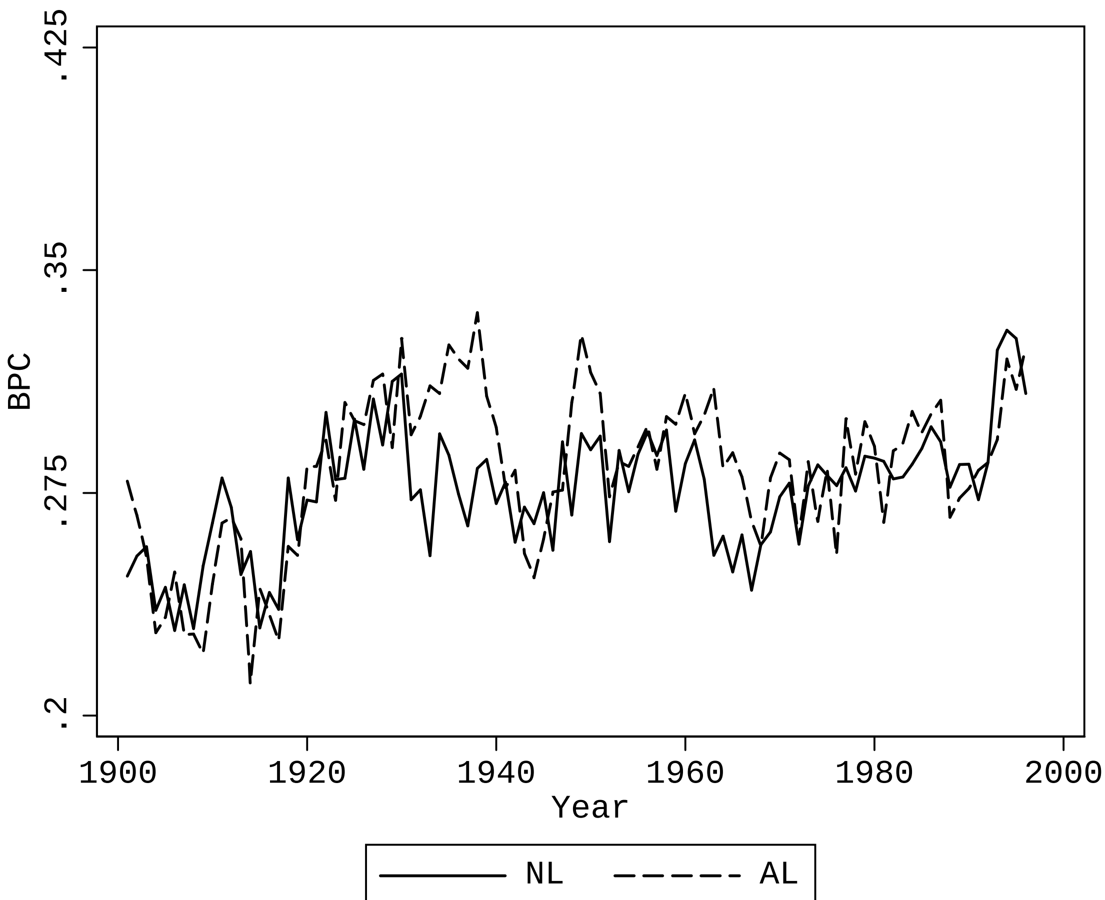
Standard errors are in the parentheses and are calculated using the method described by Lin and Wei (1989). *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The table presents estimates of the likelihood of fire for Major League Baseball managers between 1950 and 1996. The measures of excess winning percentage are constructed using data on all Major League Baseball players between 1901 and 1996 and all games played between 1923 and 1996. Experience is measured as prior to the current spell. The estimates are obtained using the proportional hazards model suggested by Cox (1972) and given by the following equation: $L = \sum_{i=1}^{N}\{ln\lambda_1(x_i, \beta) - ln[\sum_{j=i}^{N} \lambda_1(x_j, \beta)]\}$.

Figure 2.1: Age Effects
Player Regression Results



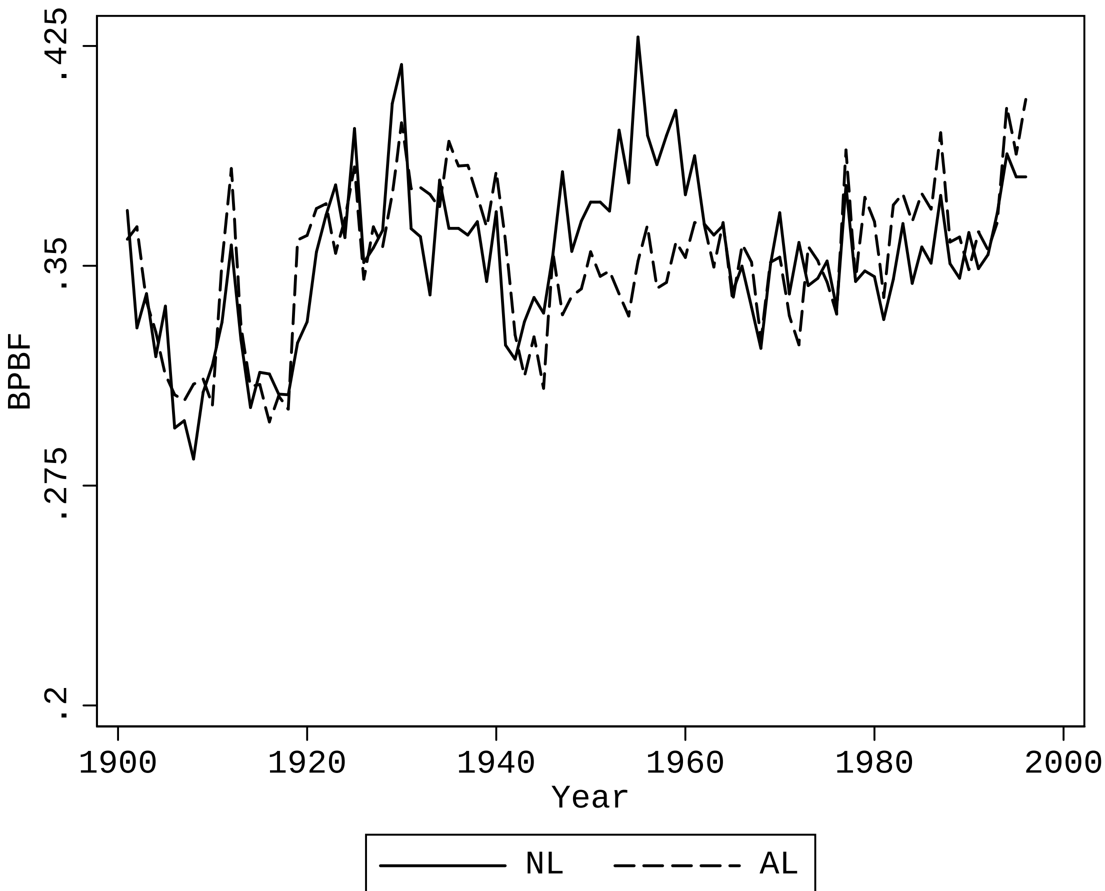
The above figure represents the collection of age dummy variables estimated in the player performance regression. The three lines represent the age effects for hitters, hitting pitchers, and pitchers. The performance measure for hitters is $BPC = \frac{TB+BB+HBP+SF+SH+SB-CS}{AB+BB+HBP+SF+SH+SB+CS}$. The performance measure for pitchers is $BPBF = \frac{(HA-HRA)*(1B\%+2*2B\%+3*3B\%)+4*HRA+BB}{3*IP+HA+BB}$.

Figure 2.2: Year Effects
Player Regressions Results



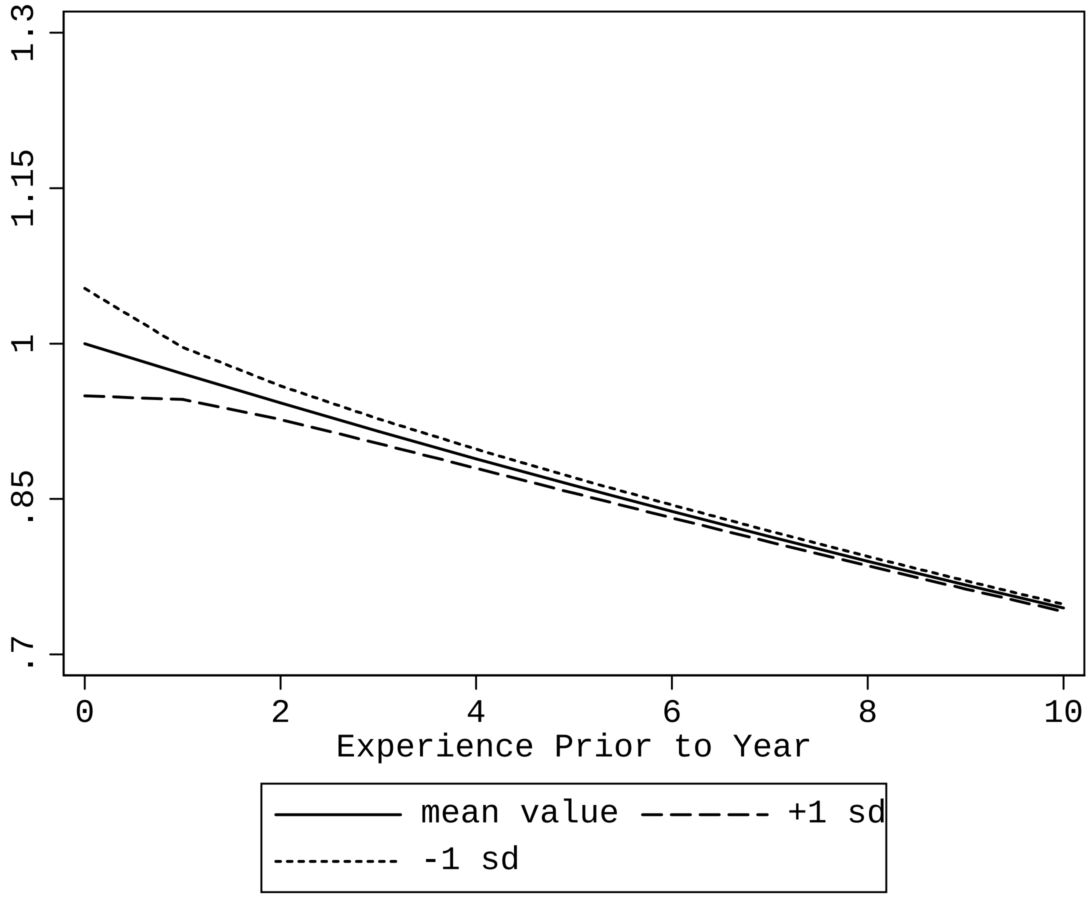
The above figure represents the collection of year dummy variables estimated in the player performance regression. The two lines represent the difference in year effects for hitter productivity (BPC) in the American and National Leagues. The year effects include the mean individual effect for each year. $BPC = \frac{TB+BB+HBP+SF+SH+SB-CS}{AB+BB+HBP+SF+SH+SB+CS}$.

Figure 2.3: Year Effects
Player Regressions Results



The above figure represents the collection of year dummy variables estimated in the player performance regression. The two lines represent the difference in year effects for pitcher productivity ($BPBF$) in the American and National Leagues. The year effects include the mean individual effect for each year. $BPBF = \frac{(HA-HRA)*(1B\%+2*2B\%+3*3B\%)+4*HRA+BB}{3*IP+HA+BB}$.

Figure 2.4: Relative, End of Season Termination Risk
WPCT - $\widehat{WPCT}_1$

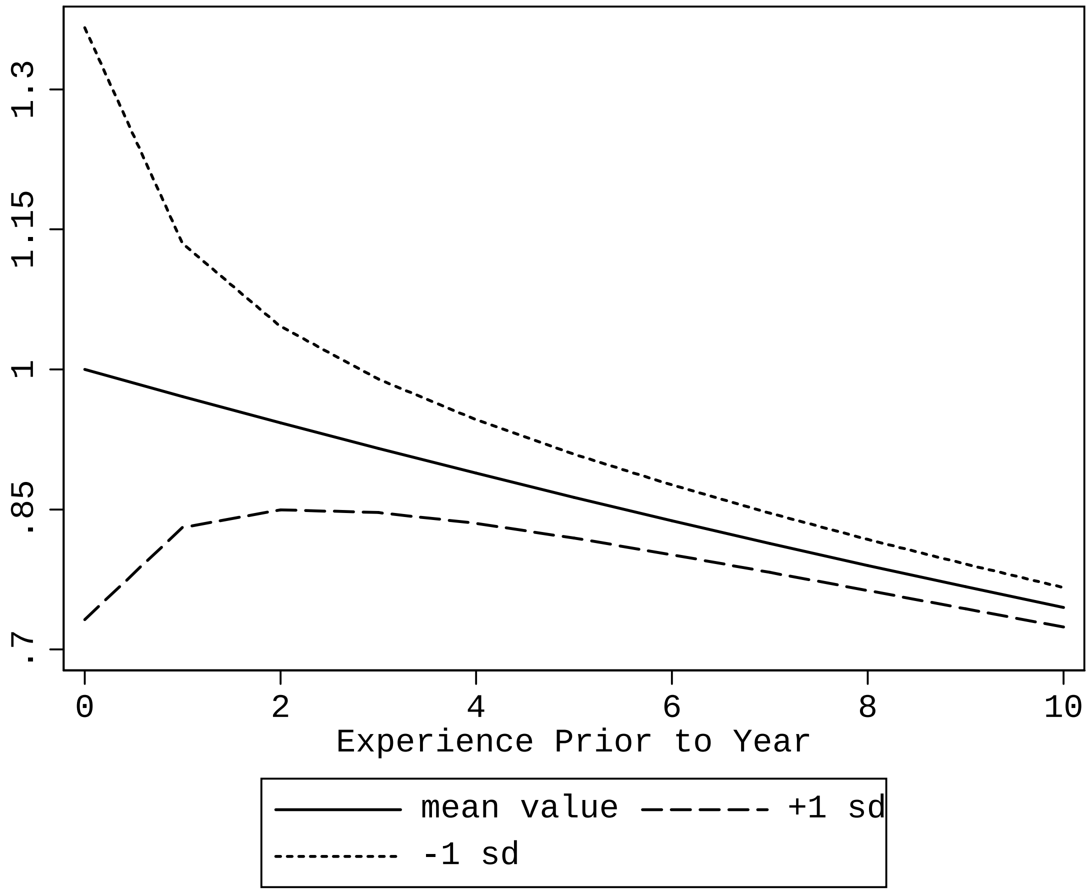


The values represented in this figure are calculated as

$$\frac{exp\{[(\frac{t}{t+1}) * \overline{X} + (\frac{1}{t+1})(\overline{X} \pm \text{s.d.}(x))] * \widehat{\beta_1} + (t) * \widehat{\beta_2}\}}{exp\{\overline{X} * \widehat{\beta_1}\}} \tag{2.24}$$

where t is years of prior experience, $\overline{X}$ is mean performance level, according to one of the performance measures, s.d.(x) is the standard deviation of the performance measure, over a season, $\widehat{\beta_1}$ is the estimated coefficient for the performance measure, and $\widehat{\beta_2}$ is the estimated coefficient on prior experience. For simplicity in the calculations, I assume that in each prior year the manager performs at the mean level for a 162 game season and that it is neither the all-star break nor the end of the season. The solid line represents mean performance in all years. The dashed line above the mean line represents performance one standard deviation below the mean level while the dotted line below the mean line represents performance one standard deviation above the mean level.

Figure 2.5: Relative, End of Season
Termination Risk
$\widehat{WPCT}_1 - \widehat{WPCT}_2$

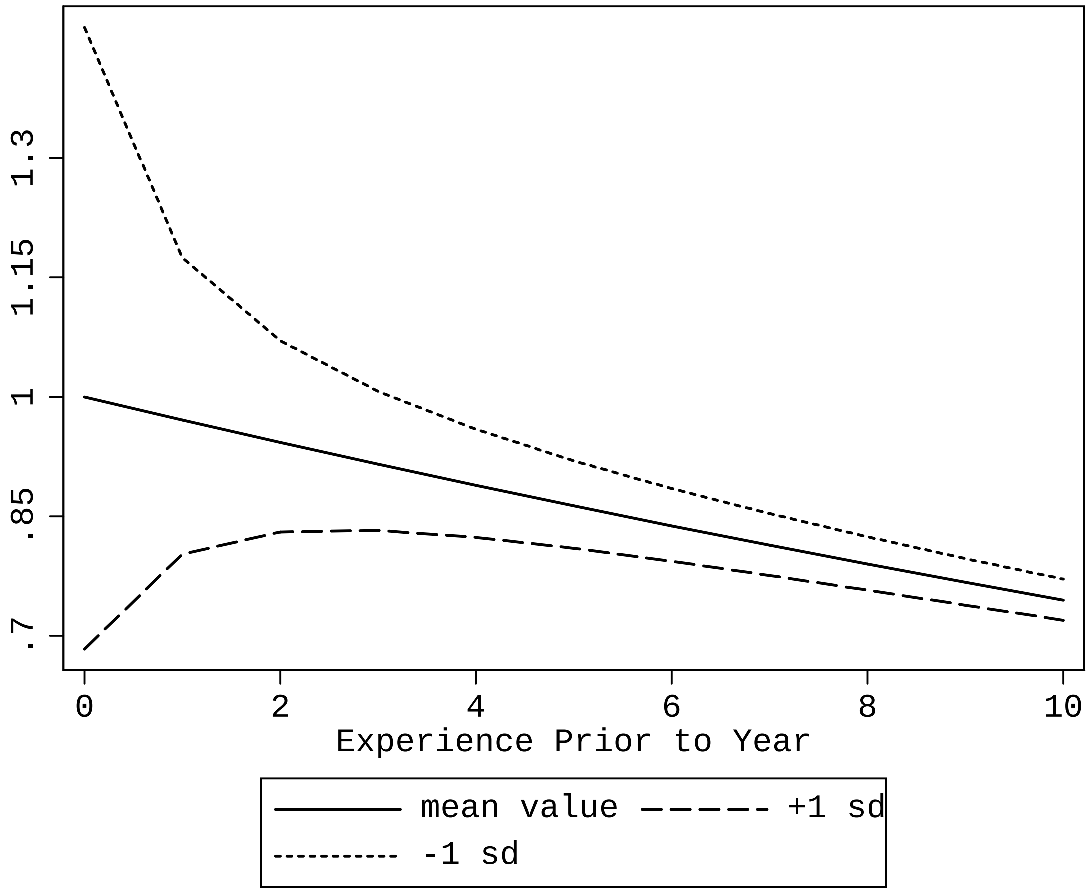


The values represented in this figure are calculated as

$$\frac{exp\{[(\frac{t}{t+1}) * \overline{X} + (\frac{1}{t+1})(\overline{X} \pm \text{s.d.}(x))] * \widehat{\beta_1} + (t) * \widehat{\beta_2}\}}{exp\{\overline{X} * \widehat{\beta_1}\}} \tag{2.25}$$

where t is years of prior experience, $\overline{X}$ is mean performance level, according to one of the performance measures, s.d.(x) is the standard deviation of the performance measure, over a season, $\widehat{\beta_1}$ is the estimated coefficient for the performance measure, and $\widehat{\beta_2}$ is the estimated coefficient on prior experience. For simplicity in the calculations, I assume that in each prior year the manager performs at the mean level for a 162 game season and that it is neither the all-star break nor the end of the season. The solid line represents mean performance in all years. The dashed line above the mean line represents performance one standard deviation below the mean level while the dotted line below the mean line.

Figure 2.6: Relative, End of Season Termination Risk
$\widehat{WPCT}_2 - \widehat{WPCT}_{IS}$

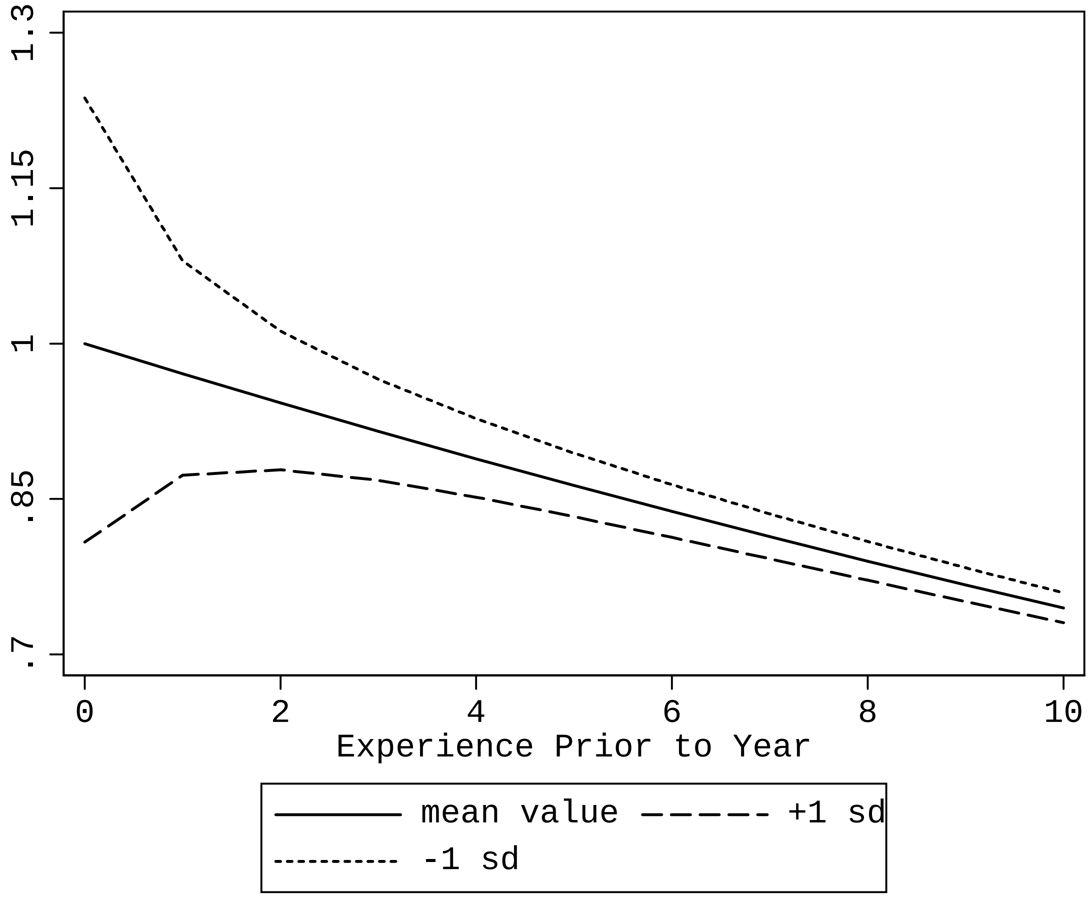


The values represented in this figure are calculated as

$$\frac{exp\{[(\frac{t}{t+1}) * \overline{X} + (\frac{1}{t+1})(\overline{X} \pm \text{s.d.}(x))] * \widehat{\beta_1} + (t) * \widehat{\beta_2}\}}{exp\{\overline{X} * \widehat{\beta_1}\}} \tag{2.26}$$

where t is years of prior experience, $\overline{X}$ is mean performance level, according to one of the performance measures, s.d.(x) is the standard deviation of the performance measure, over a season, $\widehat{\beta_1}$ is the estimated coefficient for the performance measure, and $\widehat{\beta_2}$ is the estimated coefficient on prior experience. For simplicity in the calculations, I assume that in each prior year the manager performs at the mean level for a 162 game season and that it is neither the all-star break nor the end of the season. The solid line represents mean performance in all years. The dashed line above the mean line represents performance one standard deviation below the mean level while the dotted line below the mean line.

Figure 2.7: Relative, End of Season Termination Risk
$\widehat{WPCT}_{IS}$



The values represented in this figure are calculated as

$$\frac{exp\{[(\frac{t}{t+1}) * \overline{X} + (\frac{1}{t+1})(\overline{X} \pm \text{s.d.}(x))] * \widehat{\beta_1} + (t) * \widehat{\beta_2}\}}{exp\{\overline{X} * \widehat{\beta_1}\}} \tag{2.27}$$

where t is years of prior experience, $\overline{X}$ is mean performance level, according to one of the performance measures, s.d.(x) is the standard deviation of the performance measure, over a season, $\widehat{\beta_1}$ is the estimated coefficient for the performance measure, and $\widehat{\beta_2}$ is the estimated coefficient on prior experience. For simplicity in the calculations, I assume that in each prior year the manager performs at the mean level for a 162 game season and that it is neither the all-star break nor the end of the season. The solid line represents mean performance in all years. The dashed line above the mean line represents performance one standard deviation below the mean level while the dotted line below the mean line.

Chapter 3

The Structure of Promotions by Gender: Addressing Partial Observability

3.1 Introduction

Over the last two decades the gender wage gap has narrowed.[1] The closing of the gap is seen as a lessening of the discrimination women have faced in the labor market. While the decreasing of the wage differential is encouraging, wage is only one part of the labor market. It is a commonly held belief that women face a 'glass ceiling' with regard to internal upward mobility. Discrimination in the market for promotions may explain any persistence in the wage gap since promotions are a significant source of wage growth.[2]

Previous empirical studies that have addressed discrimination in internal labor markets have relied on data from a specific firm or industry. Some of the work has addressed the discrimination in promotion of lawyers, school teachers, workers in U.S., Canadian, and Japanese firms, and white collar federal employees.[3] While these studies are an important contribution to the literature, the results from these studies are hard to generalize because of their narrow scope. More recent studies have attempted to produce more general-

[1] Blau and Kahn (2000) provides a detailed overview of the gender wage gap.

[2] McCue (1996) estimates that between 9 and 18% of wage growth is due to promotion.

[3] Spurr (1990); Eberts and Stone (1985) and Joy (1998); Paulin and Mellor (1996); Cannings (1988) and Cannings and Montmarquette (1991); Ariga et al (1999); Lewis (1986), respectively. Other studies have also addressed promotion differences by gender in the Humanities (Ginther and Hayes (1999) and in the Economics profession (McDowell et al (1999).

izable results by using more representative data. These studies have used the Panel Study of Income Dynamics, the National Longitudinal Study of Youth (NLSY), the *Encuesta de Estructura, Conciencia y Biografia de Clase*, and the British Household Panel Survey.[4] These studies yield more general results but still fail to address a particular selection issue that is present in any estimation of promotion probability that relies on longitudinal work histories to observe promotions. Specifically, previous studies neither address the issue that for an individual to receive a promotion that individual must stay on the job nor the issue that an individual may turn down a promotion and leave the firm or leave when not offered a promotion.

In the current study, I address the determinants of promotions using the 1990 round of the NLSY. I estimate a bivariate probit model of promotion. The primary equation is an equation for promotion and mirrors equations presented in previous literature. The secondary equation is an equation for 'staying on a job.' Since only 70% of individuals make themselves available for promotion in the sample, it is likely that selection is an issue. The stay equation addresses the selection issue present in the observed promotions. Allowing correlation in the error terms across the equations and estimating the bivariate probit refines the estimates and yields more informative results. The significance of the estimated correlation in the bivariate probit model suggests the univariate estimates for promotion conditional on staying on a job are biased. This result suggests that the unobservables in the equation for promotion are correlated with the unobservables in the equation for staying on a job. As such, the magnitude of the marginal effects vary across the univariate and

[4] McCue (1996), Pergamit and Veum (1999) and Gjerde (2002), Garcia-Crespo (2001), Groot and van der Brink (1996), respectively.

bivariate models. Gender-separated estimation of the univariate and bivariate models highlights the differences in the market for promotions across gender. Specifically, the results suggest that the univariate estimates of promotion for women are not biased while the univariate estimates of promotion for men are biased. The bivariate probit model also allows the probability of an observed promotion (i.e. the joint probability of staying and receiving a promotion offer) to be decomposed in the probability of promotion conditional on staying on a job and the probability of staying on a job. These estimates suggest that women are less likely to receive a promotion *a priori* than men all else equal. The estimates also suggest that women are more likely to remain on a job than men all else equal. Furthermore, there is evidence that women stay on jobs in order to signal attachment to the labor market.

3.2 Data

This study of promotions uses data from the National Longitudinal Survey of Youth (NLSY). This data set contains work histories for a representative sample of United States citizens born between 1957 and 1964 starting in 1979. The survey itself covers a broad range of topics but with a focus on labor market issues. The survey contains information for each respondent on education, training, earnings, hours worked, and other job characteristics. The information regarding promotions and job changes are of particular interest for the present study.

In defining the sample, I eliminated respondents that did not exhibit a reasonable attachment to the labor market. I eliminated respondents that worked for less than 15 weeks or less than 20 hours per week in both 1989 and 1990. This restriction eliminates workers that are seasonal. I also eliminated respondents that are either self-employed, working in a farming occupation or industry, or in the armed forces in either 1989 or 1990. This restriction removes those individuals that face considerably different job and promotion structures than the typical worker.[5]

Of particular interest is the identification of promotions in the sample. To establish a promotion, I begin by identifying all main jobs held in 1989. These jobs are the sample of jobs that are 'at risk' for a promotion between the interview date in 1989 and the interview date in 1990. A necessary condition for an observed promotion is that the respondent must remain on the job between 1989 and 1990. Therefore, I identify the respondent as a 'job-stayer' if he or she reports that the main job in 1989 is also the main job in 1990. From the sample of 'job-stayers', I identify valid promotions. In 1990, the respondent was asked if he or she had received any promotions from the employer on the main job since the previous interview. I classified these reported promotions as a valid promotion if the respondent reported the promotion for the current job and the respondent is in the sample of 'job-stayers.' It is important to note that this formulation understates the total number of promotions because it is possible that the respondent was promoted at a job that was not the main job in 1989 but is the main job in 1990 as a result of the promotion.[6]

3.3 Univariate Probit

3.3.1 Model Specification

In order to correctly estimate promotion probabilities, it is useful to begin with models previously estimated. The model is a univariate probit of

[5]These restrictions follow those used in McCue (1996).

[6]There are 275 cases where the respondent reports a promotion but is not classified as such in the data.

the following form:

$$y_i = X\beta + \epsilon_i \tag{3.1}$$

where $y = 1$ if the individual was promoted at the current job and $y = 0$ if the individual was not promoted. X is a set of covariates, β is a vector of parameters to be estimated, and ϵ is an error term that is assumed to have a standard normal distribution. The set of covariates includes characteristics about the individual and her job.[7]

An important consideration in the estimation of equation 3.1 is the sample used. The decision lies in the classification of individuals who do not remain on the same job from year t to year $t + 1$. These individuals can be classified as either 'not promoted' or they can be removed from the sample. The former case treats leaving and staying but not getting promoted as the same outcome when factors that make one of these outcomes more likely may affect the other outcome oppositely. The latter case solves the problem of confounding the determinants of two distinct outcomes but the estimation yields only a conditional probability. That is, the promotion probabilities are conditional on individuals having stayed on a job and will be biased if the unobservables affecting the receipt of a promotion offer are correlated with the unobservables affecting the stay decision.

[7] It is important to note that this empirical model of promotion incidence differs from some previous studies. For example, Hersch (1995), Hersch and Viscusi (1996), and Garcia (2001) each consider the number of promotions an individual receives at an employer as the dependent variable while Gjerde (2002) uses an indicator for having received at least one promotion at an employer as the dependent variable. The current formulation does follow the specification of Pergamit and Veum (1999).

3.3.2 Results

The summary statistics for the full sample and men and women only sub-samples are presented in table 3.1. In the full sample, 23% of respondents stayed on the main job and reported a promotion while 24.42% of male respondents and 21.29% of female respondents stayed on the main job and reported a promotion. In general, there is little difference between men and women. Men have roughly 15 more weeks of actual experience and 4 more months of positional tenure while there is little difference in experience across gender. On average, women have one half a grade more education and score higher on the Armed Forces Qualifying Test (AFQT) but men earn $1.70 more per hour than women and work more roughly 4 more hours a week. The training requirement for the average job is quite similar. 60.7% of men are in jobs that require special training or experience while 61.5% of women are in jobs that require special training or experience. However, 44% of men supervise other workers at their job while only 36% of women supervise other workers at their job. Finally, there appears to be little difference in the racial makeups of the two samples. The men only sample is 38.5% non-white while the female only sample is 41.3% non-white.

3.3.2.1 Probability of Promotion

The results of the single equation conditional job-stayer probit estimation are presented in the first column of table 3.2. The marginal effect for x^i is calculated as

$$\frac{\Delta Pr(y=1)}{\Delta x^i} = \Phi[(\overline{x}^i + \text{s.d.}_{(x^i)})\widehat{\beta}_i + \overline{X}^j\widehat{\beta}_j] - \Phi(\overline{X}\widehat{\beta}) \tag{3.2}$$

where Φ is the standard normal distribution function, $\overline{X}^j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta}_j$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta}_i$ is the estimated coefficient.

The results of the estimation suggest that experience, employer tenure, positional tenure, hourly wage, educational level, and whether or not an individual supervises others are significant determinants of promotion. It also appears that gender plays a role in promotion. The marginal effects associated with each of these coefficients have absolute magnitudes that range from 1.47 to 6.49 percentage points. The coefficient on the highest grade completed is significant and positive. The coefficient suggests that a one standard deviation increase above the mean raises the likelihood of promotion by 2.19 percentage points all else equal. This change represents an 10.4% increase. The implication is that acquiring more education makes a worker more productive and more likely to receive a promotion. In the case of experience, employer tenure, and positional tenure, I included a squared term to allow for non-linearity in the effect. The coefficients on the experience variables are jointly significant. The coefficient on the linear term is positive and significant while the coefficient on the quadratic term is negative and significant. The coefficients are also jointly significant at the one percent level.[8] Given the coefficients, the likelihood of promotion increases up until 300 weeks (5.77 years) of experience and then declines. This result implies that the probability of promotion is increasing in the first 5 years and decreasing thereafter. The coefficients on the employer tenure variables are also jointly significant.[9] However, the signs on the coefficients do not follow the same pattern. The coefficient on the linear

[8]The χ^2 statistic is 13.73 and the associated p-value is .001.
[9]The χ^2 statistic is 12.52 and the associated p-value is .0019.

term is negative while the sign on the quadratic is positive. The likelihood of promotion decreases from the start of time with an employer until 350 weeks (6.73 years) of tenure and then the likelihood of promotion begins to increase. The coefficients on the positional tenure variables exhibit the same sign pattern as employer tenure and are jointly significant.[10] Initially increasing positional tenure reduces the likelihood of promotion but after 137.5 months (11.49 years) the likelihood of promotion increases with positional tenure. The fact that increasing both employer tenure and positional tenure initially decreases the likelihood of promotion may reflect workers learning about jobs over time. It is also possible that this result reflects a selection of individuals into long employer or positional tenure.

A variable of interest in the estimation is the dummy variable for females. The coefficient is significant at the 95% level and carries a marginal effect of -.0338. This effect suggests that females are less likely to receive a promotion than their male counterparts all else equal.[11] The unconditional probability of promotion in the sample is 23%. However, there is a difference in this unconditional probability across gender of stayers. For men, the unconditional probability is 24.42% while for women, it is only 21.29%. This fact coupled with the significance and magnitude of the coefficient on the female dummy variable suggests that internal labor markets differ across gender. In an effort to capture these differences, I estimated the model of promotions separately for men and women. The results of these estimations are presented in the third and fifth columns of table 3.2. The results from the estimations strengthen the notion that internal labor markets differ across genders.

[10]The χ^2 statistic is 12.63 and the associated p-value is .0018.

[11]This estimate is not unlike the marginal effects reported by Gjerde(2002, -.053) and Pergamit and Veum (1999, -.042).

The models differ significantly with regard to the experience, employer tenure, and positional tenure variables. For men, the coefficients on the experience variables are jointly significant while they are not jointly significant for women.[12] In both models, the coefficient on the linear term is positive while the coefficient on the quadratic term is negative. This result follows the interpretation of the full sample model that promotions do not occur at the start of the career but do happen relatively early in careers. How early differs considerably by gender. For men, the likelihood of promotion increases until 287.5 weeks (5.53 years) of experience while for women, the likelihood of promotion increases until 650 weeks (12.5 years). The significantly longer period of increasing likelihood of promotion for women and the considerably smaller effect at the mean (-.26 vs. -4.69 percentage points) of experience suggests that experience has a smaller effect on the likelihood of promotion for women than men.[13] A possible explanation for this result is that women may be in jobs where they acquire less human capital. Another possible explanation is that are less able to reveal their ability. The results with regard to positional tenure also support these explanations. The magnitude of the effect of positional tenure on the likelihood of promotion of women is larger (-1.69 percentage points) but it also appears that positional tenure affects the likelihood of promotion of women less than for men. The coefficients on the positional tenure variables are jointly significant for the men only sample but not for the women only sample.[14] The employer tenure variables are jointly significant

[12]For men, the χ^2 statistic is 14.85 and the associated p-value is .0006. For women, the χ^2 statistic is 1.87 and the associated p-value is .3923.

[13]The experience-promotion likelihood profile for women is much flatter than the the profile for men.

[14]For men, the χ^2 statistic is 10.35 and the associated p-value is .0056. For women, the χ^2 statistic is 2.43 and the associated p-value is .2972.

in both the men only and women only samples.[15] The marginal effect at the mean of employer tenure is larger for women than men (-.0274 vs -.0223). It is possible that employer tenure is a signal of labor force attachment. If this is the case, it suggests that attachment to the labor force is observed noisily from outside the employer. It is also possible that the number of hours worked per week is a signal of labor force attachment. In the full sample, the coefficient on hours worked per week is positive but is not significant. In the women only sample, the coefficient is positive and significant. In the men only sample, the coefficient is negative but insignificant. A reasonable explanation for this difference is that women who work more hours are signaling to employers that they are committed to the labor market and will not drop out of the work force.

The results from the estimations presented in table 3.2 suggest that women are less likely to be promoted than men. It appears that white women are 16.1% less likely to be promoted than their male counterparts.[16] The implication is that the market for promotions is considerably different for men and women. Furthermore, the decision to stay on a job is likely an important consideration in estimating the likelihood of promotion. As such, it is useful to estimate a bivariate probit model that considers both promotion and staying on a job.

[15]For men, the χ^2 statistic is 5.63 and the associated p-value is .06. For women, the χ^2 statistic is 7.58 and the associated p-value is .0226.

[16]The percentage is calculated as the marginal effect divided by the predicted probability at $\overline{X}$. In this case, the value is $\frac{-.0338}{.2101} = -.1609$

3.4 Bivariate Probit

3.4.1 Model Specification

As presented in this paper, promotions are the product of two decisions. The first decision involves individuals staying on or leaving a job while the second decision involves individuals either receiving or not receiving a promotion offer. It is possible that the unobserved determinants of receiving a promotion offer are correlated with the unobserved determinants of staying on a job. As such, it is necessary to develop a model that addresses this issue. The present model follows the form of the bivariate probit with partial observability presented in Poirier (1980).[17]

Let $y_{i1} = 1$ if an individual remains on a job and $y_{i1} = 0$ otherwise. Let $y_{i2} = 1$ if an individual receives a promotion offer and $y_{i2} = 0$ otherwise. In the present data, I observe $y^* = y_{i1} * y_{i2}$ and y_{i1}. This information is useful in the estimation. As such, the present model follows more closely the model presented as case three in Meng and Schmidt (1982). The model is as follows:

$$
\begin{aligned}
y_{i1}^* &= X_{i1}\beta_1 + \epsilon_{i1} \\
y_{i2}^* &= X_{i2}\beta_2 + \epsilon_{i2}
\end{aligned}
\tag{3.3}
$$

where for j = 1,2

$$
\begin{aligned}
y_{ij} &= 1 \text{ if } y_{ij}^* > 0 \\
y_{ij} &= 0 \text{ if } y_{ij}^* \leq 0.
\end{aligned}
\tag{3.4}
$$

[17]The bivariate probit model has been used to study the Union status of workers (Abowd and Farber (1982) and Farber (1983)), the migration decisions of workers (Eliasson et al (2003)), and the employment status of teens (Mohanty (2002)). Gjerde (2002) uses the bivariate probit to model promotions but the authors 'secondary' equation is job choice rather than the decision to stay on a job as in the present paper.

The possible *observed* outcomes are

$$(y_{i1} = 1, y_{i2} = 1) \tag{3.5}$$
$$(y_{i1} = 1, y_{i2} = 0)$$
$$(y_{i1} = 0, y_{i2} = \bullet).$$

The log-likelihood function is then:

$$\begin{aligned} \ln L(\beta_1, \beta_2, \rho) = \sum_{i=1}^{N} \{ & y_{i1} y_{i2} \ln\Phi_2(X_{i1}\beta_1, X_{i2}\beta_2, \rho) \\ & + y_{i1}(1 - y_{i2})\ln[\Phi(X_{i1}\beta_1) - \Phi_2(X_{i1}\beta_1, X_{i2}\beta_2, \rho)] \\ & + (1 - y_{i1})\ln\Phi(-X_{i1}\beta_1)\}. \end{aligned} \tag{3.6}$$

$\Phi(\cdot)$ represents the standard normal distribution and $\Phi_2(\cdot, \rho)$ represents the bivariate normal distribution function. In the case of the bivariate normal distribution, ρ is the correlation between the corresponding unobservables from the 'remain on a job' and promotion offer equations defined in equation 3.3 (ϵ_{i1} and ϵ_{i2}, respectively). X_{i1} and X_{i2} are the explanatory variables for the corresponding equation. β_1, β_2, and ρ are parameters to be estimated. It is important to note that identification of the parameters is dependent upon at least one variable appearing in either X_{i1} or X_{i2} but not in the other.

3.4.2 Results

The summary statistics for the full, women, and men only samples are presented in table 3.3. These samples differ from those presented in table 3.1. In the current samples, all respondents are used whether or not they stayed on a job. As such, the observed promotion rates are lower in these samples. In the full sample, 16.11% of respondents stayed on the main job and reported a promotion while 17.11% of male respondents and 14.92% of female respondents stayed on the main job and reported a promotion. In general, there is still little difference in human capital characteristics across gender. Men have more weeks of experience and positional tenure but the mean level of employer tenure is the same across gender. Men also earn $1.50 more than women, work roughly 4 more hours a week, and are more likely to be a supervisor (42.6 vs. 35.7). Women are slightly more likely to experience a change in marital status, are slightly more likely to be in a job that requires special training or experience, and have more education and higher AFQT test scores.

The results of the bivariate probit estimation are presented in table 3.4. In this estimation, it is possible to use the sample of job stayers and non-stayers as described in section 3.2. Identification of the parameters requires the explanatory variables in the stay equation to differ from the explanatory variables in the promotion offer equation. In the present model, a dummy variable for change in marital status and a dummy variable for whether the individual is living in her 'home' Metropolitan Statistical Area (MSA) serve in this capacity. It is reasonable to argue that neither variable affects the likelihood of receiving a promotion offer while both affect the likelihood of remaining on a job. It is likely that either getting married or divorced affects whether an individual remains on a job held prior to the change in marital status. It is not clear that this variable affects the likelihood of promotion. The dummy variable for living in home MSA takes the value 1 if the individual is living in the same MSA in 1989 as she was in 1979.[18] The presumption is that an individual may be more or less likely to remain on a job if they are near home but it is not clear why this variable should affect whether or not

[18] This information is available in the NLSY geocode data.

the individual receives a promotion offer. The advantage of the bivariate probit is that it allows a correlation between the error terms between the 'promotion' and 'stay' equations and corrects any bias due to this correlation. The null hypothesis of no correlation can be rejected at the 5% level. This result suggests that there is a correlation in the error terms. Specifically, the unobservables associated with staying on a job positively affect whether an individual is promoted. Given the significance of the estimated correlation, the bivariate probit is an improvement over the univariate probit.

3.4.2.1 Probability of Promotion

The results from the bivariate probit are presented in table 3.4. The marginal effects constructed from the univariate probit presented in table 3.2 are based on the sample of job-stayers only. It is possible to use the results from the 'stay' equation (y_{i1}) and the promotion equation (y_{i2}) to construct these same marginal effects using the full sample of both stayers and non-stayers. Given the significant estimated correlation between the unobserved determinants of staying and those of receiving a promotion offer, it is possible that these marginal effects will differ significantly from those reported in table 3.2. The conditional probabilities are calculated in the following way:

$$Pr(y_{i2} = 1|y_{i1} = 1) = \frac{Pr(y_{i2} = 1, y_{i1} = 1)}{Pr(y_{i1} = 1)} = \frac{\Phi_2(X_{i1}\beta_1, X_{i2}\beta_2, \rho)}{\Phi(X_{i1}\beta_1)} \tag{3.7}$$

where $\Phi(\cdot)$ and $\Phi_2(\cdot, \rho)$ represent the standard normal and bivariate normal distribution functions, respectively, X_{i1} and X_{i2} are the explanatory variables for the corresponding equation, and β_1, β_2, and ρ are estimated parameters. The conditional probabilities are then used to construct the marginal effects, which are presented in the column labelled $\Delta Pr[y_{i2}=1|y_{i1}=1]$ of tables 3.4, 3.5, and 3.6. The marginal effects for x^i are calculated as:

$$\begin{aligned}\frac{\Delta Pr[y_{i2}=1|y_{i1}=1]}{\Delta x^i} =& \frac{\Phi_2[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}},(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i2}}+\overline{X}_2^j\widehat{\beta_{j2}},\rho]}{\Phi[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}}]} \\ &- \frac{\Phi_2[\overline{X}\beta_1,\overline{X}\beta_2,\rho]}{\Phi[\overline{X}\beta_1]}\end{aligned} \tag{3.8}$$

where $\Phi(\cdot)$ and $\Phi_2(\cdot,\rho)$ represent the standard normal and bivariate normal distribution functions, respectively, $\overline{X}_j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta_j}$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta_i}$ is the estimated coefficient.

The results of the bivariate probit are not unlike the results for the univariate probit presented in table 3.2. While the significance of the estimated correlation suggests that the bivariate probit is the correct model, the cost to estimating a simple univariate probit appears to be low. In general, the magnitudes of marginal effects and standard errors differ only slightly. The differences across the univariate and bivariate models represent a 'refinement' of the estimates of the likelihood of promotion. This result is expected since the bivariate probit is a more efficient and unbiased model given the structure suggested by equations 3.3-3.5. There is one considerable change across the models. In the univariate probit the coefficients on the experience, employer tenure, and positional tenure variables are all significant. In the bivariate probit, only the coefficients on the experience variables are significant in the promotion equation. The coefficients on the employer tenure variables are not jointly significant while the coefficients on the positional tenure variables are jointly significant.[19] However, the null hypothesis that the set of employer and positional tenure coefficients are jointly equal to zero cannot be rejected.[20] The implication is that employer and positional tenure do not determine whether an individual is promoted.

The results from the univariate and bivariate probits suggest that women and men differ in their likelihood of receiving a promotion. Given this finding, it is important to consider separate estimation of the bivariate probit for men and women. Estimating the model separately for men and women allows the correlation between the error terms in the stay and promotion equations to differ by gender. The results from the separate women and men estimations are presented in tables 3.5 and 3.6, respectively.

There is an important difference in the separate bivariate models. In the full sample bivariate probit, the estimate of ρ is significantly different from 0. This result suggests that the unobserved determinants of receiving a promotion offer are correlated with the unobserved determinants of staying on a job. In the men only bivariate probit, this result is repeated. The estimated correlation is positive and indicates that the unobservables associated with staying on a job affect the likelihood promotion. It is likely that men consider internal mobility in the decision to stay on a job. If a man is likely to receive a promotion he will stay while if he is not likely to receive a promotion he will leave.[21] In the women only bivariate probit, the estimated correlation is not significantly different from zero. The implication is that the unobserved

[19]For the employer tenure coefficients, the χ^2 statistic is .68 and the associated p-value is .7112. For the positional tenure coefficients, the χ^2 statistic is 5.02 and the associated p-value is .0811.

[20]The χ^2 statistic is 5.71 and the associated p-value is .22147.

[21]This notion is tested in Velamuri and Prisinzano (2004).

determinants of receiving a promotion are not correlated with the unobserved determinants of staying on a job for women. As such, separately estimated univariate equations for women are consistent.

The return to education appears to differ considerably across gender. For men, increasing the highest grade completed by one standard deviation above the mean increases the likelihood of promotion by 11.3% all else equal while the same increase only increases the likelihood of promotion by 5.5% for women. The fact that it appears men have a higher return to education suggest that there is a glass ceiling that women face in the market for promotions. An explanation for the difference in the return to education is that employers discount women's extra education because they are more likely to leave the labor market. As such, employers may be hesitant to reward women with promotions. The univariate probit results suggest a similar difference across gender. In the univariate case, for men, education level (highest grade completed) is a significant determinant of promotion while for women, the coefficient on the highest grade completed is insignificant and the marginal effect associated with the coefficient is relatively small. The difference in the models suggest that the return to education is higher for men in terms of increased promotion likelihood.

The effects of experience, employer tenure, and positional tenure differ considerably across genders. In the men only model, the coefficients on the experience variables are jointly significant.[22] The likelihood of promotion increases with the first 250 weeks of experience and then decreases. The effect at the mean of the covariates is negative and reduces the likelihood of promotion by 15.6%. For women, the experience variables are not jointly significant and

[22]The χ^2 statistic is 8.15 and the associated p-value is .017.

the 'peak' of the effect is at a larger value for women (284 weeks) than men.[23] This result suggests that experience does not affect the likelihood of promotion as much for women as it does for men. The effect at the mean of the covariates for women is negative and it is considerably smaller than the effect for men (-18.9% vs -3.1%). The implication is that women's promotions are delayed relative to men. A possible explanation for the delay is the fact that women need to signal attachment to the labor force in order to receive a promotion. For the period of time that they are signaling attachment, women are 'underemployed.' That is, women are in jobs that do not reflect their ability. The coefficients on the employer tenure variables are not significant in either model.[24] For men, the likelihood of promotion only increases with the first 10.5 weeks of employer tenure while for women, the likelihood of promotion increases with the first 367 weeks of employer tenure. This implies that women benefit more than men from being with an employer. The effect at the mean in both models is negative. For men, increasing employer tenure reduces the likelihood by 6.5% while for women, increasing employer tenure decreases the likelihood of promotion by 21%. As such, the likelihood of promotion declines faster with employer tenure for women than men. The exact opposite result is found in the coefficients on positional tenure. The 'minimum' of the effect is later for men than women (158 vs. 104 months) but the overall negative effect is larger for men than women (-15.78% vs. -11.4%). Given the seemingly contradictory results evident in the employer and positional tenure variables, it is not clear that women face a glass ceiling. It is possible that the 'extra' benefit women receive from employer tenure reflects the fact that employers delay

[23]The χ^2 statistic is 1.82 and the associated p-value is .4025.

[24]The χ^2 statistic is 1.49 and the associated p-value is .4756 for women. The χ^2 statistic is .9 and the associated p-value is .6366 for men.

the promotion of women. It is only when employers can observe a woman's attachment to the firm that she is promoted. Furthermore, it is possible that the extra cost women face with regard to positional tenure is due to the fact that they are promoted in large steps to offset the underemployment.

In the univariate probit estimates, the marginal effect associated with the coefficient on the hourly wage differs considerably across gender. For men, increasing the hourly wage by one standard deviation above the mean decreases the likelihood of promotion by 11.5%. For women, the same increase has no effect on the likelihood of promotion.[25] In the men only bivariate probit, the same increase reduces the likelihood of promotion by 10.35% while for women, the same increase increases the likelihood of promotion by .37%. Since promotions may be associated with wage increases, it is reasonable that higher wages reduce the likelihood of promotion. The fact that the direction for women is positive suggests that women may receive a wage that does not reflect their productivity. As such, a higher wage does not preclude women from receiving a promotion. It is important to note that the coefficient on the hourly wage is significant in the men only univariate probit estimation but not the bivariate probit estimation. This discrepancy is an artifact of the bias and inconsistency associated with a univariate probit in the presence of correlation between the unobservables in the stay and promotion equations.

3.4.2.2 Probability of Staying on a Job

The bivariate probit estimation not only provides estimates for the likelihood of receiving a promotion but also estimates for the likelihood of staying on a job. In the model specification, the equation for staying on a job

[25] The percentage change in the likelihood is .07.

is represented by y_{i1} in equation 3.6. The probability of staying on a job is computed in the following way:

$$\begin{aligned} Pr(y_{i1}=1) &= Pr(y_{i2}=1, y_{i1}=1) + Pr(y_{i2}=0, y_{i1}=1) \\ &= \Phi_2[X_{i1}\beta_1, X_{i2}\beta_2, \rho] + \Phi[X_{i1}\beta_1] - \Phi_2[X_{i1}\beta_1, X_{i2}\beta_2, \rho] \\ &= \Phi[X_{i1}\beta_1] \end{aligned} \tag{3.9}$$

where $\Phi(\cdot)$ and $\Phi_2(\cdot, \rho)$ represent the standard normal and bivariate normal distribution functions, respectively, X_{i1} and X_{i2} are the explanatory variables for the corresponding equation, and β_1, β_2, and ρ are estimated parameters. The probabilities are then used to construct the marginal effects, which are presented in the column labelled $\Delta\mathrm{Pr}[y_{i1}=1]$ of tables 3.4, 3.5, and 3.6. The marginal effects are constructed as in equation 3.2.

It is reasonable to expect that individuals with high levels of experience, employer tenure, and positional tenure are more likely to remain on a job. In the case of experience, the expectation is that individuals with high levels of experience are older and less willing to move to new jobs. It is also likely that 'job-shopping' occurs early in careers. In the case of employer tenure, the presumption is that individuals with high employer tenure have acquired significant amounts of employer-specific capital. Similarly, individuals with high levels of positional tenure have gained significant amounts of job-specific capital. Given these presumptions, the effects of these variables on the likelihood of staying on a job should be positive. In each of the models, the effects are positive. The full, women, and men only samples provide similar estimates of the effect of experience. The models suggest that increasing experience by one standard deviation above the mean increases the likelihood between 3 and 5%. The coefficients on the experience variables are also jointly significant in each of the models.[26] The models do differ in the estimate of the effects of employer and positional tenure. In each of the models, the coefficients on the employer tenure variables are jointly significant.[27] However, increasing employer tenure by one standard deviation above the mean increases the likelihood of staying on a job by 17% for women but only 13% for men. The implication of this difference is that women are more attached to employers. It is likely that women remain with employers to reveal their attachment to the labor market and advance in their careers. This notion is also supported by the results presented in section 3.4.2.1. The estimates of the effect of positional tenure also differ across gender. The coefficients on the positional tenure variables are significant in the full and men only samples but not the women only samples.[28] The magnitude of the effect for men is larger than it is for women (7 vs. 2%). This difference is reasonable if women make large jumps internally rather than a series of small steps.[29]

The coefficient on the number of hours worked per week varies across the three models. In both the full and women only samples, the marginal effect is positive and the coefficient is significant. It suggests that working more hours per week increases the likelihood of remaining on a job. In the men only sample, the marginal effect is positive but the coefficient is insignificant. Furthermore, the effect of increasing the number of hours worked per week one standard deviation above the mean is much larger for women than men (3.9 vs .4%). An explanation for this difference is that women who work

[26] The χ^2 statistics are 13.73, 9.88, and 5.02 with associated p-values of .001, .0071, and .0815 for the full, women only, and men only samples, respectively.

[27] The χ^2 statistics are 184.17, 113.87, and 75.44 with associated p-values of .000, .000, and .000 for the full, women only, and men only samples, respectively.

[28] The χ^2 statistics are 23.93, 1.7, and 26.39 with associated p-values of .000, .428, and .000 for the full, women only, and men only samples, respectively.

[29] It is not possible to test this with the current data.

more hours are less likely to leave a job for reasons such as childbirth. The effect of education on the likelihood of staying on a job also varies across gender. The coefficient on the highest grade completed is not significantly different from zero in the full or women only sample estimations. In the men only estimation, the coefficient is significant. It is also the case that for men, increasing education level by one standard deviation above the mean level increases the likelihood of staying on a job by 2.2% all else equal. For women, the same increase decreases the likelihood of staying on a job by 1%. A possible explanation for this difference is that women may begin careers at less than ideal jobs because they need to establish their attachment to the labor market. As such, more educated women may be more likely to job shop. The effect of whether an individual supervises others supports this notion. In each of the models, the effect of being a supervisor is negative. The implication is that individuals who are supervisors and likely more productive are less likely to stay on a job. For women, this effect is twice as large as it is for men (9 vs 4.2%). The implication is that women who are more productive and are recognized as such by an employer are more likely to job shop.

It is not obvious what effects changes in marital status or gender will have on an individual's likelihood of remaining on a job, *a priori*. The results from all three models suggest that individuals whose marital status has changed are less likely to remain on a job all else equal. However, the coefficient is significant and negative in the full and women only samples but insignificant and negative in the men only sample. Furthermore, the marginal effects suggest that a change in marital status decreases the likelihood of staying on a job by 6.5, 8.2, and 4.4% for the full, women only, and men only samples, respectively. Given the women only effect doubles the men only effect, it is a reasonable interpretation that women are tied movers more often than men. The results from the full sample suggest that there is a difference across gender in the likelihood of staying on a job. It appears that women are 3% more likely than men to remain on a job. This result is interesting since the sample rate of staying on a job by gender is almost identical. Of 2561 women in the sample, 70.06% stayed on their job from 1989 to 1990 while of the 3039 men in the sample, 70.05% stayed on their job from 1989 to 1990. This result supports the notion that women must signal their attachment to the labor force. It is possible that labor force attachment is observed noisily outside of the firm. As such, women may need to remain with an employer in order to experience career growth in terms of wage and promotion.

3.4.2.3 Probability of Stay *and* Promotion

An advantage of the bivariate probit estimation is that it allows a construction of the probability of staying on a job and receiving a promotion offer. This joint probability depends on the probability of staying *and* the probability of receiving a promotion offer conditional on staying. This probability is constructed in the following way:

$$Pr(y_{i2} = 1, y_{i1} = 1) = \Phi_2(X_{i1}\beta_1, X_{i2}\beta_2, \rho) \tag{3.10}$$

where $\Phi_2(\cdot, \rho)$ represents the bivariate normal distribution function, X_{i1} and X_{i2} are the explanatory variables for the corresponding equations, and β_1, β_2, and ρ are estimated parameters. These probabilities are then used to construct marginal effects, which are presented in the column labelled $\Delta Pr[y_{i2} = 1, y_{i1} = 1]$ of tables 3.4, 3.5, and 3.6. The marginal effects for x^i are calculated as:

$$\Delta Pr[y_{i2}=1,y_{i1}=1] = \Phi_2[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}},(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i2}}+\overline{X}_2^j\widehat{\beta_{j2}},\rho] - \Phi_2[\overline{X}\beta_1,\overline{X}\beta_2,\rho] \quad (3.11)$$

where $\Phi_2(\cdot,\rho)$ represents the bivariate normal distribution function, $\overline{X}_j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta}_j$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta}i$ is the estimated coefficient.

The predicted probability at $\overline{X}$ differs considerably across the estimated models. In the full sample, $\Pr[y_{i2}=1,y_{i1}=1]$ is .1662. The same probability is .1816 in the men only sample and only .1244 in the women only sample. These estimates are different than the unconditional sample probabilities. In the case of men, the estimate is larger than the sample probability (.1711) while in the case of women, the estimate is lower than the sample probability (.1492). The marginal effect of the coefficient on the female dummy variable, in the full sample estimation, suggests that *a priori* the likelihood of promotion is 12.4% lower for women than men all else equal. This effect can be decomposed into women's 3.14% *higher* likelihood of staying on a job and their 15.1% *lower* likelihood of promotion given having stayed on the job.

There is evidence of a signaling model of promotion for women in the estimates of $\Pr[y_{i2}=1,y_{i1}=1]$. The coefficients on the all four experience variables are significant in each model.[30] The direction of the effects differs by gender. For men, the effect is negative while it is positive for women. This difference suggests that *a priori* women with more experience are more

[30]The χ^2 statistics are 50.16, 11.57, and 16.03 with associated p-values of .000, .0208, and .003 for the full, women only, and men only samples, respectively.

likely to stay on a job and get promoted. It is likely that women with more experience have successfully signalled their attachment to the labor force all else equal. This notion is also supported by the effect of hours worked per week on $\Pr[y_{i2} = 1, y_{i1} = 1]$. In the full model, the marginal effect of increasing the number of hours worked per week by one standard deviation above the mean increases the likelihood of staying on a job and being promoted by 5.6%.[31] This effect increases to 17% in the women only sample and decreases to .11% in the men only sample.[32] The implication is that women who work a larger number of hours are more attached to the labor market and therefore, more likely to stay at a job and receive a promotion.

3.5 Conclusion

In this paper, I examined the structure of promotion. Specifically, I modelled a promotion as the result of two decisions: the decision to stay on a job and the promotion offer decision. The latter decision has been addressed previously in the literature. The former decision is one that has been overlooked. By estimating a bivariate probit, I accounted for potential bias that may result from correlation between the unobservables in the equation for promotion and the unobservables in the equation for staying on a job. I found that there is a significant correlation. The presence of the correlation suggests that univariate estimates of promotion are potentially biased. In the present case, it appears that the cost to ignoring the correlation is low since the differ-

[31]The null hypothesis that the coefficients on the number of hours worked per week are jointly equal to zero can be rejected. The χ^2 statistic is 7.57 and the associated p-value is .0227.

[32]The null hypothesis that the coefficients on the number of hours worked per week are jointly equal to zero can be rejected in the women only sample. The χ^2 statistic is 17.54 and the associated p-value is .0001. The null cannot be rejected in the men only sample (χ^2=.26, p-value=.878).

ences across the models is small. However, there are significant differences in the structure of promotions across gender. First, both univariate and bivariate estimates suggest that women are less likely to be promoted all else equal. The estimated gap is roughly 15%. This effect is large and implies that the market for promotions differs by gender. Estimating gender-separated models supports this notion. A considerable difference is the fact that for men, there is a significant positive correlation between the unobservables in the equation for promotion and the unobservables in the equation for staying on a job while for women, there appears to be no correlation. This implies that men who are more likely to stay are more likely to be promoted. The same is not true for women. In fact, the absence of a significant correlation suggests that for women, the two decisions are independent. A possible explanation for this difference is that men and women have different career expectations. Men may only remain on jobs when they are likely to receive a promotion while women remain for other reasons. The other reasons may include signaling attachment to the labor market. The results from the estimated probabilities of being promoted given having stayed on a job, of staying on a job, and of staying on a job and being promoted support this notion. The estimates suggest that *a priori* women with more experience are more likely to stay on a job and be promoted while *a priori* men with more experience are less likely to stay on a job and be promoted. It is possible that employers do not promote women as often because of the perceived risk of women leaving the firm. By increasing experience, women signal their attachment. This is supported by the results of the estimated probability of promotion given having stayed on a job. In these results, it appears that women benefit from experience and employer tenure more than men. Since each variable is a reasonable measure of labor force attachment, the results support the signaling explanation for promotion differences. The results also suggest that women are more likely than men to stay on a job all else equal and it appears that women who work more hours per week are more likely to stay on a job. This result suggests that women who are more attached to the labor market (as signalled through hours worked per week) remain on jobs to possibly signal attachment and present themselves as a viable promotion candidate.

Table 3.1: Descriptive Statistics - Univariate Probit

	Total		Men		Women	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Promotions	.2299	.4208	.2442	.4297	.2129	.4095
Experience	244.7092	152.2203	252.2602	151.8579	235.748	152.2061
Employer Tenure	161.2414	142.1795	161.5744	144.0446	160.8462	139.9729
Positional Tenure	38.7721	36.4793	40.7764	37.9605	36.3935	34.4992
Training Required	.6072	.4884	.6054	.4889	.6093	.4881
Hours worked per Week	42.5328	8.2741	44.3316	8.732	40.398	7.1312
Highest Grade Completed	13.2011	2.2883	12.969	2.3663	13.4766	2.1605
Hourly Wage	9.6765	4.7501	10.4508	4.982	8.7575	4.2827
Supervise Work of Others	.4048	.4909	.4425	.4968	.3601	.4802
AFQT	44.8468	28.6478	44.3495	29.9099	45.437	27.0702
Non-White	.3982	.4896	.3852	.4867	.4136	.4926
Observations	3923		2129		1794	

The sample includes all respondents who remained on a job between 1989 and 1990. Experience and Employer Tenure are measured in weeks. Positional Tenure is measured in months. Experience is measured prior to current employer. Employer tenure is measured prior to current position.

Table 3.2: Probit Estimation Promotion

	Full Sample		Women		Men	
	Coefficient	$\frac{\partial\Phi(\cdot)}{\partial x}$	Coefficient	$\frac{\partial\Phi(\cdot)}{\partial x}$	Coefficient	$\frac{\partial\Phi(\cdot)}{\partial x}$
Experience	.0018***	-.0281	.0013	-.0026	.0023**	-.0469
	(.0007)		(.001)		(.001)	
(Experience)^2	-3.00e-06***		-1.00e-06		-4.00e-06***	
	(1.00e-06)		(2.00e-06)		(2.00e-06)	
Employer Tenure	-.0021***	-.0273	-.0025**	-.0274	-.0019**	-.0223
	(.0007)		(.001)		(.0009)	
(Employer Tenure)^2	3.00e-06***		4.00e-06*		3.00e-06**	
	(1.00e-06)		(2.00e-06)		(2.00e-06)	
Positional Tenure	-.0055***	-.0305	-.0044	-.0169	-.0066**	-.0372
	(.0021)		(.0034)		(.0027)	
(Positional Tenure)^2	.00002		.00002		.00003	
	(1.00e-05)		(.00002)		(.00002)	
Special Training Required	.0197	.0057	.0807	.0197	-.0167	-.005
	(.0478)		(.0722)		(.0643)	
Hours worked per Week	.0024	.0058	.0101**	.0176	-.0009	-.0027
	(.0029)		(.0049)		(.0036)	
Highest Grade Completed	.0322**	.0219	.0164	.0085	.0355**	.026
	(.0131)		(.0204)		(.0174)	
Hourly Wage	-.0108*	-.0147	.0001	.0001	-.0177**	-.0258
	(.0058)		(.0094)		(.0073)	
Supervise Work of Others	.2083***	.0649	.2315***	.0608	.1903***	.0612
	(.0477)		(.0717)		(.0643)	
AFQT	.0005	.0043	-.0004	-.0032	.0012	.0109
	(.0011)		(.0018)		(.0015)	
Female	-.1235**	-.0338	.		.	
	(.0484)					
Non-White	-.0119	-.0034	.059	.0143	-.0716	-.021
	(.0525)		(.0797)		(.0704)	
Constant	-1.006***		-1.3687***		-.8145***	
	(.2158)		(.3228)		(.2897)	
Predicted Probability at $\overline{X}^a$	.2101		.1517		.2266	
Observations	3923		1794		2129	
Log-Likelihood	-2049.753		-897.3952		-1144.2	
χ^2 statistic	130.9549		63.1314		78.7295	

Standard errors are in the parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The marginal effect for x^i is calculated as $\frac{\Delta Pr(y=1)}{\Delta x^i} = \Phi[(\overline{x}^i + \text{s.d.}_{(x^i)})\widehat{\beta}_i + \overline{X}^j\widehat{\beta_j}] - \Phi(\overline{X}\widehat{\beta})$ where Φ is the standard normal distribution function, $\overline{X}^j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta_j}$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta}i$ is the estimated coefficient. [a] The predicted probabilities are calculated at mean levels of the explanatory variables and each dummy variable set to 0.

Table 3.3: Descriptive Statistics - Bivariate Probit

	Total		Men		Women	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Promotions	.1611	.3676	.1711	.3767	.1492	.3563
Stays	.7005	.4581	.7006	.4581	.7005	.4581
Experience	259.0338	15.8997	268.1836	15.3994	248.1761	15.8019
Employer Tenure	135.48	135.3122	135.9059	137.2786	134.9746	132.9661
Positional Tenure	33.5766	34.7078	35.0704	36.2396	31.804	32.7162
Training Required	.5996	.49	.6002	.4899	.599	.4902
Hours worked per Week	42.2466	9.0017	44.1981	9.3538	39.9309	7.9691
Highest Grade Completed	13.113	2.307	12.8717	2.3772	13.3995	2.187
Hourly Wage	9.1322	4.6638	9.8398	4.8912	8.2924	4.2287
Supervise Work of Others	.3945	.4888	.4258	.4945	.3573	.4793
AFQT Score	43.2814	28.5872	42.7572	29.906	43.9036	26.9312
Change in Marital Status	.1005	.3007	.0935	.2911	.1089	.3116
In Home MSA[a]	.6529	.4761	.6525	.4762	.6533	.476
Non-White	.4064	.4912	.3978	.4895	.4166	.4931
Observations	5600		3039		2561	

The sample includes all respondents who worked in both 1989 and 1990. Experience and Employer Tenure are measured in weeks. Positional Tenure is measured in months. Experience is measured prior to current employer. Employer tenure is measured prior to current position. [a]This variable equals 1 if the respondent is in the same MSA in 1989 that was reported in 1979.

Table 3.4: Bivariate Probit Estimation
Full Sample

	Estimates		Marginal Effects		
	y_{i1}	y_{i2}	$\Delta\text{Pr}[y_{i1}=1, y_{i2}=1]$	$\Delta\text{Pr}[y_{i2}=1 \mid y_{i1}=1]$	$\Delta\text{Pr}[y_{i1}=1]$
Experience	.0004	.0018***	-.015	-.0277	.0304
	(.0005)	(.0007)			
(Experience)^2	4.22e-07	-3.28e-06***			
	(9e-07)	(1.14e-06)			
Employer Tenure	.0058***	-.0002	.0046	-.0243	.1171
	(.0006)	(.001)			
(Employer Tenure)^2	-6.14e-06***	7.67e-07			
	(1.17e-6)	(1.55e-6)			
Positional Tenure	.006***	-.0033	-.0171	-.033	.0415
	(.0019)	(.0024)			
(Positional Tenure)^2	-2.02e-05	1.14e-05			
	(1.39e-05)	(1.7e-5)			
Special Training Required	.041	.0316	.0081	.0069	.0128
	(.0397)	(.045)			
Hours worked per Week	.0052***	.004	.0093	.008	.0145
	(.002)	(.0029)			
Highest Grade Completed	.01	.0311**	.0183	.0219	.0072
	(.011)	(.0125)			
Hourly Wage	.0361***	-.002	-.0013	-.0154	.05
	(.0046)	(.0066)			
Supervise Work of Others	-.1485***	.1558***	.0382	.0501	-.0491
	(.0394)	(.0508)			
AFQT	4.30e-05	4.00e-04	.003	.0038	.0004
	(.0009)	(.0011)			
Change in Marital Status	-.1469**	.	-.0014	.0132	-.0486
	(.0593)				
In Home MSA	.0897**	.	.0006	-.007	.0274
	(.0396)				
Female	.0772**	-.0899*	-.0206	-.0333	.0237
	(.0393)	(.0475)			
Non-White	.0046	-.0099	-.0024	-.0035	.0015
	(.0427)	(.0492)			
Constant	-.9736***	-1.6568***			
	(.168)	(.2772)			
ρ	.6848**				
	(.2852)				
Predicted Probability at $\overline{X}^a$			.1662	.2207	.7532
Log-Likelihood	-5080.257				
Promotions	902				
Stays	3923				
Observations	5600				

Standard errors are in the parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The marginal effect for x^i is calculated as $\frac{\Delta Pr[y_{i2}=1|y_{i1}=1]}{\Delta x^i} = \frac{\Phi_2[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}}, (\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i2}}+\overline{X}_2^j\widehat{\beta_{j2}}, \rho]}{\Phi[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}}]} - \frac{\Phi_2[\overline{X}\beta_1, \overline{X}\beta_2, \rho]}{\Phi[\overline{X}\beta_1]}$ where $\Phi(\cdot)$ and $\Phi_2(\cdot,\rho)$ represent the standard normal and bivariate normal distribution functions, respectively, $\overline{X}_j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta_j}$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta_i}$ is the estimated coefficient. [a] The predicted probabilities are calculated at mean levels of the explanatory variables and each dummy variable set to 0.

Table 3.5: Bivariate Probit Estimation Women

	Estimates		Marginal Effects		
	y_{i1}	y_{i2}	Δ Pr$[y_{i1}=1, y_{i2}=1]$	Δ Pr$[y_{i2}=1\|y_{i1}=1]$	Δ Pr$[y_{i1}=1]$
Experience	.0004 (.0008)	.0013 (.001)	.0021	-.0051	.0374
$(\text{Experience})^2$	6.22e-07 (1.33e-06)	-2.29e-06 (1.7e-06)			
Employer Tenure	.0071*** (.0009)	-.0032 (.0027)	-.0096	-.035	.1306
$(\text{Employer Tenure})^2$	-7.9e-06*** (1.86e-6)	4.36e-06 (3.58e-06)			
Positional Tenure	.0019 (.0033)	-.0047 (.0037)	-.0118	-.0187	.0164
$(\text{Positional Tenure})^2$	-2.27e-06 (2.61e-05)	2.25e-05 (2.67e-05)			
Special Training Required	.0592 (.0597)	.0753 (.0778)	.0191	.0207	.0181
Hours Worked per Week	.0121*** (.003)	.0091 (.0073)	.0212	.0208	.0291
Highest Grade Completed	-.0099 (.0165)	.0171 (.0213)	.0057	.0090	-.0068
Hourly Wage	.0344*** (.0072)	-.0021 (.0145)	.0075	.0006	.0430
Supervise Work of Others	-.2052*** (.0598)	.246*** (.0923)	.0324	.0373	-.0684
AFQT	.0018 (.0015)	-.0006 (.0019)	-.0002	-.0033	.0148
Change in Marital Status	-.1855** (.0899)	.	-.0128	-.0040	-.0615
In Home MSA	.0985* (.0597)	.	.0064	.0020	.0296
Non-White	.0669 (.0653)	.052 (.0852)	.0148	.0147	.0204
Constant	-1.0298*** (.2389)	-1.1507 (1.0622)			
ρ	-.1698 (.7167)				
Predicted Probability at $\overline{X}^a$			.1244	.1641	.7528
Log-Likelihood	-2274.232				
Promotions	382				
Stays	1794				
Observations	2561				

Standard errors are in the parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The marginal effect for x^i is calculated as $\frac{\Delta Pr[y_{i2}=1|y_{i1}=1]}{\Delta x^i} = \frac{\Phi_2[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}},(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i2}}+\overline{X}_2^j\widehat{\beta_{j2}},\rho]}{\Phi[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}}]} - \frac{\Phi_2[\overline{X}\beta_1,\overline{X}\beta_2,\rho]}{\Phi[\overline{X}\beta_1]}$ where $\Phi(\cdot)$ and $\Phi_2(\cdot,\rho)$ represent the standard normal and bivariate normal distribution functions, respectively, $\overline{X}_j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta_j}$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta_i}$ is the estimated coefficient. [a]The predicted probabilities are calculated at mean levels of the explanatory variables and each dummy variable set to 0.

Table 3.6: Bivariate Probit Estimation
Men

	Estimates		Marginal Effects		
	y_{i1}	y_{i2}	Δ Pr[$y_{i1}=1, y_{i2}=1$]	Δ Pr[$y_{i2}=1\|y_{i1}=1$]	Δ Pr[$y_{i1}=1$]
Experience	.0002 (.0008)	.0022** (.0009)	-.0295	-.0446	.0252
(Experience)^2	5.60e-07 (1.2e-06)	-4.4e-06*** (1.56e-06)			
Employer Tenure	.0049*** (.0007)	1.30e-05 (.001)	.0100	-.0154	.0996
(Employer Tenure)^2	-5.20e-06 (1.5e-06)	6.20e-07 (1.7e-06)			
Positional Tenure	.0092*** (.0024)	-.003 (.0031)	-.0178	-.0372	.0546
(Positional Tenure)^2	-3.6e-05** (1.7e-05)	9.50e-06 (2.1e-05)			
Special Training Required	.0275 (.0536)	-.0024 (.0588)	-.0006	-.0033	.0082
Hours Worked per Week	.0013 (.0026)	8.70e-05 (.0034)	.0002	-.0008	.0037
Highest Grade Completed	.024* (.0142)	.0383** (.0158)	.0250	.0266	.0169
Hourly Wage	.0369*** (.0059)	-.0065 (.0077)	-.0080	-.0244	.0510
Supervise Work of Others	-.1036* (.0542)	.1477** (.061)	.0409	.0580	-.0326
AFQT	-.0013 (.0012)	.0005 (.0014)	.0042	.0091	-.0116
Change in Marital Status	-.1071 (.0803)	.	-.0002	.0105	-.0337
In Home MSA	.0778 (.053)	.	.0001	-.0067	.0229
Non-White	-.0419 (.0575)	-.0773 (.065)	-.0197	-.0219	-.0129
Constant	-.8783*** (.2359	-1.5625*** (.2995)			
ρ	.8122*** (.3001)				
Predicted Probability at $\overline{X}^a$			.1816	.2357	.7705
Log-Likelihood	-2788.547				
Promotions	520				
Stays	2129				
Observations	3039				

Standard errors are in the parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. The marginal effect for x^i is calculated as $\frac{\Delta Pr[y_{i2}=1|y_{i1}=1]}{\Delta x^i} = \frac{\Phi_2[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}},(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i2}}+\overline{X}_2^j\widehat{\beta_{j2}},\rho]}{\Phi[(\overline{x}^i+\text{s.d.}_{(x^i)})\widehat{\beta_{i1}}+\overline{X}_1^j\widehat{\beta_{j1}}]} - \frac{\Phi_2[\overline{X}\beta_1,\overline{X}\beta_2,\rho]}{\Phi[\overline{X}\beta_1]}$ where $\Phi(\cdot)$ and $\Phi_2(\cdot,\rho)$ represent the standard normal and bivariate normal distribution functions, respectively, $\overline{X}_j$ is the vector of means for the explanatory variables excluding variable i, $\widehat{\beta_j}$ is the vector of estimated coefficients, $\overline{x}^i$ is the mean of the variable of interest, s.d.$_{(x^i)}$ is its standard deviation, and $\widehat{\beta_i}$ is the estimated coefficient. [a]The predicted probabilities are calculated at mean levels of the explanatory variables and each dummy variable set to 0.

Chapter 4

Job Attachment Patterns of Men and Women: Promotion Expectations and Experience

(with Malathi Velamuri)

4.1 Introduction

In documenting the pattern of lifetime jobs in the US using data from the 1968-1978 period, Hall(1982) found that on average, women's jobs were of substantially shorter duration relative to men's jobs. According to Hall, this higher job turnover for women was a consequence of the long stretches of time they spent out of the labor force. Researchers have studied the implications of these gender differences in turnover behavior on various labor market outcomes. Ureta (1995) examined the effect of non-employment spells on wage growth, by studying the timing and frequency of non-work spells for a sample of young, white workers drawn from the National Longitudinal Surveys. Her estimates suggest that 12% of the male-female wage gap can be explained by women's intermittent employment spells.

One channel through which gender differences in job turnover translate into the gender wage gap is through differential rates of promotion for men and women; some contend that women face a 'glass ceiling' that prevents their upward mobility in internal labor markets (Gjerde, 2002). According to this theory, since training workers is a costly activity, firms are only willing to invest in those workers from whom they expect to recoup the costs of training.

Given that the expected time horizon to recover these costs is shorter for women, firms are unwilling to train their women workers. And since training is invariably a prerequisite for promotion, promotion rates for women tend to be smaller than those for men. These differences in promotion rates then translate into a gender wage-gap.[1]

A significant increase in the labor force participation of women over the past few decades has motivated researchers to re-examine job turnover behavior by men and women. There is evidence suggesting that more recent cohorts of women are as concerned about their careers as men, have a higher propensity to stay on their jobs and are exhibiting a strong attachment to the labor market.[2] We would expect firms to treat these women - the 'stayers' - no differently from men. However, women workers are still a heterogenous group comprising both 'stayers' and 'quitters,' with higher average turnover rates than men. If firms cannot distinguish between the two types of women workers based on observables, statistical discrimination would still result in lower promotion rates for women and a persistence of the wage gap. If, on the other hand, the stayers could successfully signal their intentions to stay in the labor force and separate themselves from the quitters, they could overcome internal labor market discrimination.

Prisinzano (2004) estimated a bivariate probit model of job-stays and promotions for men and women. His results indicate that the error terms between the job-stay equation and the promotions equations are correlated for men, suggesting that the unobservables affecting the stay decision are corre-

[1]Wages usually grow with promotions; McCue's(1996) estimates suggest that between 9%-18% of wage growth is due to promotions.

[2]See Prisinzano (2004), Light and Ureta(1992), and references therein.

lated with those affecting whether they receive a promotion or not. In contrast, the hypothesis that the estimated correlation between the error terms in the two equations for women is equal to zero cannot be rejected, implying that whether women receive a promotion offer or not is uncorrelated with their job-stay decisions. This seemingly strange result is the motivation for the current paper. It is our view that women who are concerned about their careers are using job attachment as a signal to indicate their attachment to the labor force. We expect women with little or no job market experience to have lower job turnover rates compared to men of similar experience, all else equal. Therefore, during this period, we expect women to exhibit less sensitivity to expectations of promotion, relative to men. This rationale also suggests that once women have gained adequate labor market experience and revealed themselves as stayers, their job attachment patterns should respond more closely to their expectations of promotions. Hence, we expect women with adequate job market experience to reveal job attachment patterns similar to those of men.

Accordingly, we use a longitudinal dataset to study how the expectation of promotion affects men's and women's decision to stay on a job and whether this relative pattern varies with the amount of labor market experience. The data also contains information on workers' perceived chances of promotion in their current job. We expect workers who are concerned about their careers to be sensitive to the potential for career growth in their firms. We examine how turnover behavior responds to this subjective likelihood of promotion and how this response differs by gender and experience level. Our results suggest that individuals with low expectations of promotion are less likely to stay on their jobs relative to those with high expectations of promotion. We also find evidence that women are more likely than men to stay on a job all else equal.

Furthermore, women with low promotion expectations are more likely than comparable men to stay on a job and this difference is more pronounced early in careers. The fact that the difference diminishes with experience supports our hypothesis.

The rest of the paper is organized as follows: section 4.22 gives a description of our data, the variables used in our analysis and some descriptives for our sample. In section 4.4, we describe the empirical models we use in our estimation, in section 4 we discuss the results and present our conclusions in section 4.5.

4.2 Data and Descriptives

We use data from the National Longitudinal Survey of Youth (NLSY) for the following survey years: 1979-83, 1996, 1998 and 2000.We restricted our sample to those who exhibited a reasonable attachment to the labor market. We eliminated respondents who worked for less than 15 weeks per year or less than 20 hours per week in any year. We also eliminated respondents who were either self-employed, working in a farming occupation or industry, or in the armed forces. This restriction removes those individuals that face considerably different job and promotion structures than the typical worker.

The information on job changes and the subjective perception of promotion possibilities on the current job are of particular interest for the present study. Accordingly, we identify the respondent as a 'job-stayer' in a particular year if he or she reported that the main job that year was also the main job in the previous year. In the 1979 through 1982 surveys, the NLSY includes the respondent's assessment of whether the chances for promotion in the current job are good. The responses are coded as: 1. Not true at all; 2. Not too true;

3. Somewhat true and 4. Very true. In the 1996 and 1998 surveys, a similar question is asked as follows: "Do you believe it is possible for you to get a promotion with this employer in the next two years?", and the respondent replied with a yes/no. One problem in comparing these questions is that in the 1979-82 surveys, the question does not specify a time horizon while in the 1996 and 1998, the scope of the question is limited to two years. However, we believe that the respondents interpreted the question as referring to a short time horizon in the 1979-82 surveys, especially given that they were all between 15 and 25 years old. We therefore combine the first two categories in the 1979-82 survey responses - Not true at all and Not too true - into one, and label this as "Low chances of promotion", and combine the other two categories - Somewhat true and Very true - into the "High chances of promotion category. In the 1996 and 1998 surveys, if the response to the promotion question was No, this was categorized as "Low chances of promotion" and if it was Yes, it was categorized as "High chances of promotion." This way, we construct a comparable measure of subjective perception of promotion chances on the current job.

Tables 4.1 and 4.2 present the fraction of job-stayers and job-movers among men and women for the two time periods, categorized by their self-perceived chances of promotion. In the 1979-82 period, among workers who feel they have little or no chance of promotion in their current job, a significantly larger fraction of women workers stayed on their jobs. By contrast, a much higher fraction of men stay on in jobs in which they think that the likelihood of promotion is very high, relative to women. Among the job-movers, there's no discernible pattern among women while a significant fraction among men, nearly 60%, move jobs even when they think they have good chances of promotion. We observe the same pattern in the 1996-1998 period.

The summary statistics for our sample are presented in table 4.3. Women constituted less than half the sample, as did non-whites. Although we do not see too many differences between men and women in terms of the marital status variables, on average, women had more children. Women were also slightly younger and had about an extra half-year of education. This translated into a lower average level of potential experience for women. As expected, women had lower mean wages, compared to men. However, a higher fraction of women stayed on their jobs from one year to the next compared to men, despite a substantially higher fraction of women reported facing low chances of promotion in their current jobs.

4.3 Model Specification

In the present paper, we examine the likelihood of an individual remaining on a job. It is possible to estimate this decision using a simple probit model of the following form:

$$y_i = X\beta + \epsilon_i \tag{4.1}$$

where $y = 1$ if the individual stayed on the current job and $y = 0$ if she did not stay on the job. X is a set of covariates, β is a vector of parameters to be estimated, and ϵ is assumed to have a standard normal distribution. The set of covariates includes characteristics pertaining to the individual and her job. This model is appealing because it is easy to implement and interpret. However, the model does not take advantage of the panel nature of the data. We can incorporate the panel nature of the data into the probit model and account for omitted variable bias by estimating a random-effects specification of equation 4.1. The specification used in this paper follows the model proposed by Guilkey and Murphy (1993).[3] The model is as follows:

$$y_{it}^{*} = X_{it}\beta + \mu_i + \upsilon_{it} \tag{4.2}$$

where X_{it} is a set of covariates for individual i at time t and β are parameters to be estimated. μ_i and υ_{it} are independent random variables with μ_i characterizing individual i and following a normal distribution with mean 0 and variance σ_μ^2) while υ_{it} is a random disturbance distributed as $N(0, \sigma_\upsilon^2)$. Given these conditions, we have the following:

$$E(\mu_i + \upsilon_{it}, \mu_i + \upsilon_{it}) = \sigma_\mu^2 + \sigma_\upsilon^2 \tag{4.3}$$

and

$$Corr(\mu_i + \upsilon_{it}, \mu_i + \upsilon_{is}) = \rho = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\upsilon^2}. \tag{4.4}$$

Following from a simple probit, we observe the following:

$$\begin{aligned} y_{it} &= 1 \text{ if } y_{it}^{*} > 0 \qquad (4.5)\\ y_{it} &= 0 \text{ if } y_{it}^{*} \leq 0. \end{aligned}$$

The likelihood function is then:

$$\begin{aligned} L = \prod_{i=1}^{N}\{\int_{-\infty}^{\infty}\prod_{t=1}^{T}[1 - \Phi(x_{it}\frac{\beta}{\sigma_\upsilon} + \sqrt{\frac{\rho}{1-\rho}}\frac{\mu}{\sigma_\mu})]^{1-y_{it}} \qquad (4.6)\\ \times[\Phi(X_{it}\frac{\beta}{\sigma_\upsilon} + \sqrt{\frac{\rho}{1-\rho}}\frac{\mu}{\sigma_\mu})]^{y_{it}}\phi(\frac{\mu}{\sigma_\mu})\mathrm{d}(\frac{\mu}{\sigma_\mu})\} \end{aligned}$$

[3]Heckman and Willis (1976) and Chamberlain (1980) both present a similar model. Hsiao (1986) gives a useful discussion of the literature. Butler and Moffitt (1982) describe a procedure to calculate the likelihood function.

where Φ represents the standard normal distribution, N is the number of individuals, and T is the number of observations for individual i. X_{it} is a set of covariates for individual i at time t and β, μ, and ρ are parameters to be estimated.[4]

In order to capture the differential effects of gender, promotion expectations, and experience on the probability of staying on a job, we adopt a 'difference in difference in difference' specification of X_{it}.[5] First, we examine how the probability of staying on a job differs by promotion expectations. Any difference in the probability is likely due to simple concerns regarding the career path. That is, individuals may be less likely to remain on a job if they do not expect to be promoted. Second, we examine how these concerns differ by gender. It is possible that women and men differ in how promotion expectations change their likelihood of staying on a job. The presumption is that women may have different expectations about career length. We have the following 'difference-in-difference' approach after combining the above two analyses:

$$\begin{aligned} \Delta^2 =& (Pr(y_{it} = 1)_F^L - Pr(y_{it} = 1)_F^H) \\ & -(Pr(y_{it} = 1_M^L - Pr(y_{it} = 1)_M^H) \end{aligned} \tag{4.7}$$

where $Pr(y_{it} = 1)$ represents the probability of staying on a job, the superscripts L and H represent individuals who have either low or high expectations of promotion, and the subscripts F and M represent females and males, respectively. Equation 4.7 assumes that the difference in the probability of staying

[4]A pooled probit will provide consistent estimates of $\frac{\beta}{\sigma_\epsilon}$ with incorrect standard errors. However, these estimates will equal the random effects estimates only if $\sigma_\mu^2 = 0$. If $\sigma_\mu^2 \neq 0$ then the preferred estimation method is the variance-components model of equation 4.6.

[5]The specification presented follows the example of Hamermesh and Trejo (2000).

would be similar across promotion expectation if not for gender. The equation is represented in the probit framework by:

$$Pr(y_{it} = 1) = z_{it}\gamma + \delta_1 L + \delta_2 F + \delta_3 (L * F) + \epsilon_{it} \tag{4.8}$$

where z_{it} is a set of covariates and γ is the corresponding set of parameters to be estimated. L is a dummy variable for an individual who has low expectations for promotion and F is a dummy variable for females. δ_1 and δ_2 are the associated coefficients to be estimated. δ_3 is the coefficient that identifies the difference in difference expressed in equation 4.7. Lastly, we examine whether differences in the probability of staying on a job given promotion expectations and experience level differ by gender. Following the form above, we have:

$$\begin{aligned} \Delta^3 = & [(Pr(y_{it} = 1)^L_F - Pr(y_{it} = 1)^H_F) - (Pr(y_{it} = 1^L_M) - Pr(y_{it} = 1)^H_M)]_I \\ & - [(Pr(y_{it} = 1)^L_F - Pr(y_{it} = 1)^H_F) - (Pr(y_{it} = 1^L_M) - Pr(y_{it} = 1)^H_M)]_E \end{aligned} \tag{4.9}$$

where the subscripts I and E represent individuals who are inexperienced and experienced and all other notation is defined as above. However, rather than assign an indicator for 'inexperience,' we use a continuous measure of experience and its square. This difference is incorporated in the probit framework as follows:

$$\begin{aligned} Pr(y_{it} = 1) = & z_{it}\gamma + \delta_1 L + \delta_2 F + \delta_3 (L * F) + \delta_4 E + \delta_5 E^2 \\ & + \delta_6 (L * E) + \delta_7 (L * E^2) + \delta_8 (F * E) + \delta_9 (F * E^2) \\ & + \delta_{10} (L * F * E) + \delta_{11} (L * F * E^2) + \epsilon_{it} \end{aligned} \tag{4.10}$$

where E and E^2 are potential experience and its square, respectively while δ_4 and δ_5 are the associated coefficients. δ_6 and δ_7, and δ_8 and δ_9 are the pairs of coefficients that identify the difference-in-differences for low promotion expectations and inexperience, and gender and inexperience, respectively. δ_{10} and δ_{10} are the coefficients that identify the 'difference-in-difference-in-difference' expressed in equation 4.9. The remaining notation is as defined above.

The above specification allows for comparisons across different groups. We are interested in the following differences. First, we are concerned with the difference in the likelihood of staying across gender given low promotion expectations and the same difference given high promotion expectations. The former difference is represented by $\delta_2 + \delta_3 + \delta_8 + \delta_9 + \delta_{10} + \delta_{11}$ while the latter difference is represented by $\delta_2 + \delta_8 + \delta_9$. Second, we are interested in the difference in the likelihood of staying across promotion expectation given gender. For men, this difference is represented by $\delta_1 + \delta_6 + \delta_7$. The same difference for women is represented by $\delta_1 + \delta_6 + \delta_7 + \delta_8 + \delta_9 + \delta_{10} + \delta_{11}$. Lastly, we are interested in how the difference in the likelihood of staying between low and high promotion expectation men differs from the analogous difference for women after controlling for experience level. This difference is represented by $\delta_{10} + \delta_{11}$.

4.4 Estimates

The results from the random-effects probit models are presented in table 4.4. The estimate of the correlation between the decision to stay on a job in year t and the same decision in year $t + 1$, denoted by ρ, is positive and significant. This result suggests that the random effects probit is the preferred estimation.[6] The implication of the positive sign on the correlation is that

[6]In general, there is little difference between the pooled estimates and the random effects estimates. However, the estimate of ρ is significantly different from zero in each model

individuals who stay on their job in year t are more likely to stay on their job in year $t + 1$; in other words, certain individuals may be 'stayers' while others are 'non-stayers.'

4.4.1 Basic Results

An important determinant of staying on a job is changes in marital status. We define changes in marital status for an individual as staying single from year t to $t + 1$, remaining married from year t to $t + 1$, getting married between year t and $t + 1$, or going from married to single between year t and $t + 1$. Individuals who remain married or who get married are more likely to stay on a job than individuals who are single, all else equal. The former group is 35% more likely to remain on a job while the latter group is 23.5% more likely to remain on a job.[7] It is likely that this result reflects the notion that these two groups are either more stable or desire more stability than single individuals. The stability is likely due to the fact that individuals who are married have a dependent and any decision is a 'joint' decision. The coefficient on becoming single between two time periods is positive and significant. However, the marginal effect is considerably smaller than the effects associated with marriage (14%). It is not surprising that there is a small difference in the likelihood of staying on a job for individuals who become single and those who remain single. This difference may reflect the fact that 'newly' single individuals are not that removed from marriage and have not fully realized their single status.

estimated. Given this fact, we report only the results of the random effects probits.

[7] The predicted probability of remaining on a job at the mean levels of all continuous variables and each dummy variable set to 0 is .5118.

Presumably, two important considerations that affect job turnover are the wage and the potential for promotion within the firm. The former reflects the cost to the individual of leaving the job. The coefficient on the log of the hourly wage is positive and significant. The marginal effect associated with the coefficient is sizable at 28.76%. This result coincides with the expectation that the higher the wage, the higher the cost to the individual of leaving the job. The latter is likely important to those individuals who are concerned with a career and the associated benefits. As such, we expect individuals with low promotion expectations to be less likely to stay on the job. Our estimate accords with this notion; individuals who have low expectations of promotion on their jobs are less likely to stay on their jobs.

The effect of potential experience on job turnover seems counter-intuitive; search theory predicts that job turnover will be high at low levels of experience as workers search for a good 'match.' Once good job matches are made, turnover is expected to decline. Thus, we would expect the coefficient on the linear experience term to be positive and the one on the quadratic term to be negative. Our results suggest the opposite pattern. A possible explanation for this pattern is that there are differential effects of experience by gender and by promotion expectation. We explore this hypothesis in subsequent specifications. However, it is important to note that the marginal effect associated with potential experience is negligible.[8]

The coefficient on the gender variable is of particular interest to the present study. Recent studies have found that women are more likely than

[8]The marginal effect of potential experience is calculated as the mean of effects in the sample.

men to stay at jobs.[9] Our result is consistent with this finding. The coefficient on the female dummy variable is significant and positive. It suggests that women are 12% more likely than men to stay on a job all else equal.

4.4.2 Gender-Promotion Expectation Comparisons

Column 3 of table 4.4 presents the results of the double-difference estimation. The coefficients of particular interest are those associated with the variables that are used in the 'double-difference' presented in equation 4.7. These variables are dummy variables for female and having low expectations of promotion. The results from the basic specification presented in column 2 of table 4.4 suggest that women are 12% more likely to remain on a job than men all else equal. It is not obvious why women are more likely to stay on jobs than men. The unconditional probabilities of staying on a job are very close. In our sample, 55.5% of men stayed on jobs while 56.9% of women stay on jobs. This difference represents only a 2.5% increase. A reasonable explanation for the estimated difference is that women may face a form of discrimination in hiring practices. Under this condition, women may be less likely to receive a new job offer. As such, women may hold onto jobs longer because the job search costs they face are higher than job search costs faced by men.

If individuals are concerned with career 'growth', promotion expectations are likely an important consideration in the stay decision. The basic specification supports this notion. That is, individuals with low promotion expectations are less likely to stay on a job. The presumption is that they will incur the costs of leaving a job in order to move to a job with more promotion potential. It is also possible that individuals who have low promotion

[9] For example, Prisinzano (2004).

expectations recognize they are not productive at the job. In this case, individuals may leave in order to find a job at which they are productive. The estimation presented here does not distinguish between these possibilities but as presented in the previous section, individuals with low promotion expectations are 15% less likely to stay on a job all else equal. Considering the magnitude of the marginal effect, it appears that promotion expectations are an important determinant of staying on a job.

The coefficient on the interaction between female and low promotion expectations identifies the double difference. It captures any difference in the probability of staying on a job across promotion expectation that is due to gender. The coefficient on the interaction is insignificant at conventional levels. As such, it appears that women are more likely to stay on jobs than men regardless of the promotion expectations. However, if women do need to signal attachment to the labor market, it is likely that women with low levels of experience will differ from men with low levels of experience but women with high levels of experience will not differ from men with high levels of experience. In order to capture this effect, we estimated the specification presented in equation 4.10.

4.4.3 Gender-Promotion Expectation-Experience Comparisons

The results of the triple difference estimation are presented in column 6 of table 4.4 and the marginal effects for the variables of interest are presented table 4.5. In the case of the control variables, the results of the triple difference are similar to the results of the previous specifications. In the previous estimation, we found little evidence of 'job-shopping.' We found that the net effect of potential experience decreased the likelihood of staying on a job. In the current specification, we also find this result but the inclusion of the set of interactions that identify the triple difference changes the interpretation.[10] The net effect of potential experience differs by gender, promotion expectation, and gender-promotion expectation group. In the case of men with high promotion expectations, the effect is simply the net of the coefficients on the potential experience variables. The result suggests that as potential experience increases the likelihood of staying on a job for men with high promotion expectations decreases.[11] This result is mild evidence of negative selection for men. In the previous specifications, we also found that individuals with low promotion expectations are less likely to stay on a job. In the current specification, we see a different result for men. The marginal effect associated with the coefficient on low promotion expectations also accounts for the interaction between this variable and the potential experience variables. The net marginal effect is .0004. This result suggests that men with low promotion expectations are .09% more likely to stay on a job than men with high promotion expectations.[12] Even though this result is negligible, it may reflect a negative selection of men into long tenure. That is, men who have low promotion expectations are also less likely to find comparable jobs in the labor market and therefore, stay on the current job.

[10]The set of coefficients that identifies the triple difference is Female, Low, Low*Female, Potential Experience, the square of Potential Experience, Potential Experience*Low, (Potential Experience)^2*Low, Potential Experience*Female, (Potential Experience)^2*Female, Potential Experience*Low*Female, and (Potential Experience)^2*Low*Female. The χ^2 statistic for joint significance of the full set is 192.71 and its associated p-value is .0000.

[11]The χ^2 statistic for joint significance of the coefficients on the potential experience variables is 21.99 and its associated p-value is .0000.

[12]The χ^2 statistic for joint significance of the coefficient on low promotion expectations and the interactions with the potential experience variables is 87.29 and its associated p-value is .0000.

In the double-difference specification, we found that women were 12% more likely than men to stay on a job all else equal. In the current specification, we also find that women are more likely to stay on a job than men. The marginal effect associated with women also takes into account the interaction of the potential experience variables and the female dummy variable. This effect suggests that women who have high promotion expectations are 16.5% more likely than men with high promotion expectations to stay on a job.[13] A possible explanation for this result is that since women are less likely to receive a promotion, when they are likely to receive a promotion they remain on the job. The presumption is that men who have high promotion expectations may be able to find a comparable job whereas women are not able to find a comparable job. A possible explanation for why they are not able to find a comparable job is our signaling story. Women must signal attachment to the labor market in order to receive promotions (and the likely wage increases). If attachment to the labor market is observed noisily from outside a firm, women will stay on current jobs longer than men all else equal. The difference is highlighted when we control for promotion expectations in the estimation. We also find that women with low promotion expectations are less likely to stay on a job than women with high promotion expectations. The marginal effect associated with being a women with low promotion expectations takes into account the coefficients on the female and low promotion expectations variables as well as each of the included interactions. The results suggest that women with low promotion expectations are 13.8% less likely to stay on a job than women with high promotion expectations.[14] Contrary to the result for

[13]The χ^2 statistic for joint significance of the coefficients on female and the interactions with the potential experience variables is 22.61 and its associated p-value is .0000.

[14]The χ^2 statistic for joint significance of the coefficients on low and the interactions with

men, it appears that there is *positive* selection of women into long tenure.

Given the present specification, it is possible to compare across gender and promotion expectations. A useful comparison is women to men given low promotion expectations. This difference in the likelihood staying on a job is due to the turning on of the female indicator as well as the female-potential experience and female-low interactions. The marginal effect is .0122 at the mean of experience and suggests that women with low promotion expectations are 2.5% more likely to stay on job than their male counterparts.[15] This difference in the likelihood of staying across gender increases if we consider men and women with a potential experience level that is one standard deviation below the mean. Women with low promotion expectations and 'low' potential experience are 16.6% more likely than comparable men to stay on a job. This result is of particular interest in our study. Our hypothesis is that early in their careers women are likely to respond to promotion expectations differently than men. Specifically, we expect women who are early in their careers to stay on jobs for which they have low promotion expectations more often than men. The reason for this difference is that women early in their careers must signal an attachment to the labor market that men do not have to signal. As such, 'job-shopping' by women is a negative signal regarding labor force attachment. It suggests that women who have low promotion expectations and are inexperienced are more likely to stay on a job than their male counterparts. Later in the career, the difference in the likelihood of staying on a job between men and women with low promotion expectations diminishes. For individuals with a potential experience level that is one standard deviation above the mean,

female and potential experience variables is 131.82 and its associated p-value is .0000.

[15]The χ^2 statistic for joint significance of the coefficients on female and the female-potential experience and female-low interactions is 43.15 and its associated p-value is .0000.

women with low promotion expectations are only 12.8% more likely to remain on a job than comparable men. Our hypothesis is that men and women's behavior in response to promotion expectations should be indistinguishable at high levels of experience. Even though there is still a difference, this result supports this notion.

4.4.3.1 Early Sample

As noted in section 4.2, the promotion expectations question in the 1979-82 surveys had four possible responses while the corresponding question in the 1996-98 surveys had only two possible responses. In pooling the data, it was necessary to collapse the four response categories from the earlier period into two categories. To ensure that this restriction is not affecting our results, we estimated the triple-difference specifications for the 1979-82 and the 1996-1998 periods separately. In estimating the specifications for the earlier period, we combined the two responses 'Not true at all' and 'Not too true' into one category, 'Low promotion expectations' but kept the other two responses - 'Somewhat true' and 'Very true' - separate. The results are presented in table 4.6 and the marginal effects for the variables of interest are in table 4.7.

The results for the education, wages, children, living in MSA, race and marital variables are all qualitatively similar to those of the pooled sample. The coefficients on the detailed promotion expectation categories have the expected signs; individuals who perceive their chances of promotion to be small or moderately good are less likely to stay on the job relative to those who believe that they have very good chances of getting promoted. Unlike in the pooled sample, the net effect of potential experience is positive. However the marginal effect still remains small and furthermore, the coefficients on the linear and quadratic terms are not jointly significant.[16]

Similar to the findings in the pooled sample, we find that women are more likely to stay on their job relative to men, regardless of promotion expectations. Specifically, we find that women are 29.5%, 18.3% and 21.3% more likely to stay on the job than their male counterparts for all low, moderate and high promotion expectation categories, respectively. [17] Given that most of the individuals in this sub-sample have low levels of potential experience, this results supports our hypothesis that women stay on jobs to signal attachment to the labor force. When we consider these marginal effects at one standard deviation above and below the mean level of potential experience, the results also support our hypothesis. However, we find that as potential experience increases, the gender differences in the relative probabilities of staying on the job also increase. This results is contrary to our expectation that as women gain experience, their response to promotion expectations should be similar to that of men. However, it is possible that signaling takes longer than 3.89 years.[18]

4.4.3.2 Late Sample

The results of the triple difference estimation for the 1996-1998 period are presented in column 4 of table 4.6 while the marginal effects associated with the variables of interest are in table 4.8. In the case of the control variables, these results are very similar to the results of the full sample specification. One notable change is the coefficient on the number of children. In the full

[16]The χ^2 statistic for joint significance is 1.64 with a p-value of .4407.

[17]The χ^2 statistic for joint significance of the respective coefficients are 28.19, 22.02 and 11.50 with associated p-values of .0001, .0012 and .0093 respectively.

[18]This value is the level of potential experience at one standard deviation above the mean.

sample estimation, the coefficient is significant and suggests that increasing the number of children decreases the likelihood of staying on a job by 3.2%. In the current specification, the coefficient on this variable is negative but is insignificant and carries a considerably smaller marginal effect (-1.3%). A possible explanation for this difference is the fact that the children in the household are more likely to be of school age and therefore, individuals do not have to take care of the children. One other change is the effect of experience on the likelihood of staying on a job. In the full sample estimation, we found that experience had a negative effect on the likelihood of staying on a job, albeit a very small one. In this estimation, we find that experience has a positive net effect on the likelihood of staying on a job. The effect is also considerably larger in magnitude than the effect we found in the full sample estimation (2.5% vs. -.6%). This result aligns with the expectation that individuals are more likely to 'job shop' at low levels of experience and are more stable as they gain experience. Similar to the result from the full sample estimation, we find that men with low promotion expectations are 3.5% *more* likely to stay on a job than men with high promotion expectations all else equal. This result supports the notion that for men, there is negative selection into long tenure.

We find that women with low promotion expectations are 6.8% less likely than women with high promotion expectations to stay on a job. In each of the previous estimations, we found that women are more likely to stay on jobs all else equal. This estimation yields a slightly different result. At the mean level of potential experience (17 years), women with high promotion expectations are almost 10% more likely than men with high promotion expectations to stay on a job all else equal.[19] However, women with low pro-

[19]The χ^2 statistic for joint significance of the coefficient on the female indicator variable

motion expectations are 1% *less* likely than their male counterparts to stay on a job all else equal.[20] This result supports our hypothesis that as women gain experience in the labor market (and successfully signal attachment) they will behave no differently than men. The fact that women with low promotion expectations are less likely than their male counterparts to stay on their job may reflect the fact that women's careers are delayed by the need to signal attachment to the labor force.

We find that women with low promotion expectations and potential experience that is one standard deviation below the mean level (13.93 years) are 2.6% more likely to stay on jobs than their male counterparts all else equal. We also find that women with a potential experience level that is one standard deviation above the mean level (20.7 years) and low promotion expectations are 13% more likely to remain on a job than their male counterparts. It appears that the gender difference in the likelihood of staying on a job given low promotion expectations first decreases and then increases. We expect the difference to tend toward zero and perhaps change direction as women 'catch up' with men. It is possible that the result we find is due to the fact that women may enter the labor force later than men. These women will have high levels of potential experience but still be early in their careers. In an effort to explore this result, we estimate the triple difference using the sample of individuals that appear in both time periods in the following section. This sample comprises individuals who are serious about their careers and therefore, should behave as our signaling model suggests. It also eliminates the possibility

and the interactions with the potential experience variables is 9.48 with a p-value of .0235.

[20] The χ^2 statistic for joint significance of the coefficients on female and the interactions with low and potential experience variables is 29.97 and its associated p-value is .0000.

that our results are driven by women who know they are going to drop out of the labor force and therefore, do not respond to promotion expectations.

4.4.3.3 Individuals in Both Samples

The results of the triple difference estimation are presented in column 6 of table 4.6 while the marginal effects of the variables of interest are presented in table 4.9. The results for the control variables do not differ significantly from the main results presented in table 4.4 with the exception of the coefficient on the education variable. This coefficient is insignificant in the present specification but is significant in each of the other specifications. The marginal effect is also considerably smaller in magnitude than other specifications at just .0025 percentage points. It also appears that experience level has a negative net effect but is again relatively small at -.8% for men with high promotion expectations.

The advantage to running the triple difference with just the sample of individuals who appear in both time periods is that we can eliminate the possibility that our results are driven by women who are not serious about their careers. That is, it is likely that the full sample contains some women who know they are going to leave the labor force and therefore, remain on jobs despite low promotion expectations. The results presented in table 4.6 suggest that our results are not driven by this group of women. Furthermore, the results support our signaling story. As in previous estimations, we find that women are more likely to stay on jobs than men all else equal. Women with high promotion expectations are 18.66% more likely to remain on jobs than their male counterparts all else equal while women with low promotion expectations are 2.5% more likely to remain on jobs than their male counterparts all else equal.[21] The large difference in the likelihood of staying on a job across gender for individuals with high promotion expectations likely reflects a difference in the cost of finding a similar job. We also expect women to behave more like men after they have successfully signalled attachment to the labor force. If we consider individuals with an experience level that is one standard deviation below the mean, women with low promotion expectations are 21% more likely to remain on jobs than men with low promotion expectations all else equal. For individuals with an experience level that is one standard deviation above the mean level, women with low promotion expectations are only 7.5% more likely than men to remain on a job all else equal. This result supports our explanation. It suggests that women become more responsive to promotion expectations after they have signalled labor force attachment. Given that our sample consists of only individuals that are attached to the labor force, this result is strong evidence for our signaling explanation.

4.5 Conclusion

Labor economists have explained the male-female wage differential as a consequence of women's historic lack of attachment to the labor force. However, with a rapid rise in the female labor force participation rate over the last few decades, the career profiles of recent cohorts of women workers has undergone significant changes. Studies indicate that women are now more likely to stay on their jobs compared to men of similar characteristics. In this paper, we examine how job turnover relates to concerns regarding a career path. We

[21]The χ^2 statistic for joint significance of the coefficients on female and the interactions with potential experience variables is 12.07 and its associated p-value is .0071. The χ^2 statistic for joint significance of the coefficients on female and the interactions with the low and potential experience variables is 15.74 and its associated p-value is .0076.

expect to see job turnover when promotion opportunities on the job are low. Accordingly, we study the relationship between individuals' expectations of promotion on their jobs and their turnover behavior. We examine how this relationship varies between men and women and with experience level. It is our hypothesis that early on in their careers, women who are strongly committed to a career are more likely to stay on their jobs, regardless of promotion opportunities, in a bid to signal their commitment to current and potential employers. However, once women have acquired adequate labor market experience and their commitment to the labor force is no longer in question, we predict that their turnover behavior will be more responsive to career opportunities and will be similar to that of men.

We use longitudinal data for men and women from the NLSY to test our predictions. In order to exploit the longitudinal nature of the data, we use a random-effects probit model to estimate the probability that an individual will stay on a job. We estimate three models: a basic model that includes indicator variables for female and low promotion expectations; a model that includes an interaction between female and low promotion expectations; and a model that includes interactions between female, low promotion expectations, and potential experience. The results from the basic specification suggest that as expected, individuals with low expectations of promotion are less likely to stay on their jobs than those with high expectations of promotion. This result is repeated in the model that allows for differences in the effect of low promotion expectations across gender. In this model, we also find that the tendency of women to be more likely than men to stay on a job does not vary with promotion expectations. In the third model, we find a different result. We find that the difference across gender in the likelihood of staying on a job varies by potential experience. By evaluating the marginal effect of low promotion expectations at different levels of potential experience we find support for our hypothesis that early in their career, women are more likely to stay on a job despite having low promotion expectations since they need to signal their attachment to the labor force. Later in the career, women should not differ from men in terms of their response to promotion expectations. Our results suggest that while women are still more likely to remain on their job in the face of low promotion expectations later in the career, the difference is smaller than the difference early in the career.

We repeat the third model for three sub-samples: a 1979-82 sample, a 1996-98 sample and a sample of individuals that appear in both time periods. The 1979-82 sample has more detailed information on promotion expectations. This additional information strengthens our model but does not qualitatively change the results. Similarly, the results from the 1996-98 sample do not differ significantly from those of the pooled sample. By estimating the model using the final sub-sample, we eliminate the possibility that our results are driven by women who are not serious about their careers and therefore, unresponsive to promotion expectations. These results further lend credence to our signaling story that women at low levels of experience are more likely to stay on jobs despite low promotion expectations than men of the same characteristics.

Table 4.1: Self-Reported Promotion Expectations at Job By Mobility: 1979-1983

Women				
	Job Stays		No Stays	
Response	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Not True at All	.1324	.339	.2484	.4322
Not True	.2295	.4206	.262	.4398
True	.3411	.4742	.2868	.4524
Very True	.297	.4571	.2027	.4021
Observations	**1586**		**1771**	

Men				
	Job Stays		No Stays	
Response	*Mean*	*Std. Dev.*	*Mean*	*Std.Dev.*
Not True at All	.0874	.2826	.1639	.3703
Not True	.1768	.3816	.2512	.4338
True	.3654	.4817	.3288	.4699
Very True	.3704	.4831	.256	.4365
Observations	**1601**		**2074**	

Table 4.2: Self-Reported Promotion Expectations at Job By Mobility: 1996-1998

	Women			
	Job Stays		No Stays	
Response	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Low Expectations	.4461	.4972	.4564	.4983
Observations	**2746**		**1514**	

	Men			
	Job Stays		No Stays	
Response	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Low Expectations	.3864	.4870	.4058	.4912
Observations	**3305**		**1863**	

Note: The survey question was "Do you believe it is possible for you to get a promotion with this employer in the next two years?". If the respondent replied "No", this was coded as low chances of promotion.

Table 4.3: Descriptive Statistics - Entire Sample

Variable	Total		Women		Men	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Remained on job from t to t+1	.5617	.4962	.5692	.4952	.5553	.4970
Age	28.7269	8.1292	28.6096	8.1329	28.8277	8.1252
AFQT	44.4645	28.6104	43.8316	27.0915	45.0091	29.8462
Education	12.7589	2.1648	12.9290	2.0711	12.6126	2.2320
Potential Experience	10.9685	7.9043	10.6816	7.9769	11.2154	7.8334
Low Expectations of Promotion	.4077	.4914	.4453	.4970	.3754	.4843
Log Hourly Wage	2.0009	.7648	1.8858	.7188	2.0999	.7890
Non-White	.4284	.4949	.4352	.4958	.4226	.4940
In Metropolitan Statistical Area	.7994	.4004	.8066	.3950	.7932	.4050
Number of Children	.8238	1.1720	.9137	1.1803	.7464	1.1593
Stayed Single	.4338	.4956	.4410	.4965	.4276	.4948
Stayed Married	.3745	.4840	.3595	.4799	.3873	.4872
Single-Married	.0549	.2278	.0579	.2336	.0523	.2227
Married-Single	.0218	.1460	.0252	.1567	.0188	.1360
Observations	**16394**		**7582**		**8812**	

Table 4.4: Random Effects Probit Estimation Staying on a Job, Double and Triple Difference

	Coefficient	$\phi(\overline{X}\widehat{\beta}) * \widehat{\beta}_i$	Coefficient	$\phi(\overline{X}\widehat{\beta}) * \widehat{\beta}_i$	Coefficient	$\phi(\overline{X}\widehat{\beta}) * \widehat{\beta}_i$
In Metropolitan Statistical Area[a]	-.1251*** (.0309)	-.0499	-.1251*** (.0309)	-.0499	-.1223*** (.0309)	-.0485
Number of Children	-.043*** (.0132)	-.0154	-.043*** (.0132)	-.0154	-.0429*** (.0132)	-.0153
Education	.0206*** (.0079)	.0074	.0206*** (.0079)	.0074	.0213*** (.0079)	.0076
AFQT	.0000 (.0006)	.0000	.0000 (.0006)	.0000	.0001 (.0006)	.0001
Log Hourly Wage	.4119*** (.0256)	.1472	.4119*** (.0256)	.1472	.4104*** (.0256)	.1459
Potential Experience	-.0219*** (.0081)	-.0000	-.0218*** (.0081)	-.0000	-.0562*** (.0124)	-.0031
(Potential Experience)^2	.001*** (.0003)		.001*** (.0003)		.0022*** (.0005)	
Low Promotion Expectations[a]	-.2123*** (.0239)	-.0843	-.211*** (.0328)	-.0838	-.6628*** (.074)	
Female	.1548*** (.0261)	.0613	.1559*** (.0325)	.0618	.1138* (.0647)	
(Low Chances of Promotion)*Female	.		-.0026 (.047)	-.0231	.1825* (.1021)	
(Pot. Experience)*Female	.		.		.0162 (.017)	
(Pot. Experience)^2*Female	.		.		-.0007 (.0008)	
(Pot. Experience)*Low	.		.		.0988*** (.0181)	
(Pot. Experience)^2*Low	.		.		-.0034*** (.0008)	
(Pot. Experience)*Low*Female	.		.		-.0639** (.0262)	
(Pot. Experience)^2*Low*Female	.		.		.0029** (.0012)	
Stayed Married	.4807*** (.0321)	.1833	.4808*** (.0321)	.1833	.4821*** (.0321)	.1872
Single-Married	.312*** (.0505)	.1219	.312*** (.0505)	.1219	.3024*** (.0506)	.1196
Married-Single	.1831** (.0796)	.0724	.1831** (.0796)	.0724	.1821** (.0794)	.0725
Non-White	-.0073 (.0295)	-.0029	-.0073 (.0295)	-.0030	.0035 (.0295)	.0014
Constant	-.9031*** (.0817)		-.9037*** (.0823)		-.7655*** (.0873)	
Predicted Probability at $\overline{X}$	.5118		.5116		.479	
Observations	16394		16394		16394	
ρ	.2211		.2211		.2183	
Log-Likelihood	-10365.49		-10365.49		-10326.6	
χ^2 statistic	1298.822		1298.843		1353.493	
Groups	7903		7903		7903	

Standard errors are in the parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. For the continuous variables, the marginal effect reported is the mean of the marginal effects in the sample. In the case of dummy variables, the marginal effect is calculated as $\Phi(\overline{X}_{d=1}\widehat{\beta}) - \Phi(\overline{X}_{d=0}\widehat{\beta})$ where $d = 1$ and $d = 0$ represent the dummy variable set to 1 and 0, respectively.[a]Individuals are classified as having low expectations if they thought a promotion was not likely in survey years 1979-1982 or they thought a promotion was not possible in the next 2 years in survey years 1996 or 1998.

Table 4.5: Triple Difference Marginal Effects

Base Probabilities

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Men - Low	.403	.47942	.4927
Men - High	.5586	.47898	.5092
Women - Low	.4699	.4916	.556
Women - High	.6193	.5579	.5659

Low vs. High Promotion Expectations

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Women	-.1493	-.0662	-.0098
Men	-.1555	.0004	-.0164

Women vs. Men

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Low	.0669	.0122	.0633
High	.0607	.0789	.0567

The marginal effects are calculated as $\Phi(\overline{X}_{d=1}\widehat{\beta}) - \Phi(\overline{X}_{d=0}\widehat{\beta})$ where $d = 1$ and $d = 0$ represent the set of dummy variables set to 1 and 0, respectively.

Table 4.6: Random Effects Probit Estimation Staying on a Job by Time Period

	79-83		96-98		Dual Sample[a]	
	Coefficient	$\phi(\overline{X}\widehat{\beta}) * \widehat{\beta}_i$	Coefficient	$\phi(\overline{X}\widehat{\beta}) * \widehat{\beta}_i$	Coefficient	$\phi(\overline{X}\widehat{\beta}) * \widehat{\beta}_i$
In Metropolitan Statistical Area	-.1168***	-.0465	-.1548***	-.0608	-.0978**	-.0239
	(.0447)		(.0505)		(.0421)	
Number of Children	-.3232***	-.1160	-.0240	-.0080	-.0446**	-.0158
	(.0658)		(.0164)		(.0183)	
Education	.0641***	.0230	.0443***	.0148	.0066	.0023
	(.0131)		(.0139)		(.0106)	
AFQT	.0000	.0000	-.0005	-.0002	.0003	.0001
	(.0009)		(.001)		(.0008)	
Log Hourly Wage	.5229***	.1876	.4591***	.1529	.449***	.1590
	(.0497)		(.0369)		(.0356)	
Potential Experience	-.0404	.0066	-.0169	.0153	-.0575***	-.0044
	(.079)		(.0647)		(.0165)	
(Potential Experience)^2	.0125		.0018		.0023***	
	(.0095)		(.0019)		(.0007)	
Low Chances of Promotion at Job	-.6684***		-2.547***		-.6184***	
	(.1764)		(.857)		(.0896)	
Moderate Chances of Promotion at Job	-.1352		.		.	
	(.1733)					
Female	-.2184		.1246		.1067	
	(.1963)		(.8411)		(.0828)	
(Low Chances of Promotion)*Female	.1994		3.1252**		.2143	
	(.2508)		(1.2796)		(.1317)	
(Moderate Chances of Promotion)*Female	.2220		.		.	
	(.2579)					
(Pot. Experience)*Female	.3004**		.0118		.0277	
	(.1334)		(.0981)		(.0247)	
(Pot. Experience)^2*Female	-.0402**		-.0005		-.0014	
	(.0188)		(.0028)		(.0012)	
(Pot. Experience)*Low	.0847		.3222***		.0912***	
	(.1063)		(.0992)		(.0239)	
(Pot. Experience)^2*Low	-.0089		-.0098***		-.0031***	
	(.0129)		(.0028)		(.0011)	
(Pot. Experience)*Moderate	.0011		.		.	
	(.1025)					
(Pot. Experience)^2*Moderate	-.0043		.		.	
	(.0123)					
(Pot. Experience)*Low*Female	-.1715		-.4153***		-.0759**	
	(.1679)		(.1487)		(.0374)	
(Pot. Experience)^2*Low*Female	.0322		.013***		.0035**	
	(.0232)		(.0043)		(.0017)	
(Pot. Experience)*Moderate*Female	-.2084		.		.	
	(.1745)					
(Pot. Experience)^2*Moderate*Female	.0365		.		.	
	(.0245)					
Stayed Married	.6652***	.2483	.5211***	.1811	.4527***	.1759
	(.0703)		(.0456)		(.0441)	
Single-Married	.2826***	.1115	.3581***	.0703	.2747***	.1087
	(.0688)		(.0868)		(.0686)	
Married-Single	.1183	.0472	.1872**	.1298	.2082*	.0827
	(.2722)		(.0946)		(.1101)	
Non-White	.0411	.0164	-.0485	-.0189	.0216	.0086
	(.0436)		(.0452)		(.0384)	
Const.	-1.4674***		-1.6599***		-.6445***	
	(.1945)		(.6191)		(.1149)	
Predicted Probability at $\overline{X}$	.4934		.5983		.4859	
Observations	6966		9428		8695	
ρ	.2187		.4121		.1544	
Log-Likelihood	-4454.005		-5756.515		-5431.279	
χ^2 statistic	462.9645		413.2975		832.5092	
Groups	4902		5845		2844	

Standard errors are in the parentheses. *,**,*** represent significance at the 90%, 95%, and 99% levels, respectively. For the continuous variables, the marginal effect reported is the mean of the marginal effects in the sample. In the case of dummy variables, the marginal effect is calculated as $\Phi(\overline{X}_{d=1}\widehat{\beta}) - \Phi(\overline{X}_{d=0}\widehat{\beta})$ where $d = 1$ and $d = 0$ represent the dummy variable set to 1 and 0, respectively.[a] Dual Sample refers to individuals that appear in both time periods.

Table 4.7: Triple Difference Marginal Effects 1979-1982

Base Probabilities			
Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Men - Low	.2674	.2962	.3324
Men - Moderate	.4395	.431	.4375
Men - High	.494	.4934	.5165
Women - Low	.2944	.3836	.4706
Women - Moderate	.4694	.51	.5586
Women - High	.4935	.5983	.6487

Low vs. High Promotion Expectations			
Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Women	-.1991	-.2147	-.1781
Men	-.2266	-.1972	-.1841

Low vs. Moderate Promotion Expectations			
Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Women	-.175	-.1264	-.088
Men	-.1721	-.1348	-.1051

Moderate vs. High Promotion Expectations			
Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Women	-.0241	-.0883	-.0901
Men	-.0545	-.0624	-.079

Women vs. Men			
Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Low	.027	.0874	.1382
Moderate	.0299	.079	.1211
High	-.0005	.1049	.1322

The marginal effects are calculated as $\Phi(\overline{X}_{d=1}\widehat{\beta})-\Phi(\overline{X}_{d=0}\widehat{\beta})$ where $d=1$ and $d=0$ represent the set of dummy variables set to 1 and 0, respectively.

Table 4.8: Triple Difference Marginal Effects 1996-1998

Base Probabilities

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Men - Low	.551	.6193	.6147
Men - High	.5452	.5983	.6651
Women - Low	.5652	.613	.6948
Women - High	.6149	.658	.7092

Low vs. High Promotion Expectations

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Women	-.05	-.045	-.0944
Men	.0058	.021	-.0503

Women vs. Men

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Low	.0142	-.0062	.0801
High	.0696	.0597	.0441

The marginal effects are calculated as $\Phi(\overline{X}_{d=1}\widehat{\beta}) - \Phi(\overline{X}_{d=0}\widehat{\beta})$ where $d = 1$ and $d = 0$ represent the set of dummy variables set to 1 and 0, respectively.

Table 4.9: Triple Difference Marginal Effects
Individuals in Both Samples

Base Probabilities

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Men - Low	.411	.4783	.4973
Men - High	.5772	.4859	.51
Women - Low	.4969	.4903	.5344
Women - High	.6401	.5766	.5483

Low vs. High Promotion Expectations

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Women	-.1432	-.0863	-.0139
Men	-.1662	-.0076	-.0127

Women vs. Men

Experience Level	*-1 Std. Dev.*	*Mean*	*+1 Std. Dev.*
Low	.0859	.012	.0371
High	.0629	.0907	.0383

The marginal effects are calculated as $\Phi(\overline{X}_{d=1}\widehat{\beta}) - \Phi(\overline{X}_{d=0}\widehat{\beta})$ where $d = 1$ and $d = 0$ represent the set of dummy variables set to 1 and 0, respectively.

Chapter 5

Conclusions and Extensions

In this dissertation, I examined how available information affects both turnover and promotion. In chapter 2, I found that, in the case of Major League Baseball managers, firms use multiple measures of performance that plausibly contain information on manager ability in both termination and rehire decisions. I also found that firms use information that is unlikely to reflect managerial ability in the termination decision. This result raises questions about whether baseball teams make rational termination decisions. In chapters 3 and 4, I found that the turnover and promotion decisions differs considerably by gender. I found that women are less likely to be promoted than men all else equal yet are more likely to remain on jobs. It is likely that the difference in the likelihood reflects the fact that firms are unwilling to extend offers of promotion to women since they perceive them to be more likely than men to leave the labor force. As a result, women must signal their attachment to the labor force. The results presented in chapter 3 supports this notion. In chapter 4, we expanded upon this result by testing the determinants of staying on a job and how the determinants differ by gender. We found that women are more likely than men to stay on a jobs with low promotion expectations and hypothesize that this result reflects the need for women to signal labor force attachment.

The research presented in chapter 2 is for a specific labor market relationship. This relationship carries aspects that are unlikely to be found in other relationships. However, the nature of the job of Major League Baseball manager shares many things in common with CEOs and other high-level and high-profile managers. As such, the analysis provides valuable information regarding the turnover of the same. In each of the jobs the performance of the manager is difficult to determine since observable output is highly correlated with subordinate performance. Understanding firms actions under this condition is valuable in the study of the market for high-level managers. The research also suggests that the contracts for high-level managers are more complicated than standard contract theory allows for. Future research would consider the role of 'public perception' in firms' actions. Furthermore, a useful extension would be to consider whether high-level managers are compensated for the extra risk they assume by holding 'high-profile' jobs.

The research presented in chapters 3 and 4 suggests that there are considerable differences in the market for promotions and in turnover across gender. Chapter 3 suggests that, for women, the unobservables in the promotion offer equation are uncorrelated with the unobservables in the stay equation while for men, the unobservables are correlated. The implication is that men who stay on jobs are more likely to be promoted while for women the decisions are independent. The results also suggest that men and women may have different career expectations. That is, men may only remain on jobs when they are likely to receive a promotion while women remain for other reasons. We explored this explanation in chapter 4 and found evidence that women stay on jobs in order to signal attachment to the labor force. If this signalling model is correct, it partly explains any persistent gender wage gap since women need to remain in low paying jobs in order to signal their attachment to the labor force while men can leave these jobs. There are other testable implications of this model. For example, if the model is correct women should be promoted in large steps. This promotion pattern would reflect the fact that employers are unwilling to promote women until they have successfully signalled attachment. However, once women are promoted they should 'catch up' to men. The model is also consistent with delayed promotions for women. The present research supports this notion but more work is needed.

Appendices

Appendix A

Hitter Performance Measure

The standard for hitting performance in baseball has typically been batting average. This metric is simply the number of hits divided by the number of at-bats. However, recent developments in sabermetrics have shown that batting average is a misleading statistic since it does not measure a player's effectiveness at acquiring bases, which is the prerequisite for scoring runs.[1] Sabermetricians suggest the use of on-base percentage (OBP) plus slugging percentage (SLG) where

$$OBP = \frac{H + BB + HBP}{AB + BB + HBP + SF} \tag{A.1}$$

where H is the number of hits, BB is the number of bases-on-balls, HBP is the number of hit-by-pitch, AB is the number of at-bats, and SF is the number of sacrifice flies.

$$SLG = \frac{1B + 2 * 2B + 3 * 3B + 4 * HR}{AB} = \frac{TB}{AB} \tag{A.2}$$

where 1B is the number of singles, 2B is the number of doubles, 3B is the number of triples, HR is the number of home runs, and TB is the number of total bases.

OBP is the likelihood that a player gets on base while SLG is the number of bases a player acquires per at-bat. The addition of these two metrics makes a useful measure of player performance but it neglects to account for stolen bases and arbitrarily assigns equal weight to a point of OBP and a point

[1]Sabermetrics is the study of baseball using statistics.

of SLG. Clearly, when a player steals a base, he achieves a base for his team. A better measure of player performance accounts for these acquired bases. Furthermore, a better measure does not weight SLG and OBP equally. The measure I presented in section 2.2.1.2 uses the components of OBP and SLG while accounting for stolen bases and caught stealing.

Appendix B

Pitcher Performance Measure

The two standard pitching statistics are games won and earned run average (ERA), which is defined as

$$ERA = \frac{9 * ER}{IP} \tag{B.1}$$

and is simply the number of earned runs allowed (ER) per nine innings pitched (IP), the typical length of a baseball game.[1] The difficulty with these two metrics is that each is largely dependent upon team performance. The wins credited to a pitcher depend upon the number of runs his team scores as well as the number of runs the pitcher allows to the opposition. It is possible that a pitcher can yield no runs yet if his team scores no runs he will not get credit for a win. Earned run average is an improvement because it excludes runs scored by fault of the defense but it is still correlated with team performance and managerial decisions.[2] Pitchers yield bases to hitters who turn the bases into runs. The metric I presented in section 2.2.1.2 relates the bases a pitcher allows to the opportunity hitters have to achieve bases at the expense of the pitcher.

[1] Another standard that is often used is the ratio of strikeouts to base-on-balls. Prisinzano (2000) showed that this metric is misleading because this ratio does not necessarily relate to better outcomes for the team.

[2] A pitcher is often responsible for runners on base after he has been removed from the game. If the new pitcher pitches poorly the first pitcher is charged an earned run. In this situation, the pitcher is subject to both the performance of the new pitcher and managerial decision to change pitchers.

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