

ABSTRACT

Title of dissertation: A DYNAMIC APPROACH OF TURNOVER
PROCEDURE: IT'S ABOUT TIME AND
CHANGE

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The most common theme of previous turnover research is the attempt to predict turnover. However, the majority of previous turnover literature has ignored the *dynamic* or *unfolding* nature of turnover decisions. The present study re-evaluates the relationship between antecedents and turnover from a *longitudinal* approach. The longitudinal turnover approach incorporates change in the initial status and the slopes of the important turnover predictors over time as well as change in the nature or strength of the relationships between those variables and turnover risks over time. Two types of statistical analyses, survival analysis and growth modeling, are applied to assess questions that arise from the longitudinal turnover perspective, such as questions surrounding whether and when turnover occurs or questions surrounding the systematic changes of the relationship between predictors and turnover over time. The results of survival analyses indicate that psychological indicators, including employees' general attitudes towards the organization, their job satisfaction, and their intention to quit, have strong association with turnover risks over time. Management predictors, such as employees' compensation levels and their promotion history

also have strong relations with turnover hazards over time. The results of growth modeling show that not only do initial levels of predictors have strong relationships with turnover risk, but so do their changing slopes. Overall, survival analyses and growth modeling analyses provide an opportunity for researchers to have a better understanding of the relations between predictors and turnover, longitudinally.

**A DYNAMIC APPROACH OF TURNOVER PROCEDURE: IT'S ABOUT
TIME AND CHANGE**

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements of the degree of
Doctor of Philosophy
2007

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**A Dynamic Approach of Turnover Process:
It's About Time and Change**

Employee turnover has been a critical issue lately. For example, Wilson (2000) reported that 52% of U.S. companies have experienced increasing turnover rates for the past decade. Both researchers and practitioners are aware of the potential negative consequences of turnover. For example, turnover can result in increased economic costs, productivity losses, impaired service quality, lost business opportunities, and demoralization of the employees that stay (Hom and Griffeth, 1995; Mobley, 1982).

With regard to turnover's economic costs, Hom (1992) identified three classifications of costs: separation costs, replacement costs, and training costs. Separation costs refer to the costs accrued as a result of employees leaving the organization. These costs include expenses due to conducting exit interviews, finding temporary employees, and lost client revenue. Replacement costs refer to the costs associated with recruiting and selecting new employees. Training costs refer to the costs associated with socializing and training new employees. Overall, these three categories of costs can add up to a sizable cost to organizations. Indeed, a recent national-wide survey found that 45% of medium-to-large companies report turnover costs of more than \$10,000 per leaver (William M. Mercer, 1998, "Survey Confirms High Cost of Turnover"). Given the costs associated with turnover, it is not surprising that turnover is a lively and enduring research topic. Indeed, over one thousand studies have been published on this topic in the last century (Steers and Mowday, 1981).

Beyond financial costs, studies have found that turnover affects the organization's productivity by affecting the performance of three sources: the people who actually leave, the productivity of the new replacements, and the productivity of the remaining employees. During the quitting process, the people that eventually leave the organization start to psychologically as well as behaviorally withdraw from work. This is reflected by reduction in production even before they physically leave the organization (Rosse, 1988). This reduction in productivity could be attributed to increased absences from work, increased tardiness, or increased idleness at work (Rhodes and Steers, 1990). The reduced productivity of new replacements is due to their inexperience and the extra effort that they have to exert to become familiar with their tasks as well as their work context. The reduction in productivity caused by new replacements is comparable to the reduction in work caused by the actual people that leave the organization (Price, 1977). While these first two sources are probably obvious, what is surprising is that the employees who remain with the organization also tend to show productivity losses as well. This may be due to the need to rearrange their own work schedule to cover the workload of the person leaving or to cover the productivity lag of the new replacement (Ulrick, Halbrosk, Meder, Stuchlik, & Thorpe, 1991). It could also be due to the undermining of the social integration of the organization due to turnover. When turnover occurs, the people that stay behind may re-evaluate their rationale for staying with the organization and it could affect their attitudes (e.g., job satisfaction, organizational commitment)

about work and the organization (Mueller and Price, 1989). Thus, turnover not only affects the people that leave but also the people that stay behind.

Beyond economic costs and productivity losses, turnover can also result in the loss of future business opportunities. Mobley (1982) suggested that loss of business opportunities will occur if key players in an organization are leaving. Indeed, Mandel and Farrell (1992) reported that the turnover of key personnel in an organization has negative implications for the long-term survival of the organization in competitive markets. In summary, the potential economic costs, productivity losses, missed business opportunities and even threat to the survivability of the organization associated with turnover makes it clear why employee turnover is such an important topic for both practitioners and researchers.

Given the attention given to turnover and its negative consequences, it is not surprising that, when one reviews the literature, the most common theme that emerges is the attempt to predict turnover. There are two major approaches to the investigation of turnover predictors (Schwab, 1991). The first approach is to discover the *internal* or *psychological* predictors of turnover, such as employees' attitudes, values, and other psychological or cognitive attributes. The second approach is to seek out the *external* or *environmental* predictors of turnover, including organizational environmental indicators and societal economical indicators.

With regard to the first approach, researchers have examined the psychological and cognitive bases of the turnover process. Empirical research has

demonstrated the utility of this approach by establishing several links between turnover and psychological antecedents such as job satisfaction and organizational commitment (Hom & Kinicki, 2001). While the connections between these psychological antecedents and turnover have been established, the explanation for why or how these constructs combine to result in turnover has not. Indeed, multiple conceptual models have been developed to explicate the cognitive and affective paths to the turnover decision (Hulin, Roznowski, & Hachiya, 1985; Mobley, Griffeth, Hand, & Meglino, 1979; Muchinsky & Morrow, 1980).

With regard to the second or external approach, researchers have examined how employees' turnover decisions are influenced by the broader organizations' policies and practices as well as the general economical climate (Bycio, Hackett, & Alvares, 1990; Hom & Griffeth, 1995; Steel & Griffeth, 1989). For example, organizational practices, policies, and procedures such as the type of performance appraisal used, the promotion opportunities available, and supervision styles, have all been found to have affect employee turnover decisions (Gomez-Meija & Balkin, 1992; Hom & Griffeth, 1995; Milkovich & Newman, 1993). Further, economical conditions, such as the unemployment rate and consumer confidence, have also been found to affect employee turnover decisions (Carsten & Spector, 1987; Gerhart, 1987; Hom, Caranikis-Walker, Prussia, & Griffeth, 1992; Youngblood, Baysinger, & Mobley, 1985).

Both approaches have provided useful information regarding the prediction of turnover. However, I believe that further gain in our understanding of turnover is unlikely if we keep applying these approaches in the typical static

manner as we have done in the past. In other words, what we have ignored in the majority of the past turnover literature is the *dynamic* or unfolding nature of turnover decisions. In the present study, I re-evaluate the relationship between antecedents and turnover from a dynamic approach. When one adopts a dynamic perspective, *change* and *time* are essential features that needs to incorporated and explained. The dynamic turnover perspective includes change in the initial status and the changing slopes of the important constructs over time as well as change in the nature or strength of the relationships among those variables over time. Unfortunately, despite the discussion of the benefits of the dynamic perspective in other areas of psychology (Hanges, Lord, Godfrey, & Raver, 2002; Vallacher & Nowak, 1994) and business literatures (e.g., Marion, 1999), very little research has applied a dynamic model to the turnover process.

Despite the lack of empirical data demonstrating the dynamic turnover procedure, there are hints of its dynamic nature in the conceptual models that have been proposed over the years. Many of the psychological and cognitive turnover models, including the turnover process model (Mobley, 1977), the progression of withdrawal model (Hulin, 1991), the unfolding model (Lee & Mitchell, 1994), and the integrative model (Hom & Griffeth, 1995), have described the turnover decision process as a series of operations, playing out over time until the turnover decision is reached. For example, Mobley's Turnover Process Model (1977) involves ten specific steps that employees take as they evolve from a "negative evaluation of present job" attitude to a "job dissatisfaction" attitude to an actual "employee turnover" decision. Further, in Lee and Mitchell's Unfolding Model

(1994), information process theory is applied to improve our understanding of the turnover decision process. Lee and Mitchell specify four paths by which the decisions to quit unfolds.

These turnover models which have the decision to quit evolving over time are consistent with the more classic theories of turnover. For example, turnover has been described as a decision that was developed as a result of an exchange process between employees' psychological expectation and external rewards (Porter & Steers. 1973). Porter and Steers (1973) argued that individuals have distinctive set of psychological expectations about their jobs and that these expectations can be categorized into several dimensions, such as compensation, promotions, or supervisory relations. If an organization fails to meet an individual's expectations, dissatisfaction will result. As the scope of the unmet expectations increase to multiple expectation categories, and the probability of withdrawal increases. This classic framework implicitly incorporates time and a dynamic turnover perspective. Employees need time to interact with the organization to discover areas of unmet expectations. Further, employees' expectations and organizational contexts are not static. Thus, the expectations that an employee has when they start working at an organization are probably not the same after working 20 years with that organization. Further, the kinds of benefits provided or policies adopted by organizations also evolve over time. Thus, even these classic models of turnover are consistent with the dynamic unfolding perspective.

While there is no direct empirical evidence regarding the dynamic nature of turnover, a substantial body of research exists that indicates that many of the predictors of turnover are dynamic (Bentein, Vandenberg, Vandenberghe, & Stinglhamber, 2005; Deadrick, Bennett, & Russell, 1997; Ployhart & Hakel, 1998). For example, organizational commitment has been found to be a particularly powerful predictor of turnover (Brockner, Tyler, & Cooper-Schneider, 1992; Mowday, Porter, & Steers, 1982). Organizational commitment has been conceptualized as a function of the way that employee interpret and make sense of their work context (Vandenberg & Self, 1993). Further, organizational commitment can be strengthened or weakened depending on the perceived benefits or losses accrued during the exchange between employee and the organization (Meyer & Allen, 1990; Wanous, 1992). Thus, organizational commitment varies over time and its fluctuations depend upon the repeated and complex interactions among employees and the organization.

Another variable that has shown dynamic properties is job performance. Indeed, questions about the dynamic nature of performance have a long history within the I/O Psychology literature (Barrett, Caldwell, & Alexander, 1985; Deadrick, Bennett, & Russell, 1997; Hanges, Schneider, & Niles, 1990; Ployhart & Hakel, 1998). Overall, the conclusion from this research is that while performance shows some stability, a large portion of this variable is dynamic (Deadrick & Madigan, 1990; Henry & Hulin, 1987; Hofmann, Jacobs, & Baratta, 1993; Hofmann, Jacobs, & Gerras, 1992; Hulin et al., 1985).

In summary, despite the fact that the variables shown to lead to turnover is dynamic, and despite the fact that the turnover models implicitly accept a dynamic process underlying turnover decision processes, the studies on turnover have not incorporated the dynamic nature of turnover process into their designs. Indeed, turnover and its predictors are treated as static constructs in these studies.

More specifically, the most widely-used research design in turnover studies is the predictive research design. In this design, researchers collect data on the predictors, such as employees' psychological indicators or organizational environmental variables, at the first measurement time (time 1). After some elapsed time, turnover data is collected (time 2). Time 1 indicators are then correlated with time 2 turnover decisions. This design has increasingly drawn criticism because it neglects the changing effects of turnover process over time. That is, based on this design, researchers would know whether the relationship between predictors and turnover changes over time. The nature of this type of studies is still one-time relationship. However, the length of time between the measurement of the predictors and turnover decisions has been shown to change the relationship among these variables (Harrison and Hulin, 1989). Thus, it appears that the estimated relationship between turnover and its predictors can be substantially affected by studies based on this type of time1 (predictors) and time2 (turnovers) research design.

Another widely used research design used in the turnover literature is the repeated measures design in which the predictors of turnover are repeatedly measured over some arbitrarily chosen time period (Kammeyer-Mueller,

Wanberg, Glomb, & Ahlburg, 2005; Morita, Lee, & Mowday, 1993; Trevor, 2001). While this design can be used to assess dynamic changes, researchers do not analyze their data to appropriately assess the dynamic nature of the predictors. Specifically, they take the mean of the multiple predictor measurements and correlate that mean with the turnover decision. In other words, the repeated predictor measurements are simply used to obtain a reliable estimate of each predictor. This analytic strategy only makes sense if predictors are static/stable over time. Specifically, as argued by Chan and Schmitt (2000), intraindividual change cannot be adequately conceptualized and empirically examined with this methodology. Further, Mobley (1982) states that:

“if we are to understand the process of turnover more fully, we need repeated measures of multiple antecedents over time and statistical analyses which include the temporal dimension” (pp. 135-136).”

The present study will meet this call by examining the turnover decision process dynamically. Specifically, this study will examine the dynamic nature of turnover by (a) taking multiple measures of predictors over time and then (b) analyze the data using a relatively new statistical technique, latent growth modeling (LGM), to access the intraindividual variability of the predictors over time.

In summary, the purpose of the present study is to examine the relationship between turnover and its predictors from a dynamic approach. This dissertation is structured in the following fashion. In the first section, I will integrate the theories in the turnover literature and review previous empirical

evidence to demonstrate the dynamic and longitudinal approach of turnover procedure. Then, I will introduce two recent additions to the dynamic statistical tools: survival analysis and growth modeling. In the second section, I will discuss the longitudinal relationship between two groups of antecedents and turnover risks over time, with six groups of hypotheses. Then, I will address the participants, procedure, and analyses in the method section, followed by the results section. Finally, the contribution and limitation of this dissertation, as well as future directions, will be discussed in the last section.

Dynamic Approach of Turnover Procedure

As discussed previously, the *dynamic* nature of the turnover decision process has two essential aspects: time and change. With regard to the time, the dynamic nature of turnover implies that the turnover decision process unfolds over time. Thus, repeated measurement of the predictors is needed to test for this unfolding nature of turnover. With regard to the change aspect of turnover, the dynamic nature of turnover implies that the variables affecting turnover fluctuate or vibrate over time. These fluctuations are a product of random and systematic variances. The systematic portions of this fluctuation are due to short term and long term trends that reflect movement from or toward equilibrium states in the determinants of turnover. I hypothesize that these trends might be helpful for predicting a person's eventual turnover decision. With the dynamic approach, both the change and time aspects are combined to help understand and predict turnover. The following sections discuss the theoretical and empirical evidence of the dynamic approach of turnover procedure.

Theoretical Backgrounds: It's About Time and Change

“Time is money” is a common saying. Indeed, issues of time are central to modern society, especially to modern management, as well as modern science. In the common vernacular, time refers to standard or clock time. It is rooted in a traditional view of how time is represented in science (Clark, 1985; Gurvitch, 1964): Time flows evenly and continuously. It also can be quantified in an ordinal scale and it can be clustered into meaningful segments (e.g., seconds, minutes, months). By far, social sciences have traditionally conceptualized time in this fashion (Clark, 1985).

The organizational literature is increasingly paying attention to the topic of time (Ancona, Goodman, Lawrence, & Tushman, 2001; Bluedorn & Denhart, 1988). The time construct is being introduced to various models of organizational behaviors, such as newcomer adjustment and socialization (Wanous, 1992), attraction–selection–attrition (Schneider, 1987), career development (Schein, 1978), commitment formation (Meyer & Allen, 1997; Mowday, Porter, & Steers, 1982), job matching (Jovanovic, 1979), and stress and burnout (Maslach, Schaufeli, & Leiter, 2001). Across all of these behaviors, researchers are emphasizing the importance of investigating the length and sequencing of behaviors in organizations.

Turnover researchers have been on the front line of bringing time into its theories. As discussed earlier, many theoretical turnover models have implicitly suggested that the turnover process unfolds over time (e.g., Hom & Griffeth, 1995; Hulin, 1991; Lee & Mitchell, 1994; Mobley, 1977; Mobley, Griffeth, Hand,

& Meglino, 1979; Porter & Steers, 1973; Youngblood, Mobley, & Meglino, 1983). For instance, Mobley's (1977) turnover process model identifies several cognitive states that evolve and must occur for a turnover decision to be reached. Hulin's (1991) "progression of withdrawal" model integrates the attitude-behavior and applied motivation literature into the turnover process. Employees' work-role inputs, work-role outcomes, and the labor market contexts are considered as the initial antecedents in the turnover process, which simultaneously impact employees' job attitudes that eventually lead to actual withdrawal behaviors. Lee and Mitchell's (1994) unfolding model conceptualizes turnover as a process of screening and decision making, beginning with a specific event that jars employees to make deliberate judgments about their jobs and consider quitting the job. This model explicitly recognizes that the screening and decision making process unfolds over time.

However, while time is an important aspect of dynamic processes, it is not the only aspect. Employee turnover decisions are not completely determined by the initial state of a set of predictors at the time that these employees joined the organization. Rather, the status of these predictors changes and evolves over time. Unanticipated events could occur (e.g., spouse losing job, upswings in the economy, changing values/interests) which systematically change the psychological and/or economic antecedents of turnover decisions. Thus, change is the other critical aspect that needs to be considered when trying to understand dynamic processes.

Many studies on antecedent variables predicting turnover, such as performance, commitment, socialization, and job satisfaction, have suggested that these variables fluctuate over time (Hofmann, Jacobs, & Gerras, 1992; Maslach, Schaufeli, & Leiter, 2001; Meyer & Allen, 1997; Mowday, Porter, & Steers, 1982). Indeed, prevailing turnover theories have implied that antecedents to turnover fluctuate over time. For instance, the first turnover theory, March and Simon's (1958) theory of organizational equilibrium, emphasizes the balance between the organization's inducements and employees' contributions. Each employee participates as long as the compensation matches or exceeds his or her contributions. If employees consider their contributions exceed their inducements offered by organizations, they quit. According to this theory, turnover is conceptualized as a result of the imbalance between employees and organizations. In a real work context, employees' contributions and organizations' inducements change over time. Thus, the level of balance between these variables changes as well.

Another example comes from Porter and Steers' (1973) met-expectation theory. According to this psychologically oriented theory, employees' withdrawal behaviors occur if organizations fail to meet employees' work expectations. Since attitudes (Vallacher & Nowak, 1998) and role expectations (Katz & Kahn, 1978) fluctuate over time, partly as a function of changes in the external environment (e.g., organizational context), this theory implies that the level of match between what individuals expect and what the organization provides is always changing

over time. Thus, it appears that understanding the patterns of change of these antecedents is critical to fully understand the dynamic turnover process.

Hsee and Abelson's (1991) velocity theory is another important theoretical support for the dynamic turnover approach. Their study focuses on job satisfaction. They argue that there exists more than one relation between job satisfaction and its outcome. The simplest relation that is also the relation most researchers have focused on, is that satisfaction depends on the actual value of the outcome. In the present study, it refers to the positive (negative) relationship between the status of the predictors and turnover. The second relation between job satisfaction and its outcome is the change relation, which has rarely been the center of researchers' attention. This relation focuses on whether dependent variables depend on the change in job satisfaction. Hsee and Abelson argue that in certain situations, the second relation plays a bigger role than the first relation. For example, individuals tend to be more concern with the direction and rate of change of their compensation, in stead of the initial or average amount of their pay, because the changing pattern of their pay provides information about their progress.

Empirical Evidence: Taking Time and Change into Account

Unfortunately, while the conceptual models have incorporated time and suggested that turnover is a dynamic, unfolding decision, the most widely applied research design used in this literature has considered time and its dynamic nature in a perfunctory manner. For example, many early turnover studies have used survey designs, in which both the antecedents and turnover decisions were

measured at a single time period. Correlational analyses were conducted to establish a relationship between the antecedents and turnover decisions. A meta-analysis by Cotton and Tuttle (1986) collected over 100 turnover studies in major journals from 1979 to mid-1984. They reported that the majority of the studies included in their meta-analysis used the aforementioned survey designs and correlation analyses. Clearly, this research paradigm is inadequate to infer causality among hypothesized antecedents and turnover decisions. At best, the researcher following this design can conclude that there is some connection among these variables. Without allowing the passage of time between the measure of antecedents and turnover decisions, it is impossible to discuss either causality or the dynamic nature of turnover.

As discussed previously, the simplest and the most commonly used research design that incorporates time is the predictive design. In this design, the collection of the predictive simply precedes the measurement of the turnover dependent variable. With this design, researchers need to explicitly decide on and report the time interval between the measurement of predictors and criteria. While this design is an improvement over the aforementioned cross-sectional design, it does not contain sufficient information (i.e., predictors are measured only once) with which to study the dynamic nature of turnover.

Another research design, the repeated measures design, is more consistent with the spirit of the dynamic turnover perspective. Unfortunately, this research design is not commonly used in turnover research (Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005; Morita, Lee, & Mowday, 1993; Trevor, 2001). The

repeated design has some advantages. First, it can help researchers detect the effect of measurement time lags on the magnitude of the relationship between predictors and turnover. Harrison and Hulin (1989) have shown that time lags have an impact on the relationship between predictors and turnover (Harrison & Hulin, 1989). Second, the repeated measurement design gathers information about changes in antecedents believed to be critical in the determination of turnover. Unfortunately, while the repeated measurement design has these potential benefits, the way this data is typically analyzed (i.e., averaging values of antecedents over time) prevents these benefits from materializing. The change effect over time is still not included into the investigation.

In summary, while the turnover literature has identified potential predictors of turnover, this literature has not adequately explored the dynamic nature of this construct. The dynamic perspective should cause researchers to ask questions such as whether the nature of relationships between various predictors and turnover decisions vary across time. Are the initial conditions of some variables important indicators of later turnover? Are the change patterns exhibited by certain predictors indicative of a later turnover decision? Such questions are a direct consequence of taking a dynamic perspective to turnover, and to date, these questions have not been explored. Fortunately, new statistical techniques, such as the survival analysis and growth modeling, have created the opportunity to allow these more dynamically oriented questions to be addressed. I will describe these techniques and address their potential applications in turnover research in the following section of this proposal.

Recent Additions to the Statistical Toolbox: Survival Analysis and Growth

Modeling

As indicated earlier, two statistical analyses have been developed that can assess questions that arise from the dynamic turnover perspective. More specifically, the dynamic perspective raises two themes of questions: (a) questions surrounding whether and when turnover occurs; and (b) questions surrounding systematic changes over time. These two types of questions respectively emphasize the two aforementioned essential aspects of a dynamic process: time and change. More specifically, the first theme covers questions such as: “Which set of employees eventually quit?”, “Among those employees that quit, when are these employees most susceptible to quitting?”, and “How does the risk of quitting vary by employees’ characteristics?” The second theme covers questions such as: “Do the predictors of turnover change over time?”, “If they do change, what are the rates of change?”, and “How do these change rates differentiate among those that leave and those that stay?” Survival analysis addresses the first theme and growth modeling is useful when addressing the second theme.

- ***Survival Analysis***

Time will explain it all.

- Euripides

As discussed before, previous turnover studies face many design and analytic difficulties by neglecting the time element in the unfolding nature of the turnover process. However, the introduction of time into the research design is not without difficulties. For example, one fundamental problem that arises once time

is incorporated into the research design is how to handle censored observations. Censored observations refer to cases in which the time period for the study ends before some outcome (i.e., turnover) is achieved by everyone in the sample. Typically, censored observations are simply abandoned or coded as someone who will stay with the company in many turnover studies. Indeed, for all jobs, turnover is more a matter of “*when*” than “*if*” a person will quit. Survival analysis overcomes these difficulties and allows researchers to account for censored observations in their analysis. It is also able to describe time-dependence of turnover occurrence, compare these patterns among groups, and build statistical models of the risk of turnover occurrence over time (Morita, Lee, & Mowday, 1989, 1993; Murnane, Singer, & Willett, 1988; Peters & Sheridan, 1988; Sheridan, 1992).

Survival analysis, also known as event history analysis or hazards modeling, was originally developed by biostatisticians in biomedical life sciences to track the life expectancies of patients with life-threatening diseases (Cox, 1972; Cox & Oakes, 1984; Miller, 1981). Because the method of survival analysis adapts easily to psychological phenomena, it has been applied in multiple psychological research areas such as mental health (Greenhouse, Stangl, & Bromberg, 1989), social psychology (Gardner & Griffin, 1989), and organizational behavior (Levinthal & Fichman, 1988; Morita, Lee, & Mowday, 1989). Among all the longitudinal articles published in 10 popular APA journals in 2003, approximately 5% of them have already applied survival analysis to explore time dependent effects (Singer & Willett, 2003). By analogizing

employment durations and lifetime, survival analyses can easily apply to turnover research. A few turnover studies have used survival analyses to trace retention rates during employment, estimate quit rates at various states of tenure, and identify peak termination periods (Dickter, Roznowski, & Harrison, 1996; Hom & Kinicki, 2001; Trevor, Gerhart, & Boudreau, 1997).

The logical foundation of survival analysis is simple. Starting with some basic information, such as the turnover status of employees and their tenure with the organization, survival analysis estimates a probability function relating the percentage of organizational retention as a function of time. This probability function can be described as either a survivor function or a hazard function. The survivor function reflects the unconditional probability of staying beyond time t for a group of employees. The hazard function reflects the probability of turnover during a small interval of time anchored at time t . Combining these two functions allows us to investigate how turnover probabilities change with time t .

More specifically, the survivor function represents the probability that a randomly selected employee will stay longer than each time assessed – until every employee quits or data collection ends. Mathematically, we can estimate the value of the survivor function at time t , $S(t)$, by the empirical survivor function,

$$\hat{S}(t) = (\text{No. of employees staying past time } t) / (\text{Total No. of employees at beginning of study}) \quad (1)$$

At the beginning of the study, the survival probability is 1.00. As time passes and employees leave, the survivor function drops toward 0. When the sample survivor function reaches .50, half of the employees have left and half

have stayed. When the sample survivor function reaches .25, only one fourth of the employees have stayed and three fourth of them have left. The implied assumption of survivor function is that all employees will leave at certain time t . All survivor functions have similar shapes of a negatively accelerating extinction curve - a monotonically decreasing function of time (see Figure 1).

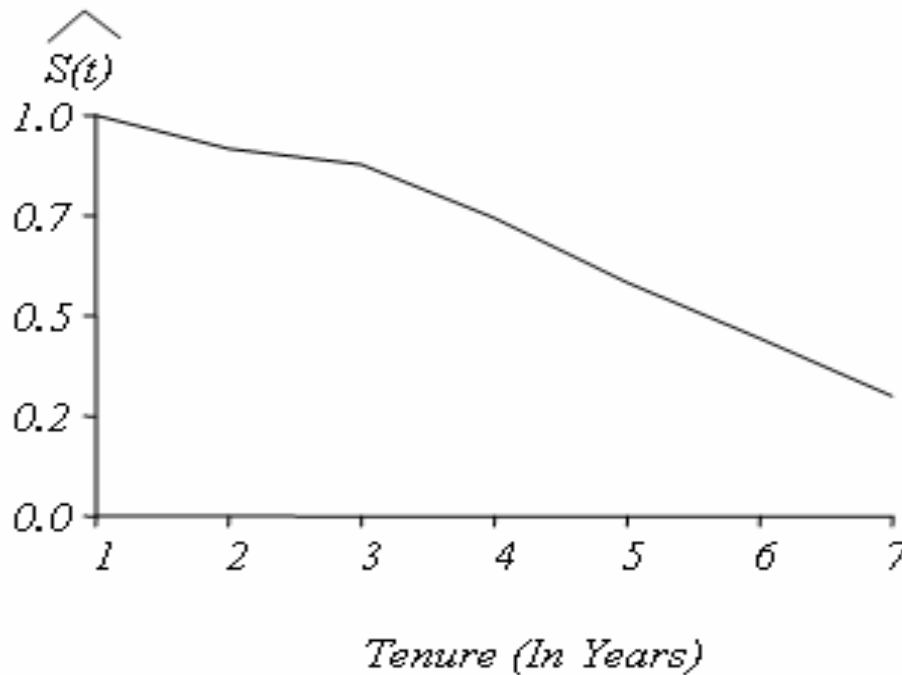


Figure 1. Job tenure survival function.

Different from the survivor function, which describes the probability of staying, the hazard function effectively captures the distribution of the turnover risk across time. In the present context, hazard refers to the risk of quitting in each discrete time period. Based on the estimator of the survivor function, an estimator for the hazard function at time t is

$$\hat{h}(t) = 1 - [\hat{S}(t) / \hat{S}(t-1)] \quad (2)$$

In equation 2, $h(t)$ represents the conditional probability that employees will quit when time = t . Because the hazard function represents the risk of quitting in each discrete time period, it provides information regarding whether and when turnover occurs. The hazard function is a probability estimate and thus, it is bounded by 0 and 1. Within these limits, the hazard function can widely vary. The larger the hazard function, the greater the risk the employees will leave. The lower the hazard function, the risk of turnover is diminished (See Figure 2).

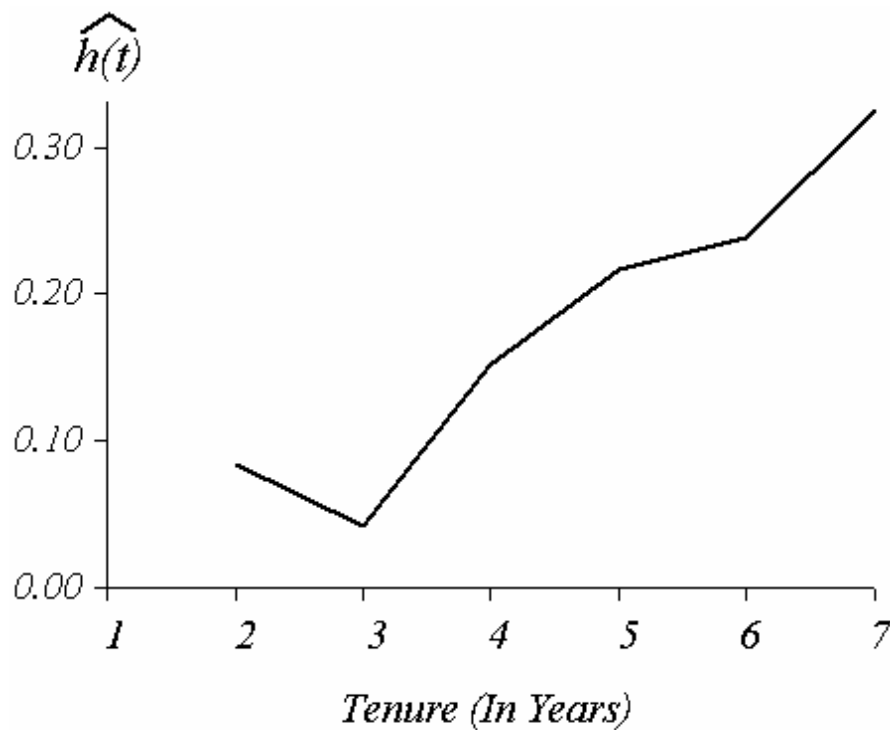


Figure 2. Job tenure hazard function.

Analysis of survival data typically begins with an examination of the sample survivor and hazard profiles. Researchers can use a variety of demographic characteristics of their participants (e.g., part-time/full-time status;

minority-majority status) and determine the survival or hazard function separately for two or more groups. These functions are then compared to determine (a) the shape of the survivor and hazard function for each group and (b) differences among the survival and hazard function for the groups. When we compare survivor or hazard profiles for two or more groups, the characteristic used to categorize the sample is implicitly treated as a predictor of the survivor or hazard profile. Thus, profile comparisons provide information regarding the relationship between turnover and some category variable. For example, Hom and his colleagues (1993) investigated the impact of realistic job interviews on turnover. They divided their sample into two subgroups – whether employees had internship experience or not. They contrasted the survival rates for these two groups and found that the survival distributions differed significantly between these two groups (see Figure 3).

If we divide the sample in other ways and treat those divisions as predictors of turnover, we can investigate the impact of those predictors on turnover process by comparing survivor or hazard profiles across groups. However, graphical displays and eye-ball judgments cannot answer complex research questions. Especially, when the predictor is continuous, we have to compare cumbersome collection of profiles. Additionally, these methods cannot explore the effects of several predictors simultaneously and evaluate the influence of interactions among predictors.

To deal with continuous predictors and several predictors simultaneously, the proportional hazard models were developed (Singer & Willett, 1991). The

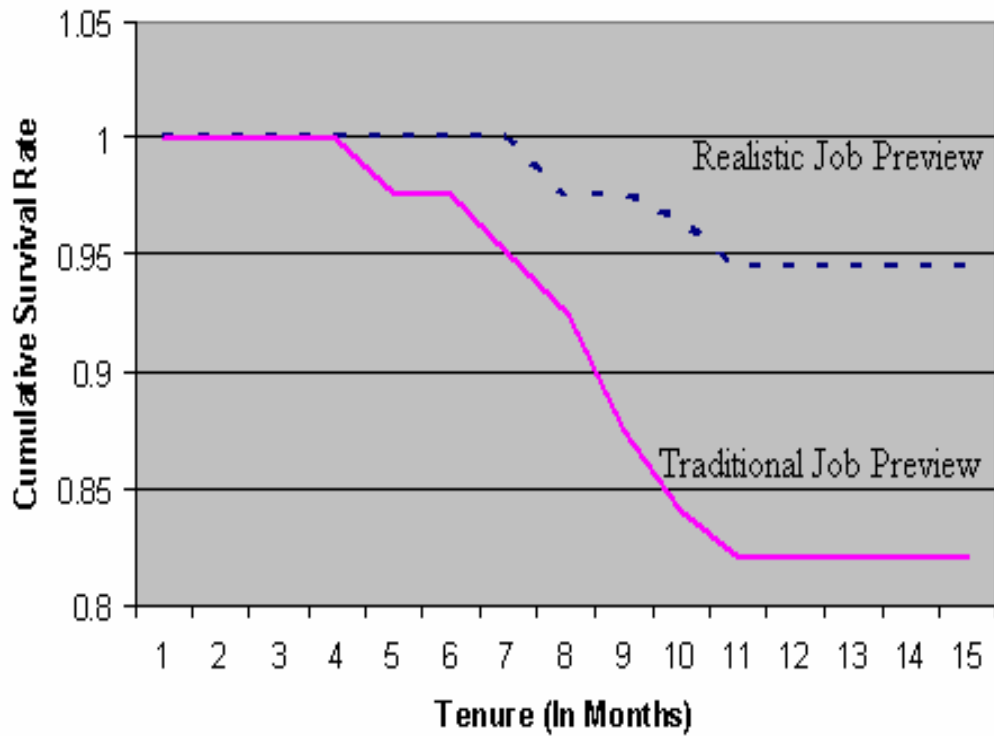


Figure 3. Survival Rates as Functions of RJPs and Job Tenure

simplest proportional hazard model consists of one time-invariant predictor. This simplest proportional hazard model can be present algebraically, like:

$$\text{Log } h(t) = \beta_0(t) + \beta_1 \text{Predictor1} \quad (3)$$

In this equation, $h(t)$ is the population hazard profile. $\beta_0(t)$ refers to the baseline log-hazard profile and represents the hazard value when the predictor score is zero and $\beta_1 \text{Predictor1}$ describes the influence of predictor 1 on the hazard profile.

When a hazard model includes multiple time-invariant or time-varying predictors, more complex models are needed. In such models, time-invariant predictors describe immutable characteristics of employees, such as gender and race.

Time-varying predictors are those variables whose values fluctuate over time. For example, one possible population hazard model might include time-invariant *Predictor 1* (i.e., race) and time-varying *Predictor 2* (i.e., performance) as follows:

$$\text{Log } h(t) = \beta_0(t) + \beta_1 \text{Predictor1} + \beta_2 \text{Predictor2}(t) \quad (4)$$

Where $\beta_2 \text{Predictor2}(t)$ represents that the influence of predictor 2 on turnover may vary over time.

Survival analysis provides a powerful set of data analytic tools that are particularly useful in understanding behavioral processes that unfold over time. Because survival analysis explicitly incorporates time as a variable of interest, it is more flexible and better able to extract and use information from longitudinal studies than methods more commonly used on applied psychology. Survival analysis allows researchers to answer research questions about whether and if critical events occur. This method is powerful, flexible, and applicable to many research questions arising in turnover research.

In summary, time and change are two essential characteristic of dynamic processes. In the previous section, I discussed survival analysis and its ability to capture the time effect in turnover process. The next section focuses on change aspect of the dynamic turnover process. When the turnover process and related variables are described as changing over time, questions such as: (a) “How does each employee’s turnover function change over time?”; and (b) “Do employees’ trajectories of change vary across leavers and stayers?” can be addressed.

- ***Growth Modeling***

Change is inevitable. Change is constant.

- Benjamin Disraeli

The simplest way to know how a person changes over time is to examine his or her empirical growth plot. An empirical growth plot is a temporally sequenced graph reflecting the status of some variable over time. These empirical growth plots can be fitted with various equations to help the researcher summarize and understand the nature of the change that has occurred in his/her sample over time. More precisely, separate models are fit to each person's empirical growth trajectory. After separate models are estimated for each individual, question such as: "Does everyone change in the same way?" or "Are the trajectories significantly different across people or groups?" can be addressed. While many different models have been developed over the years, Latent Growth Modeling (GLM) has received increasing attention. To have a better understanding of the statistical logic of GLM, I will first introduce the Hierarchical Linear Modeling (HLM) in the following section. GLM can be considered as a structure-equation-modeling (SEM) version of HLM. The basic statistical equations behind these methods include (a) to estimate the change trajectory of each individual, which is considered as the level 1 analysis; and (b) to compare the change trajectories across all individuals, which is considered as the level 2 analyses.

- ***Hierarchical Linear Modeling (HLM)***

Hierarchical Linear Modeling (HLM) was originally designed to investigate hierarchically ordered systems. Researchers in sociology (Mason, Wong, & Entwistle, 1983), education (Burstein, 1980), and organizational

behaviors (Mossholder & Bedeian, 1983) have all discussed issues related hierarchically ordered systems using HLM. The two basic aspects of HLM are the within-unit (or within-group) differences and the between-unit (or between-group) differences. HLM has recently gained widespread acceptance as a powerful approach to the description, measurement, and analysis of longitudinal change (Bryk & Raudenbush, 1987; Deadrick, Bennett, & Russell, 1997). In the context of longitudinal research, the central features of HLM are the ability to estimate within-individual change patterns and the between-individual differences on those change patterns. In other words, HLM is a multilevel model for change, which simultaneously fits a pair of equations at two or more levels of analysis. At the simplest level (referred to as level-1), models that describe the change process of each person are estimated. At the next level (referred to as level-2) models that describe how these changes differ across people are fit. Taken together, these two components form that is know as a multilevel statistical model to address both within-individual and between-individual questions. .

The level-1 component of HLM represents the change we expect each member of the population to experience during the time period under study. In general, we assume that Y_{it} , the observed status of individual i at time t , is a function of a systematic growth trajectory or growth curve plus random error. The simplest level-1 model can be represented as:

$$Y_{it} = \pi_{0i} + \pi_{1i} \text{TIME}_{ij} + \varepsilon_{it} \quad (5)$$

Where π_{0i} represents an individual i 's true initial status on the dependent variable (i.e., the value of Y_{it} when $\text{TIME}_{ij} = 0$). Further, π_{1i} represents individual i 's true

rate of change during the period under study. Finally, ε_{it} represents that portion of individual i 's outcome that is unpredicted on occasion j .

The level-2 component of HLM focuses on the relationship between interindividual differences in change trajectories and employees' turnover status (stayers or leavers). The focus of the level 2 model is the growth parameters captured in the fitted level 1 model. This allows us to test for the predictive power of level 2 variables to differentiate the "change" process. Specifically, categorical or continuous level 2 variables (e.g., full-time/part-time; personality) are used to predict the level 1 model parameters. Mathematically, two related models can be used to posit the level-2 submodel for interindividual differences in change. One is for true initial status (π_{0i}) and a second is for true slope of change (π_{1i}):

$$\pi_{0i} = \gamma_{00} + \gamma_{01} \text{Turnover}_i + \xi_{0i} \quad (6)$$

$$\pi_{1i} = \gamma_{10} + \gamma_{11} \text{Turnover}_i + \xi_{1i} \quad (7)$$

In these equations, γ_{00} and γ_{10} are the level-2 intercepts, which represent the population average initial status and slope of change. Further, γ_{01} and γ_{11} , the level-2 slopes, provide information about the change trajectories, such as whether they are increasing over time or decreasing over time. ξ_{0i} and ξ_{1i} are the level-2 residuals, which represent those portions of initial status or slopes that cannot be explained at level-2. The equation (5) demonstrates characteristics of the change within individuals while the equation (6) and (7) demonstrate the characteristics of the change between individuals. The set of these three equations are the basic models of HLM to investigate relationships occurring across multiple levels.

Burstein (1980) has phrased the three equations of HLM under the labels of

“intercepts-as-outcomes” and “slope-as-outcomes.” These labels appropriately describe the conceptual logics of HLM, because the intercepts and slopes parameters estimated for each individual at level-1 are used as outcome measures (i.e., dependent variables) in the level-2 model.

- ***Latent Growth Modeling (LGM)***

Similar to HLM, GLM was designed to address questions concerning intraindividual change (Chan & Schmitt, 2000). As informed earlier, LGM is a flexible structural equation modeling (SEM) technique that comprehensively assesses the within-individual changes and between-individual differences in these changes (Singer & Willett, 2003). By mapping the multilevel model for change onto SEM, LGM is an alternative approach to capture within-individual change patterns and it also extends the analytic power of growth modeling.

As same as HLM, LGM represent the longitudinal data by modeling inter-individual differences in the parameters (i.e., intercept and slope) of intra-individual changes over time (i.e., individual growth trajectories). The simplest model is the univariate LGM, which is demonstrated as Figure 4. Two parameters - intercept (representing initial status) and slope (representing rate of change) – indicate the intra-individual change pattern over time. $Y_{i1} - Y_{i3}$ represent the three-time measurements of certain constructs, such as antecedents of turnover. Applying the HLM level-1 model, the intraindividual differences of this LGM model can be written as:

$$Y_{i1} = \pi_{0i} + \pi_{1i} \text{TIME}_1 + \varepsilon_{i1}$$

$$Y_{i2} = \pi_{0i} + \pi_{1i} \text{TIME}_2 + \varepsilon_{i2}$$

$$Y_{i3} = \pi_{0i} + \pi_{1i} \text{TIME}_3 + \varepsilon_{i3} \quad \dots \quad (8)$$

Figure 4 also shows the between-individual differences on the growth trajectories by comparing the stayers group and the leavers group. Using the HLM level-2 models, the interindividual differences of this LGM model can be represented as:

$$\begin{aligned} \pi_{0i} &= \gamma_{00} + \gamma_{\pi_{0i}} + \xi_{0i} \\ \pi_{1i} &= \gamma_{10} + \gamma_{\pi_{1i}} + \xi_{1i} \end{aligned} \quad (9)$$

As demonstrated in Figure 4, LGM develops a trajectory of change along each of the focal constructs for each individual across time, through multiple times of measurements of these constructs (at least three times). More precisely, each of the longitudinal measurements of a focal construct displays a separate loading on two latent factors, one defining initial status (i.e., π_{0i}) and one defining the rate of change (i.e., π_{1i}). The LGM analysis can estimate the means and variances of the two latent factors (i.e., the intercept – π_{0i} and the slope – π_{1i}). It can also examine whether these two latent factors are correlated with each other. Examining each individual's growth parameters (i.e., π_{0i} and π_{1i}) at the intraindividual level (by the equations - 8) and at the interindividual level (by the equations - 9), researchers can investigate the association between individual growth parameters and the hypothesized variables. For example, in turnover research, LGM can be used to examine the relationship between individual performance change and their turnover decisions. The turnover status or turnover intentions are treated as other latent variables to predict employees' performance change patterns.

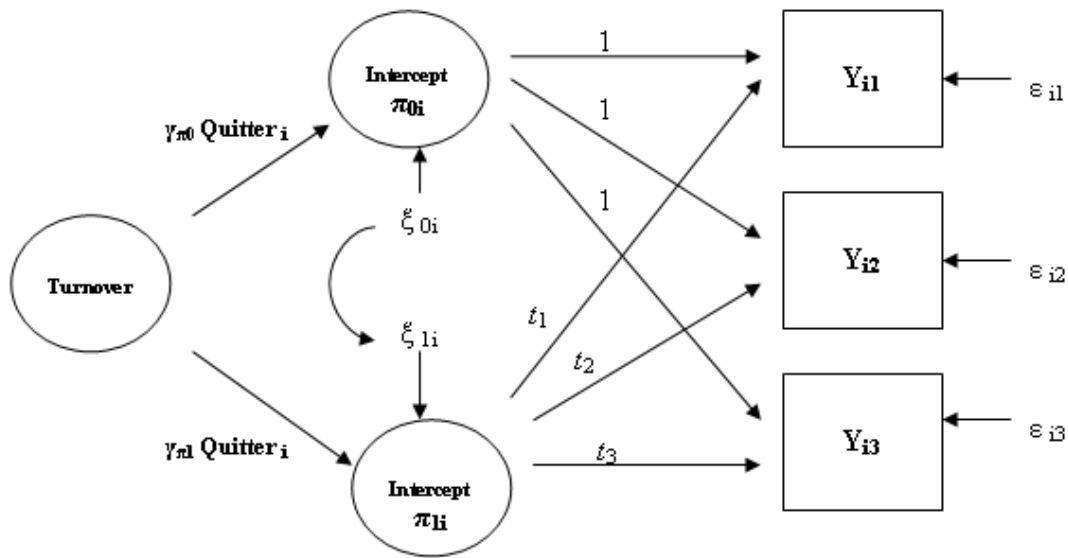


Figure 4. Hypothesized path diagrams of a LGM for turnover

Figure 4 demonstrates the simplest univariate LGM model. Different univariate LGM models can be combined to form a multivariate LGM, which allows researchers to investigate the cross-domain associations, such as the correlations between different change trajectories. More specifically, when the rate of change of predictor 1 (π_{1i}) is correlated with the rate of change of predictor 2 (π'_{1i}), their correlation can be represented and calculated by the multivariate LGM. For example, previous studies have indicated that the change of performance and the change of compensation are tied with each other and both of them are strong predictors of turnover. Multivariate LGM is perfectly suitable for studying the dynamic relationships between dynamic performance, dynamic compensation, and turnover.

There are two benefits of applying multilevel models to investigate a dynamic process. First, interindividual differences on the turnover process are determined by the intraindividual change. In other word, the dependent variables of level 2 models, π_{0i} and π_{1i} , are the parameters of level 1 model. This allows us to have a more completed understanding of the turnover process. Second, each level-2 submodel allows individuals from the same group (either the stayers group or the leavers group) to have different individual change trajectories. These two benefits allow researchers to address the following questions of the dynamic turnover process: (a) the form of the intraindividual change trajectories, (b) the systematic individual differences at initial status and in the rate of intraindividual change, (c) the consequences and antecedents of both an individual's initial status on the construct of interest and his or her rate of change on that construct across time, (d) whether there is a relationship between an individual's initial status and rate of change on the construct of interest, and (e) whether the change in one variable is related to the change in another.

LGM has its strong potentials in turnover research, because it overcomes many of the problems characterizing the traditional methodologies in longitudinal studies (Chan, 1998; Duncan, Duncan, Strycker, Li, & Alpert, 1999; Lance, Meade, & Williamson, 2000). Although LGM has much potential for turnover research, few studies have used this approach to study turnover process (see one exception: Bentein, Vandenberg, Vandenberghe, & Stinglhamber, 2005). The present study will have a better opportunity to understand turnover and its predictors dynamically, by applying multivariate LGM to turnover research.

The following section will have a discussion on potential antecedents of a dynamic turnover process. One important purpose of the next section is to develop a dynamic turnover process model for further analyses.

Potential Antecedents of a Longitudinal Turnover Process

The aforementioned conceptual models have identified several potential antecedents of turnover. These antecedents can be classified into two categories: employee characteristics and organizational/economic contexts. However, given the disconnection between theory and research design, one has to question the evidence for a causal relationship between these antecedents and turnover. As discussed by Mitchell and James (2001), the issue of time and causal relationships are linked in a complex manner. They suggest that in any investigation of a causal relationship between two variables, the time when these two variables are believed to occur and when they are measured are crucial for determining causality or for providing an unbiased estimate of the magnitude of that relationship. In other words, researchers need to have theoretical and/or empirical guides about: (a) when X and Y occur; and (b) when X and Y should be measured. Without these guides, researchers run the risk of drawing inappropriate conclusion about the strength, order, and direction of causal relationships. Thus, it is necessary to include time in turnover studies to accurately illustrate the relationship between predictors and turnover. In this section, I will review and discuss the potential antecedents of the dynamic turnover process. Two major groups of questions will be addressed, which focus on the time effect and the change effect of the dynamic turnover process.

Specifically, the following questions will be discussed: (a) What are the potential antecedents? (b) Are these antecedents time-invariant? (c) If they are, what are the changing trajectories of these antecedents? (e) Do those changing trajectories differ between stayers and leavers? (f) Are these antecedents related to employment duration? And (g) if they are, what impact they have on the survivor and hazard functions?

Employee Characteristics

Many reviews of the antecedents and correlates of turnover have appeared over the years. Employee characteristics, such as demographic and personal characteristics, job attitudes, performance, promotion opportunities, benefits, and compensation, have been repeatedly found to predict employment stability (Hom & Griffeth, 1995; Hulin, Roznowski, & Hachiya, 1985; Mobley, Griffeth, Hand, & Meglino, 1979; Muchinsky & Tuttle, 1979; Porter & Steers, 1973; Price, 1977; Steers & Mowday, 1981). A large number of theoretical formulations demonstrating the turnover process have also underscored the prediction of these antecedents to turnover decisions, such as Price and Mueller's (1981) Model of Turnover, Mobley et al.'s (1979) Expanded Model of Turnover, and Hulin, Roznowski, and Hachiya's (1985) Labor-Economic Model of Turnover.

- ***Demographic and Personal Characteristics***

The demographic and personal characteristics found to predict turnover decisions include tenure, age, and gender. Previous studies that have used one of the traditional research designs have indicated that all of these individual attributes modestly predict turnover, although the magnitude of their relationships

with turnover varies. A meta-analysis by Hom and Griffeth (1995) shows the significant influence of age, sex, and tenure on employee turnover decisions. Hom and Griffeth (1995) reported that older employees with longer tenure were more loyal than younger employees with shorter tenure. It was also reported that women tend to quit more than men. Although age and tenure are treated as time-variant predictors in this meta-analysis, only the initial age of the participants could have been used in these studies. In the present study, gender will be treated as a time-invariant variable whereas age will be allowed to vary across time.

Hypothesis 1a: Female employees will be more likely to quit than male employees.

Hypothesis 1b: Older employees will be less likely to quit than younger employees.

- ***Job Performance***

Previous studies on performance and turnover have clearly found a relationship between these two variables. In multiple meta-analysis studies, researchers have found a significant negative relationship between performance and turnover. This repeated finding suggests that lower performers have higher probabilities to quit (Bycio et al., 1990; McEvoy & Cascio, 1987; Williams & Livingstone, 1994). Recent research, however, has suggested that the true nature of this relationship is curvilinear (Trevor et al., 1997; Williams, & Livingston, 1994). Specifically, both high and low performers are more likely to leave an organization. Unfortunately, most of these studies have rarely investigated this nonlinear relationship between the changing trajectories of performance and

turnover. Interestingly, the issue of the dynamic nature of performance has been debated for many years (Deadrick, Bennett, & Russell, 1997; Hanges, Schneider, & Niles, 1990; Hofmann, Jacobs, & Gerras, 1992; Ployhart & Hakel, 1998). Since prior research has established that performance is an antecedent of turnover and since prior research has established that performance is dynamic, it seems reasonable to hypothesize the consequences of dynamic changes in performance for turnover decisions.

In addition to performance affecting the turnover decision over time, two empirical studies have found that the relationship between performance and turnover fluctuates over time (Harrison, Virick, & William, 1996; Sturman & Trevor, 2001). Given these results, I will treat performance as a time-variant variable in this study. In particular, I hypothesize that both the initial status of performance and the nature of the change in performance over time will affect turnover.

Hypothesis 2a: There will be a curvi-linear relationship between initial performance and turnover. Specifically, median level performers will have longer tenure than either high or low performers. Both high performers and low performers are more likely to leave the organization.

Hypothesis 2b: Those individuals that leave and those that stay with the organization will have different growth trajectories in their performance over time. Specifically, the slope of performance scores for individuals that stay with the company will be more positive than the slope of performance scores for individuals that leave the company.

- ***Compensation***

Compensation is commonly believed to be strong antecedents of turnover by both researchers and practitioners (Gomez-Meija & Balkin, 1992; Milkovich & Newman, 1993). Unfortunately, very little evidence for this relationship has been found. This lack of empirical support might be due to the non-dynamic research designs used in these previous studies. A static design only looks at salary level and it is possible that level of employees' salary does not have a strong influence on turnover decisions because salary levels frequently fall into acceptable tolerance range when compared to the individual's desires and market forces. However, the dynamic perspective emphasizes the change of employees' salary over time. It is possible that the rate of change will have a strong influence on employee turnover decisions. In the present study, employees' compensation will be treated as a time-variant variable. The slope of compensation change will also be included.

Hypothesis 3a: There will be a negative relationship between compensation and turnover. Specifically, employees with higher pay will have longer employment duration than those with lower pay.

Hypothesis 3b: Employees who leave the organization and those who stay will have different compensation growth trajectories. Specifically, the slope of compensation growth trajectories for stayers will be more positive than the slope of compensation growth trajectories for leavers.

- ***Promotion***

Previous research on promotion and turnover has indicated that promotions exhibit a moderate correlation with turnover (Hom and Griffeth, 1995). More precisely, satisfaction about promotion and perceived opportunities for promotion modestly predicted turnover whereas actual promotion strongly predicted turnover decisions. In the present study, I only focus on actual promotions. Similar to benefits and other types of incentive pay, actual promotions are events that happen infrequently and only to some employees. Thus, promotions should be viewed as critical events that influence employees' assessment of their environment. I therefore hypothesize that it will affect their turnover decisions.

Previous studies on the influence of promotions on turnover have rarely adopted a dynamic perspective. Additionally, previous research has not compared the effect of promotions between those that stay and those that leave an organization. Thus, it is unclear whether promotions really influence the turnover process.

Hypothesis 4: Promotions will be related to employment duration. Specifically, promotions will extend employees' employment duration.

- ***General Employees' Attitudes***

Many turnover studies have employees' general attitudes as antecedents of resignation. Beyond regular job satisfaction, employees' general attitudes towards the organization focuses on employees' overall attitudes about their organization, in terms of operations, administrations, climates, and values. As same as job satisfaction, those attitudes will also affect employees' turnover decision. A few

studies have provided empirical supports for this view. For instance, it has been found that employees quit their jobs if their experiences disconfirm the expectations they had about their organizations; they will remain employed if their experiences confirm their initial expectations (Porter & Steers, 1973; Wanous et al., 1992).

However, previous studies have rarely investigated the relationship between employees' general attitudes and turnover from a longitudinal approach. That is, employees' general attitudes toward their organization have been treated as static variables, although researchers have debated about the instability nature of attitudes, which are normally considered as exchange ties between employees and organizational environments. For example, scholars have suggested that employees' attitudes toward organizations were calculative attitudes, which is resulted from employees' exchange relationship with the organization. In the present study, employees' general attitudes will be treated as time-variant variables. Thus, the hypotheses are addressed below:

Hypothesis 5.1a: Employees with different attitudes will have different employment duration. Specifically, employees with more positive attitudes towards the organization will have longer employment tenure than employees with more negative attitudes.

Hypothesis 5.1b: The attitudes trajectories for employees that stay with an organization will be more positive than the attitude trajectories of employees that leave an organization.

- ***Job Satisfaction***

Almost all models of turnover have employees' job satisfaction as turnover predictors. Low levels of job satisfaction and organizational commitment are considered as the initial steps along of the turnover process (Hulin, Roznowski, & Hachiya, 1985; Price & Mueller, 1981; Mobley, 1977; Mobley, Griffeth, Hand, & Meglino, 1979). Consistent with these theoretical perspectives, job dissatisfaction and organizational commitment have been found to be related resignations by many empirical studies (Hom & Griffeth, 1995; Steers & Mowday, 1981; Porter & Steers, 1973; Price & Mueller, 1986). Three meta-analysis studies have shown that dissatisfaction employees are more likely to abandon their present employment than satisfaction employees (Carsten & Spector, 1987; Hom & Griffeth, 1995; Steel & Ovalle, 1984). For example, in their meta-analysis of seventy-eight studies covering 27,543 employees, Hom & Griffeth (1995) found that job satisfaction is significantly correlated ($r = -.19$) with resignation.

As same as the discussion about employees' general attitudes, these previous studies have rarely examined the longitudinal relationship between job satisfaction and turnover risks. That is, job attitudes have been treated as static variables, although researchers have suggested job attitudes are time-variant. In the present study, job attitudes will be treated as time-variant variables. Not only the levels of job satisfaction but the change slopes of job satisfaction will be included into investigation.

Hypothesis 5.2a: Employees with different job satisfaction will have different employment duration. Specifically, employees with higher job

satisfaction will have longer employment tenure than employees with lower job satisfaction.

Hypothesis 5.2b: The trajectories of employees' job satisfaction would be different for stayers and leavers. Specifically, employees who stay with the organization will have more positive slopes than those who leave.

- ***Intention to Quit***

Intention to quit, conceptually and empirically, has been used as one of the most important turnover predictors. Different from actual turnover behaviors, intention to quit presents employees' psychological attitudes, which may or may not directly lead to actual turnovers. In many theoretical turnover models, intention to quit is proposed to be the most direct predictor of turnover behaviors (Mobley, Griffeth, Hand, & Meglino, 1986; Price & Mueller, 1986; Steers & Mowday, 1981). Consistent with these theoretical perspectives, intention to quit has also been found to be closely related to turnover behaviors in multiple empirical studies. For example, the latest meta-analysis by Griffeth and colleagues shows that quit intentions remain the best turnover predictors among all the psychological factors ($r = 0.38$).

Also, as same as studies on other attitudes predictors, intention to quit is also considered as being stable over time. In the present study, turnover intention will also be treated as dynamic variable. That is, the levels of turnover intention, as well as the slopes of turnover intention, will be included into the analysis to understand the relations between turnover intentions and turnover behaviors over time.

Hypothesis 5.3a: Employees with different turnover intention will have different employment duration. Specifically, employees with lower turnover intention will have longer employment tenure than employees with higher turnover intention.

Hypothesis 5.3b: The changing trajectories of employees' turnover intention would be different for stayers and leavers. Specifically, employees who stay with the organization will have more negative slopes than those who leave.

External Economic Contexts

Many of the turnover models have illustrated the importance of the availability of alternative job opportunities during employees' turnover decision process (Hom & Griffeth, 1991; Hulin, Roznowski, & Hachiya, 1985; Mobley, 1977; Mobley, Griffeth, Hand, and Meglino, 1979). It has been suggested that turnover plans would be contingent on the availability of alternative employment opportunities. The availability of alternative employment is presented by two factors in the present study: local unemployment rate and local household income. Although the aforementioned turnover models have suggested the impact of these contextual variables on turnover, empirical evidences are limited.

- ***Local Unemployment Rate***

As discussed previously, alternative job opportunities come from within an organization as well as forces outside the organization (e.g., external economic conditions). With regard to the external job opportunities, the unemployment rate is the best indicator. A meta-analysis by Hom and his colleagues (1992) found

that unemployment rates moderated the link between employees' attitudes and turnover. Gerhart (1987) found that regional unemployment rates moderate correlations between satisfaction and turnover. Carsten and Spector (1987) also found that economic expansion facilitates dissatisfied employees to reach their decision to quit.

Unfortunately, even though the external economic conditions are dynamic, a dynamic research design has rarely been used to investigate the external economic conditions to turnover relationship. The present study will treat unemployment rate as a time-variant variable. Both the economic conditions at the beginning of the study period and the trajectories of the local unemployment rate will be included in this study to investigate its dynamic influence on employees' turnover decisions.

Hypothesis 6a: Local unemployment rate will affect employees' employment duration. Employees living in high local unemployment rate area tend to have longer employment duration than employees living in low local unemployment rate area.

Hypothesis 6b: The change of local unemployment rate will affect employees' turnover decision. The slope of local unemployment rate change lines for stayers will be more positive than slope of local unemployment rate change lines for leavers.

- ***Local Household Income***

Local household income, as the other factor to present local economic situation, is also included in the present study. Local income levels have been

used as one important indicator to demonstrate the economic status of the local area. Although previous research rarely includes local household income in the turnover studies, local household income, as an important external economical indicator, is related to turnover risks. That is, employees living in an area with high local household income are more likely to have higher income, which has been indicated to extend the employment duration and decrease the turnover risks. As same as other time-varied predictors, the hypotheses on local household income are addressed below:

Hypothesis 7a: Local household income will affect employees' employment duration. Employees living in high household income area tend to have longer employment duration than employees living in low household income area.

Hypothesis 7b: The change slopes of local household income will be different for employees who stay with the organization and those who leave. The slope for stayers will be more positive than slope for leavers.

Summary

Following the direction of numerous turnover theories and models, the purpose of this dissertation is to investigate the relationship between multiple antecedents and employee turnover behaviors. However, different from most previous turnover research, the present study focuses on the dynamic nature of turnover process to accurately illustrate the relationship between predictors and turnover. The time effect and the change effect, which are the two essential aspects of the dynamic turnover process, are addressed in this study. Two

categories of antecedents are included: (a) employee characteristics, including demographic and personal characteristics (H1), job performance (H2), compensation (H3), promotion (H4), and job attitudes (H5); and (b) economic contexts, including local unemployment rate history (H6) and local household income (H7).

METHODS

Participants and Procedure

The initial pool of potential participants consisted of all the employees of a national wide healthcare company. The primary services that the company provides include: health care and well-being services, health benefit plans and services, and pharmaceutical development and consulting services. There was no sampling issue in this study. All the employees in the organizations were included. The original data set consisted of 100,877 employees. The data was collected over a six year period with: $N_{\text{year}1} = 49,752$, $N_{\text{year}2} = 50,783$, $N_{\text{year}3} = 51,074$, $N_{\text{year}4} = 50,801$, $N_{\text{year}5} = 49,494$, $N_{\text{year}6} = 48,407$. Of these employees, 17,984 respondents (18%) had data for all six years. The average new hire rate across the six year period was approximately 19%. The average turnover rate across six years was approximately 12%. Table 1 shows the number and percentage of new hires and turnovers for each of the 6 years.

The data used in the present study was obtained from three different sources: 1) data available from the company's Human Resource Information System (HRIS) (e.g., employee compensation level, employee job performance, and employee demographic information), 2) data obtained from employee surveys

(e.g., employee job satisfaction, intention to quit, and general attitudes towards the organization), 3) data obtained from external archival documents (e.g., local unemployment rates and local household income). The HRIS data was collected at the end of each fiscal year. The employee survey was developed and administrated during the summer of each year. The external archival data was mainly obtained from the U.S. Bureau of Labor Statistics and the U.S. Census Bureau.

Table 1. Turnovers and New Hirers by Years

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
Leavers *	17,495	14,903	13,813	12,516	11,108	9,057
- Voluntary Turnover	6,801	7,105	6,832	5,180	4,078	4,702
- Involuntary Turnover	1,542	1,613	2,951	3,496	3,706	2,909
- Business Turnover	4,382	2,866	1,502	1,330	1,034	68
- Other Turnover	4,770	3,319	2,528	2,510	2,290	1,378
New Hirers	9,255	11,453	9,760	9,952	8,162	7,811
Involuntary Turnover Rate	14%	14%	13%	10%	8%	10%
New Hire Rate	19%	23%	19%	20%	16%	16%
Total	49,752	50,783	51,074	50,801	49,494	48,407

*Note: The leavers included all four types of turnovers.

The data was obtained from employees that were geographically dispersed throughout the United States. In the original data set, the average age was 38.8 (SD = 0.50) and the average tenure was 5.3 years (SD = 5.54). Approximately 76% of the respondents were female, 77% were Caucasians, and 96% were employed full-time. The average annual pay (across the six year period) for the respondents was \$45,416 (SD = \$53.925) and the average promotion rate was 8%. Approximately 29% of employees were rated as high performers and 4% of employees were rated as low performers.

One issue about participants that needs to be addressed when conducting survival analyses later. This issue focused on how to deal with employees who were still with the organization when the study was over. Figure 5 illustrates this issue. As seen in this figure, employees A and C leave the organization during the study period. The employment duration for these two individuals can be calculated exactly. However, employees B and D are still with the organization by the end of the observation point of the study. Calculation of the employment duration for these individuals is artificially truncated. In reality, employees B and D have an unknown turnover date. That is, they may leave the organization one year after the observation period ended. They may leave the organization five years after the observation period ended or they may leave twenty years after the observation period ended. Thus, a major issue for turnover studies is deciding how to portray in the analysis the employment duration of individuals like employees B and D.

In this study, I applied the approach of treating individuals like employees B and D as *right censored* participants. In other words, the data set provides some information about these individual's employment duration, but the data set does not provide this information exactly. For these individuals, their complete employment duration was cut off (or *censored*) at the right side of the study interval.

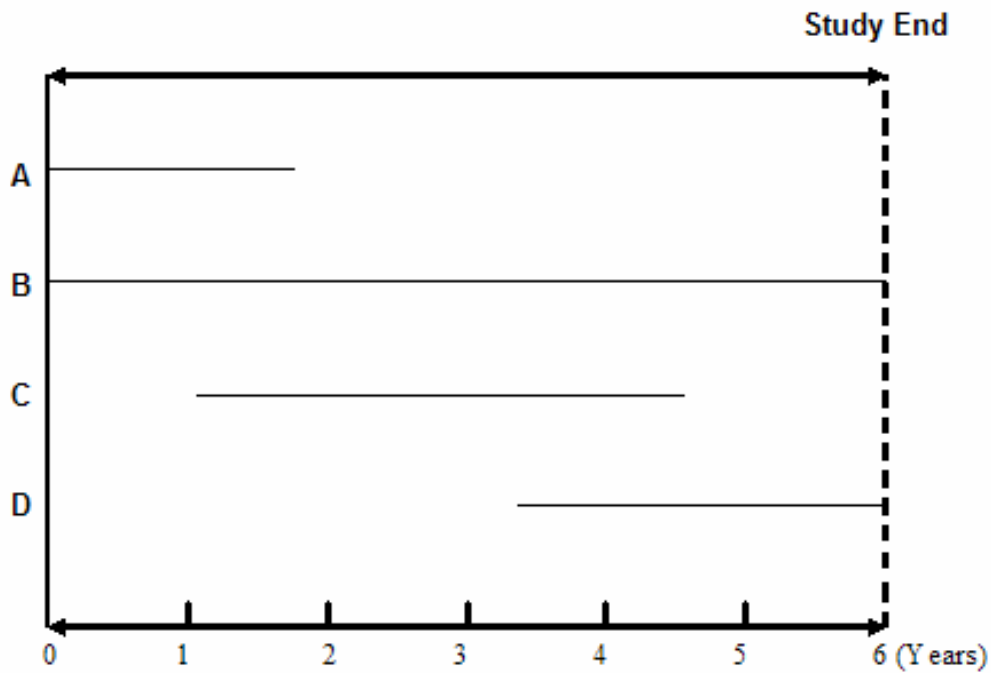


Figure 5. Examples of censoring situation

Measures

Turnover. Turnover information was obtained from the HRIS data file. Specifically, this file contained the records of each employee's hire and turnover (if it occurred) dates. The difference between these two dates (or the time between being hired and the date of data collection) was used as the measure of duration of employment. The reason for turnover was also included in this data set. Specifically, employees' turnover behaviors were separated into four distinct categories defined by the organization: voluntary turnover, business decision turnover, involuntary turnover, and other turnover. Voluntary turnover included all the employee-initiated turnover behaviors, such as job abandonment, personal reasons, or return to school. Business decision turnover referred to the turnover

behaviors part of the organization reduction in force. Involuntary turnover behaviors were turnover based employee performance (e.g., attendance or dishonesty). Other turnover referred to turnover behaviors that were initiated by ambiguous, unclear, or undefined reasons, such as retirement or death. Consistent with the turnover theories and hypotheses discussed earlier, only voluntary turnover behaviors were included into the turnover analysis of the present study. A total of 30,174 individuals, or 30% of the 100,877 respondents, left the organization voluntarily during the six-year study period. The average employment duration for those who voluntarily left the organization was 2.58 years (SD = 3.88).

Employment Duration. Beside actual turnover behaviors, employees' employment duration was also calculated in the present study. All employees have their entry date. If they left the organization, they would have an exiting date. If they stayed with the organization until the end of the study, they would be considered as being right censored. The time between employees' entry date and their exiting date was calculated as their employment duration. The employment duration was recorded by days.

Demographic variables. Demographic variables were obtained from the HRIS data file. *Gender* and *age* were included in the turnover analysis of the present study. *Gender* was dichotomized as 1 = *female*, 2 = *male*. *Age* was measured at employee's first hiring year. I held *age* constant at the first hiring year for this study because the rate of age change is constant across all the individuals.

Job performance. Job performance was also obtained from the HRIS data file. Job performance was evaluated through the standardized employee performance appraisal system of the organization. Three categories were used to rate employee's job performance: a) Needs improvement, b) Meets expectations, and c) Exceeds expectations. Across the six years, 20% employees were rated as "Exceeds expectations", 69% employees were rated as "Meets expectations", and 11% employees were rated as "Need improvement".

Compensation. Employees' compensation data was obtained from the HRIS data file. Annual pay rate (full time equivalent) was used to measure the employee compensation level. Annual pay rate was calculated to permit meaningful comparisons among both annually-paid employees and hourly paid employees. I did not include overtime pay, long-term incentive pay, short-term incentive pay, and other type of payments in this measure. Base pay accounted for approximately 73 % of individuals' total income. The average annual pay was \$45,416 with SD = \$53.925.

Promotion. Employee promotion records were also obtained from the HRIS file. Four types of promotion were identified (i.e., regular promotion, promotion with pay change, planned promotion, and replacement promotion). For each year, if an employee was promoted (regardless of promotion type), the promotion variable for that year was coded as 1. Otherwise, the employee's promotion variable was coded as 0 – No promotion for that year. The average promotion rate across six year was 12%. Among employees who had had

promotions in the last six years, 78% had one promotion, 18% of had two times of promotions, and 4% of them had three or more promotions.

Employee attitudes towards the organization. Employees' attitudes about the organization were obtained from the organization's annual employee attitude survey data. The survey was designed and developed to access employees' attitudes about the organization regarding four dimensions of: D1 = whether the organization has clarity and confidence in its direction (3 items), D2 = whether the organization support employee development and advancement (2 items), D3 = whether the organization values employees (2 items), and D4 = whether the organization has good workforce engagement (5 items) (see Table 4 for the description of the scale items). Each item was a statement of the organization management. Employees were asked to make judgments on the extent to which they agree or disagree with these statements (1 = Strongly Agree, 2 = Agree, 3 = Neither Agree Nor Disagree, 4 = Disagree, 5 = Strongly Disagree, 6 = Don't Know/Not Applicable). The reliability of the whole scale across years was $\alpha = .87$ ($\alpha_{Year4} = .86$, $\alpha_{Year5} = .89$, and $\alpha_{Year6} = .87$). The reliabilities of these four scales over years were $\alpha_{D1} = .75$ ($\alpha_{Year4} = .71$, $\alpha_{Year5} = .79$, and $\alpha_{Year6} = .73$), $\alpha_{D2} = .71$ ($\alpha_{Year4} = .61$, $\alpha_{Year5} = .77$, and $\alpha_{Year6} = .72$), $\alpha_{D3} = .85$ ($\alpha_{Year4} = .82$, $\alpha_{Year5} = .88$, and $\alpha_{Year6} = .83$), and $\alpha_{D4} = .84$ ($\alpha_{Year4} = .83$, $\alpha_{Year5} = .87$, and $\alpha_{Year6} = .82$). Respondents indicated employees' attitudes towards their organization in terms of its operation, administration, values, and working environments.

Employee job satisfaction. Besides employees' attitudes towards the organization, employees' job satisfaction was also included in the measurement. It

was a single item at the end of the survey: “Considering everything, how would you rate your overall satisfaction in the Company at the present time?” It was a 5-point Likert item ranging from 1 (Very satisfied) to 5 (Very Dissatisfied).

Employee intention to quit. In addition, overall *intention to quit* was measure by a question on “expect to continue working for the organization” on 6 point scale (1 = Less than 1 year, 2 = 1-3 years, 3 = 3-5 years, 4 = 5-10 years, 5 = 10 years, and 6 = Until Retirement). The list of the statements used to measure job attitudes are presented in Appendix A.

Unemployment rate. Local unemployment rate was also included in the present study because it is an important external economic indicator. Local unemployment rate was obtained from the annual Local Area Unemployment Statistics reported by the Bureau of Labor Statistics (BLS). Based on the zip codes of employees’ home addresses, the unemployment rates at the zip-code level were assigned to each employee. The average local unemployment rate was 4.25% (SD = 1.73).

Local household income. Local household income was obtained from the annual Income report by the U.S. Census Bureau. The local household income was linked to each employee by the zip code of the employee’s home address. The average local household income was \$55,312 (SD = \$12,220).

Data Analyses

In the present study, different types of variables were included into one calculation process. The effects of the variables associated with dependent variables could be influenced by the different quantitative unit they have. In order

to facilitate the comparison of the comparative association or prediction strength across different variables, all continuous variables, except categorical ones, were standardized at the variable level before conducting the analyses.

Confirmatory factor analyses. All constructs measured by survey scales (e.g., employee job attitudes) were subject to confirmatory factor analysis (CFA) to verify the dimensionality of each measure. After specifying a priori factor structures, CFA matches the observed and theoretical factor structures for a given data set to determine whether the theoretical structure “fits” the observed data (Long, 1983).

In the present study, the factor structure for all constructs measured through multiple items was assessed to verify that a) hypothesized number of dimensions were obtained and b) the stability of the factor structure was maintained over time. More specifically, the job attitudes were hypothesized to measure four subfactors. Each factor consisted of 3 to 5 survey items. Figure 6 contains the conceptual model for the job attitudes construct that was tested.

As stated previously, the fit statistic of CFA results test how well the conceptual models fit the data. Four fit statistical indicators were used to assess the empirical support for the hypothesized models. The first indicator used here was the chi square goodness of fit statistic. The chi square statistic tests the null hypothesis that there is no statistically significant difference in the observed and theoretical covariance structure matrices. The chi-square statistic has been referred to as a "lack of index fit" (Mulaik, James, Van Alstine, Bennet, Lind & Stilwell, 1989) because a statistically significant result yields a rejection of the fit

of a given model. Unfortunately, the chi-square statistic is very sensitive to sample size, rendering it unclear in many situations whether the statistical significance of the chi square statistic is due to poor fit of the model or to the size of the sample. This uncertainty has led to the development of many other statistics to assess overall model fit (Stevens, 1996).

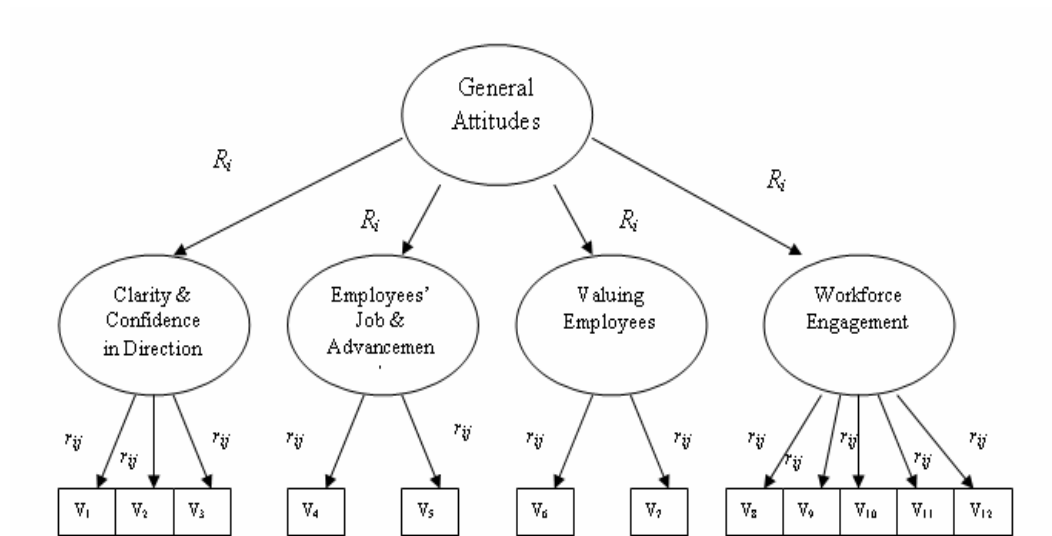


Figure 6. Factor structure of employees' attitudes towards the organization

Another popular way to evaluate the model fit was the so-called fit indexes, such as comparative fit index (CFI) (Bentler, 1990). The fit indexes are the measure of the relative amount of variances and covariances explained by the model (Joreskog & Sorbom, 1986). This index can be thought of as being roughly analogous to the multiple R squared in regular regressions. The closer the CFI is to 1.00, the better is the fit of the model to the data. CFI is less sensitive to sample

size than the chi square statistic. The CFI above .90 is considered good (Hu & Bentler, 1999).

Root mean square error of approximation (RMSEA) was also used in the present study to evaluate the model fit. According to Hu and Bentler (1999), good models have an RMSEA of .05 or less. Models whose RMSEA is .10 or more have poor fit. Proc Calis function of SAS program was used to apply CFA to analyze the data. Further details of the Proc Calis CFA models used in the present study are provided in Appendix B.

Survival analyses. Survival analyses were used in the present study to answer two questions: a) what are the characteristics of people that leave the organization, and b) for those who leave, when do they exit. In survival analyses, a hazard function is the main dependent variable. The hazard function showing the probability of individuals with certain characteristics would leave the organization as a function of time t (Dickter et al., 1996; Morita et al., 1993; Singer & Willett, 2003). That is, survival analysis can provide an estimate of the probability that employees with a particular set of characteristics would leave the organization at a specific time point.

Two indices were calculated to provide an understanding of how employee turnover probability changes over time. The first index was the survival function over the six year study period. As discussed previously, the survival function refers to the ratio of people staying with the organization at time t over the number of people who stayed at time $t-1$. Thus, the survival function illustrates the relationship between time and survival function: $S^{\wedge}(t)$. The survival

curve provides a visual illustration of the relationship between time and survival probability. The second index was the hazard function and how it changed over the six year period. The hazard function is the inverse of the survival curve and it shows the relationship between time and the probability of turnover: $\hat{h}(t)$.

Besides providing these two indices of turnover, another primary value of survival analysis is that it evaluates the relationship between the survival or hazard functions and other theoretically relevant variables. This function is especially valuable when it is used to assess the relationship of explanatory variables to survival duration. Two approaches can be applied to examine this relationship. The first approach is to compare the survival or hazard curves for individuals classified by certain variables. If the curves of different groups shape differently, we say there is a relationship between survival time and the category variable. For example, Mowday and Lee (1986) compared the survival functions between cadets having high commitment and those having low commitment. The second approach applies some form of mathematical modeling, such as the Cox proportional hazard (PH) approach, to estimate the significant of the relationship. The Cox PH model provides *hazard ratios* to quantitatively evaluate the influence of explanatory variables on survival function. Hazard ratios in survival analysis were similar to regression coefficients in linear regression or odds ratios in logistic regression, which could also be understood as the percentage difference in turnover risk associated with a one-unit difference in the value of the predictor (Singer & Willett, 2003). A formula can be used to demonstrate this association: $100 * (\text{hazard ratio} - 1)$. For example, when the hazard ratio for age = 1.0 then the

risk of leaving does not change with the change of age. If the hazard ratio for age = 1.20, then a one unit increase in age results in a 20% increase in risk of leaving. If the hazard ratio for age = 0.75, then a one unit increase in age results in a 25% decrease in risk of leaving. Proc PHREG function of SAS program was used to apply survival analysis on the data. Further details of the specification SAS program used to conduct the survival analyses in the present study are provided in Appendix C.

Latent growth modeling. Among all the independent variables, some variables are constant over time, such as gender. Some variables are changing with time but are treated as static variables, because: a) the changing is constant for every individual, such as age, or b) the changing was not considered sensitive with time, such as promotion. The other variables, such as employees' compensation, job performance, job attitudes, local unemployment rate, and local household income, were treated as dynamic variables. That is, the changing patterns of these variables over time were taken in account when these variables were used to predict turnover behaviors. Latent growth modeling (LGM) was used in the present study to examine the patterns of change for all the dynamic variables over time. As discussed previously, in the present study, LGM were applied to understand two critical questions related to the dynamic turnover predictors: a) the form of the intra-individual change trajectories, b) the systematic inter-individual differences in the intra-individual change trajectories. Mathematically, two parameter estimates, γ_{00} and γ_{10} , can be used to answer these questions. Here, γ_{00} indicates whether employees have different initial status (or

intercept) on their turnover predictors. And, γ_{10} indicates whether employees have different change rate (or slope) on their turnover predictors. If both γ_{00} and γ_{10} are significant for a dynamic variable, we can say that the change trajectories of this variable vary from person to person.

LGM can also be applied to answer another important question related to the relationship between dynamic predictors and turnover. That is, LGM can be used to evaluate whether predicting variables' changing trajectories are related to turnover decision. LGM estimates two parameters, γ_{01} and γ_{11} , to evaluate the impact of dynamic predictors on turnover behaviors. The first parameter indicates the initial status of predicting variables that leavers have. The second parameter indicates the changing rate of turnover predictors that leavers have. If both γ_{01} and γ_{11} are significant, we can say that leavers have different change trajectories of turnover predictors from people who stay with organization. Proc Mixed function of SAS program was used to apply LGM to analyze the data. Further details of the specification SAS program used to conduct LGM analyses for the present study are provided in Appendix D.

Results

Descriptive Statistics

The descriptive statistics for the independent variables across time are presented in Table 2. The correlation matrix showing the relationships between variables from year 1 to year 6 are shown in Table 3. Due to the large sample size (average n across time = 47,836) in the present study, a large number of the correlations were statistically significant even when the magnitude of these coefficients were small. The results in Table 4 suggested high reliability of the measurement of all the variables over time. The range of correlations among same measurements across years was (0.30, 0.43) ($p < .0001$). The range of alpha of the measurements across years was (0.61, 0.89).

The results also indicated that the correlation patterns between variables were similar across time. Involuntary turnover was found to be correlated with employees' attitudes towards the organization, their job performance, and their annual pay rates. The correlations between employees' job attitudes towards the organization and voluntary turnover across years were Year 4 = $-.19$ ($p < .001$), Year 5 = $-.18$ ($p < .001$), and Year 6 = $-.25$ ($p < .001$). The average correlation between employees' job performance and voluntary turnover across years was $-.06$ ($p < .001$), ranging from $-.05$ ($p < .001$) to $-.07$ ($p < .001$). The average correlation between employees' annual pay rate and voluntary turnover across years was $-.08$, ranging from $-.05$ ($p < .001$) to $-.13$ ($p < .001$). The involuntary turnover predictors were also found to be associated with each other. For example, the average correlation among employees' attitudes towards the organization, their

performance ratings, and their annual pay rate across years were all significant at .001 level, ranging from .15 ($p < .001$) to .17 ($p < .001$). Additionally, local unemployment rate was found to be negatively correlated with local household income.

Confirmatory Factor Analysis (CFA) Results

Employees' Attitudes towards the Organization. CFA was applied to evaluate the construct validity of employees' attitudes measure over time. As demonstrated by Figure 6, the measurement model of employee attitudes indicated the 14 job attitude statements loaded on four specific job attitude factors: "clarity & confidence in direction", "job and advancement", "valuing employees", "workforce engagement". In Figure 6, the magnitudes of the loadings were represented by parameters, r_{ij} where the subscript i refers to a particular latent factor and subscript j refers to a particular item. These four job attitude factors were hypothesized to load on an overall second order latent factor, *employee overall attitudes*. The magnitude of the connections between the general attitude factor and the four specific attitude factors were indicated by R_i .

Before evaluating the validity of the overall secondary-factor model, the CFA was first used to test the validity of the four subscales of the overall model. The CFA results indicated that, except the subscale on "job and advancement" (CFI = .75, RMSEA = .25), all the other three subscales yielded a robust validity over time (see Table 4). Specifically, the CFI and RMSEA for subscale on "clarity & confidence in direction" were .99 and .05; the CFI and RMSEA for subscale on "valuing employees" were 1.00 and .02; and the CFI and RMSEA for

Table 2. Independent Variables Descriptive Statistics over Time – Continuous Variables

	Year 1		Year 2		Year 3		Year 4		Year 5		Year 6	
Continuous Variables	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Age	37.8	56.6	37.5	65.6	38.0	39.5	38.1	39.7	39.2	35.2	39.3	34.0
Tenure	4.46	5.53	4.21	5.46	4.26	5.41	4.43	5.48	4.80	5.60	5.10	5.70
Performance Rating*	2.23	0.51	2.26	0.51	2.18	0.52	2.18	0.54	2.19	0.53	2.12	0.55
Annual Pay Rate	\$42,473	77,690	\$43,239	71,061	\$42,384	56,233	\$43,526	31,556	\$46,639	33,088	\$49,245	34,455
Employee Attitudes	-	-	-	-	-	-	1.26	1.39	1.26	1.28	1.60	1.39
Job satisfaction	-	-	-	-	-	-	2.36	0.93	2.34	0.91	2.42	0.94
Intention to quit	-	-	-	-	-	-	1.87	2.28	2.06	2.31	2.36	2.30
Local unemployment rate	3.11	1.52	3.12	1.37	3.71	1.36	4.93	1.64	4.84	1.65	4.55	1.54
Local household income	\$53,747	\$12,284	\$53,451	\$12,180	\$53,213	\$12,203	\$53,343	\$12,380	\$53,920	\$12,672	\$54,554	\$12,653
Categorical Variables	Percent		Percent		Percent		Percent		Percent		Percent	
Gender – Female	77%		77%		76%		75%		74%		74%	
Promotion	9%		11%		6%		7%		7%		6%	
Performance Rating – E	27%		30%		24%		25%		25%		28%	
Performance Rating – M	69%		67%		70%		68%		69%		65%	
Performance Rating – N	4%		3%		6%		7%		6%		7%	

* Performance Rating: “Needs improvement” coded as “1”, “Meets expectations” coded as “2”, and “Exceeds expectations” coded as “3”

Table 3. Variables Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Gender	1.00																			
2. Age	-0.02	1.00																		
3. Voluntary Turnover Y1	-0.01	-0.02	1.00																	
4. Voluntary Turnover Y2	0.00	-0.03	0.12	1.00																
5. Voluntary Turnover Y3	-0.02	-0.02	0.12	0.11	1.00															
6. Voluntary Turnover Y4	-0.02	0.00	0.13	0.12	0.14	1.00														
7. Voluntary Turnover Y5	-0.02	0.03	0.13	0.13	0.14	0.17	1.00													
8. Voluntary Turnover Y6	-0.01	0.04	0.10	0.12	0.12	0.15	0.14	1.00												
9. Performance Rating Y1	0.02	0.01	-0.05	-0.03	-0.02	0.00	0.02	0.02	1.00											
10. Performance Rating Y2	0.02	0.00	-0.01	-0.06	-0.03	-0.01	0.00	0.02	0.63	1.00										
11. Performance Rating Y3	0.00	0.01	0.00	0.00	-0.07	-0.04	0.01	0.00	0.26	0.37	1.00									
12. Performance Rating Y4	0.00	0.01	-0.01	0.01	0.00	-0.06	-0.03	-0.01	0.19	0.22	0.41	1.00								
13. Performance Rating Y5	0.00	0.00	0.01	0.01	0.01	0.00	-0.05	-0.03	0.15	0.17	0.22	0.41	1.00							
14. Performance Rating Y6	0.00	-0.01	0.02	0.02	0.01	0.00	0.01	-0.06	0.15	0.17	0.20	0.26	0.42	1.00						
15. Pay Y1	0.11	0.00	-0.05	-0.04	-0.02	-0.01	0.01	0.03	0.15	0.15	0.10	0.09	0.09	0.08	1.00					
16. Pay Y2	0.12	0.00	-0.01	-0.03	-0.04	-0.01	0.00	0.03	0.15	0.16	0.12	0.11	0.10	0.09	0.72	1.00				
17. Pay Y3	0.15	0.01	-0.01	-0.02	-0.07	-0.05	-0.02	0.00	0.18	0.17	0.16	0.14	0.11	0.11	0.68	0.95	1.00			
18. Pay Y4	0.28	0.03	-0.02	-0.02	-0.05	-0.13	-0.06	-0.02	0.20	0.19	0.18	0.17	0.14	0.13	0.37	0.57	0.68	1.00		
19. Pay Y5	0.30	0.04	-0.02	0.00	-0.03	-0.05	-0.10	-0.04	0.20	0.19	0.18	0.17	0.15	0.14	0.79	0.78	0.92	0.96	1.00	
20. Pay Y6	0.30	0.04	0.00	0.02	0.00	-0.01	-0.03	-0.08	0.20	0.19	0.18	0.17	0.15	0.17	0.79	0.73	0.88	0.91	0.94	1.00
21. Promotion Y1	0.01	-0.01	-0.07	0.01	0.01	0.00	0.00	0.00	0.12	0.09	0.04	0.05	0.05	0.04	-0.01	-0.01	0.00	0.02	0.03	0.03
22. Promotion Y2	0.01	0.00	-0.02	-0.08	-0.02	0.01	0.02	0.01	0.08	0.14	0.09	0.06	0.05	0.04	-0.03	0.00	0.00	0.02	0.02	0.02
23. Promotion Y3	0.00	-0.01	-0.01	-0.01	-0.06	-0.01	0.02	0.00	0.02	0.05	0.13	0.05	0.04	0.05	-0.03	-0.02	0.00	0.01	0.01	0.02
24. Promotion Y4	0.00	-0.01	-0.01	-0.01	-0.02	-0.06	-0.01	0.00	0.01	0.02	0.06	0.19	0.08	0.05	-0.03	-0.04	-0.03	0.01	0.00	0.00
25. Promotion Y5	0.00	-0.01	0.00	0.01	-0.01	-0.01	-0.05	-0.02	0.02	0.04	0.03	0.10	0.21	0.08	-0.04	-0.04	-0.04	-0.03	0.01	0.01
26. Promotion Y6	0.01	-0.03	0.00	0.00	-0.01	0.00	-0.01	-0.06	0.01	0.02	0.02	0.04	0.07	0.19	-0.03	-0.02	-0.03	-0.03	-0.02	0.02
27. Job Attitudes Y4	-0.01	0.05	0.00	-0.01	-0.05	-0.19	0.04	0.01	0.02	0.02	0.06	0.08	0.01	-0.01	-0.08	-0.05	-0.02	0.03	-0.02	-0.01
28. Job Attitudes Y5	0.02	0.05	-0.01	-0.01	-0.01	-0.04	-0.18	0.00	0.00	0.01	0.02	0.07	0.09	0.03	-0.08	-0.05	-0.03	0.01	0.06	0.02
29. Job Attitudes Y6	-0.01	0.05	0.00	-0.01	-0.01	-0.01	-0.04	-0.25	0.00	0.00	0.01	0.03	0.05	0.07	-0.09	-0.07	-0.06	-0.03	0.00	0.03
30. Unemployment Rate Y1	-0.07	-0.01	0.01	0.01	0.00	0.00	-0.02	-0.02	-0.05	-0.04	-0.03	-0.01	0.01	0.00	0.02	-0.02	-0.04	-0.13	-0.12	-0.14
31. Unemployment Rate Y2	-0.07	0.00	-0.02	0.01	0.01	0.01	-0.01	-0.02	-0.05	-0.05	-0.04	-0.02	0.00	-0.01	0.01	-0.04	-0.06	-0.14	-0.14	-0.16
32. Unemployment Rate Y3	-0.07	-0.01	-0.02	-0.01	0.02	0.01	0.00	-0.02	-0.08	-0.07	-0.05	-0.03	-0.01	-0.02	0.00	-0.05	-0.06	-0.14	-0.14	-0.16
33. Unemployment Rate Y4	-0.05	-0.01	-0.02	-0.01	-0.01	0.03	0.02	-0.01	-0.07	-0.06	-0.03	-0.03	-0.02	-0.03	0.00	-0.05	-0.06	-0.10	-0.10	-0.11
34. Unemployment Rate Y5	-0.04	-0.01	-0.02	-0.01	-0.02	-0.01	0.01	-0.01	-0.05	-0.05	-0.03	-0.02	-0.01	-0.03	-0.08	-0.07	-0.09	-0.08	-0.07	-0.09
35. Unemployment Rate Y6	-0.03	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.06	-0.05	-0.04	-0.02	-0.02	-0.04	-0.10	-0.08	-0.09	-0.09	-0.08	-0.08
36. Household Income Y1	0.09	0.01	0.00	0.03	-0.01	0.00	0.00	0.02	0.06	0.08	0.05	0.04	0.03	0.02	0.06	0.10	0.12	0.26	0.26	0.25
37. Household Income Y2	0.10	0.01	0.01	0.02	-0.04	-0.02	0.00	0.02	0.06	0.08	0.06	0.05	0.04	0.03	0.06	0.10	0.13	0.27	0.27	0.25
38. Household Income Y3	0.09	0.01	0.02	0.02	-0.04	-0.04	-0.01	0.02	0.07	0.08	0.07	0.07	0.05	0.04	0.07	0.12	0.14	0.28	0.28	0.26
39. Household Income Y4	0.10	0.02	0.02	0.03	0.02	-0.05	-0.03	0.01	0.08	0.09	0.08	0.08	0.05	0.04	0.08	0.16	0.19	0.29	0.29	0.26
40. Household Income Y5	0.11	0.02	0.03	0.03	0.02	0.01	-0.04	0.01	0.08	0.10	0.09	0.08	0.05	0.05	0.24	0.23	0.27	0.29	0.29	0.26
41. Household Income Y6	0.10	0.03	0.03	0.04	0.02	0.02	0.02	0.01	0.08	0.09	0.09	0.07	0.04	0.05	0.23	0.22	0.26	0.27	0.27	0.26

Variables	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41
21. Promotion Y1	1.00																				
22. Promotion Y2	0.08	1.00																			
23. Promotion Y3	0.06	0.06	1.00																		
24. Promotion Y4	0.08	0.07	0.03	1.00																	
25. Promotion Y5	0.07	0.07	0.04	0.04	1.00																
26. Promotion Y6	0.03	0.04	0.04	0.03	0.01	1.00															
27. Job Attitudes Y4	0.13	0.15	0.10	0.16	0.11	0.05	1.00														
28. Job Attitudes Y5	0.14	0.16	0.11	0.12	0.16	0.08	0.42	1.00													
29. Job Attitudes Y6	0.09	0.10	0.07	0.08	0.07	0.10	0.30	0.33	1.00												
30. Unemployment Rate Y1	-0.01	-0.01	-0.02	0.00	0.02	-0.01	-0.03	0.02	-0.03	1.00											
31. Unemployment Rate Y2	0.00	0.00	-0.01	0.02	0.02	-0.01	0.01	0.06	0.02	0.94	1.00										
32. Unemployment Rate Y3	0.01	0.01	0.00	0.02	0.03	0.00	0.03	0.08	0.04	0.88	0.92	1.00									
33. Unemployment Rate Y4	0.02	0.02	0.01	0.01	0.02	0.01	0.03	0.08	0.02	0.76	0.76	0.89	1.00								
34. Unemployment Rate Y5	0.03	0.03	0.02	0.02	0.02	0.00	0.07	0.07	0.01	0.77	0.74	0.85	0.93	1.00							
35. Unemployment Rate Y6	0.03	0.03	0.02	0.03	0.03	0.00	0.11	0.11	0.00	0.82	0.81	0.87	0.90	0.93	1.00						
36. Household Income Y1	0.02	0.02	0.01	-0.02	-0.03	0.02	-0.04	-0.05	0.01	-0.55	-0.58	-0.51	-0.40	-0.41	-0.50	1.00					
37. Household Income Y2	0.02	0.03	0.02	-0.03	-0.03	0.02	-0.04	-0.05	0.01	-0.55	-0.57	-0.51	-0.40	-0.41	-0.50	1.00	1.00				
38. Household Income Y3	0.02	0.02	0.02	-0.02	-0.03	0.01	-0.03	-0.05	0.01	-0.54	-0.57	-0.51	-0.39	-0.40	-0.50	1.00	1.00	1.00			
39. Household Income Y4	0.01	0.02	0.02	-0.01	-0.03	0.01	-0.02	-0.04	0.02	-0.55	-0.58	-0.53	-0.38	-0.40	-0.50	1.00	1.00	1.00	1.00		
40. Household Income Y5	0.01	0.01	0.01	-0.03	-0.03	0.01	-0.06	-0.02	0.03	-0.56	-0.59	-0.55	-0.41	-0.40	-0.49	1.00	1.00	1.00	1.00	1.00	
41. Household Income Y6	0.00	-0.01	0.00	-0.04	-0.04	0.01	-0.07	-0.08	0.03	-0.58	-0.61	-0.57	-0.43	-0.43	-0.50	1.00	1.00	1.00	1.00	1.00	1.00

Note. $n = 46587$. Correlations greater than .02 are significant at $p < .05$; correlations greater than .03 are significant at $p < .001$; Correlations greater than .05 are significant at $p < .0001$. Y1 to Y6 refer to Year1 to Year6.

subscale on “workforce engagement” were .96 and .08. Thus, the subscale on “job and advancement” was deleted from the over model, because of its low construct validity over time. The CFA was applied to a three-factor secondary factor model.

The CFA results of the overall model were also shown on Table 4. The correlation matrix for the 10 items was used in this analysis. The results using the unstandardized correlation matrix did not differ substantially from the standardized correlation matrix, thus, only the results using the standardized correlation matrix were reported. A multigroup CFA was used to evaluate the validity of the overall factor model over time.

Although the Chi-square tests for the multigroup secondary three-factor model were significant ($\chi^2 = 13779.69$, $df = 32$, $p < .001$), which indicated a poor fit of the theoretical model. However, The CFI was .90 and RMSEA was .06 for the proposed three-factor model, which suggested that the proposed secondary three-factor model had a acceptable fit for the observed data cross years.

The standardized parameter estimates for the associations between factors and items (R_i and r_{ij}) were also presented in Table 4. As presented on the table, items loadings ranged from .60 to .85. All the loadings were statically significant ($p < .001$). There were also significant associations between secondary factor and lower level factors. The average association between *clarity & confidence in direction* and the secondary factor was .98 ($R_1 = .99, .98, .96$ respectively, $p < .001$). The average association between *valuing employees* and the overall factor was .93, ranging from .88 ($p < .001$) and .98 ($p < .001$). And, the average association between *workforce engagement* and the general factor was .94,

Table 4. Multigroup CFA Results for Employee Attitude Measurements over Time

Overall Model Cross Years			
<i>Goodness-of-Fit Results for the overall model cross years</i>			
$\chi^2(df)$	13779.69(32)***		
CFI	.90		
RMSEA	.06		
<i>Standardized estimates of associations for each year</i>	Year 4	Year 5	Year 6
R_1 : Clarity & Confidence in Direction	0.99***	0.98***	0.96***
R_2 : Valuing Employees	0.88***	0.92***	0.98***
R_3 : Workforce Engagement	0.92***	0.97***	0.94***
Factor 1: Clarity & Confidence in Direction			
<i>Goodness-of-Fit Results for this factor</i>			
$\chi^2(df)$	538.08(8)***		
CFI	0.99		
RMSEA	0.05		
<i>Standardized estimates of associations for each year</i>	Year 4	Year 5	Year 6
- The company has a clear sense of direction	0.70***	0.74***	0.71***
- The changes of the company make us a better company.	0.65***	0.70***	0.68***
- Senior management's actions consistent with their words.	0.68***	0.79***	0.69***
Factor 2: Valuing Employees			
<i>Goodness-of-Fit Results for this factor</i>			
$\chi^2(df)$	7.66(1)**		
CFI	1.00		
RMSEA	0.02		
<i>Standardized estimates of associations for each year</i>	Year 4	Year 5	Year 6
- Senior management demonstrates that employees are important to the success of the business.	0.86***	0.85***	0.78**
- The company takes a genuine interest in the well-being of its employees.	0.80***	0.77***	0.70***
Factor 2: Workforce Engagement			
<i>Goodness-of-Fit Results for this factor</i>			
$\chi^2(df)$	5249.288(31)***		
CFI	0.96		
RMSEA	0.08		
<i>Standardized estimates of associations for each year</i>	Year 4	Year 5	Year 6
- Overall, the company is an effectively managed, well-run business.	0.60***	0.72***	0.60***
- I feel proud to work for the company.	0.83***	0.87***	0.82***
- Overall, the company is a good place to work, compared to other organizations I know about.	0.73***	0.79***	0.71***
- I am enthusiastic about my future with the company as a place to work and develop my skills.	0.75***	0.79***	0.76***
- My work gives me a feeling of personal accomplishment.	0.60***	0.60***	0.60***

Note. *** $p < .001$, ** $p < .01$.

CFI: Bentler's Comparative Fit Index.

RMSEA: Root Mean Square Error of Approximation.

ranging from .92 ($p < .001$) and .97 ($p < .001$). Additionally, the standardized model parameter estimates indicated that the magnitudes of the links within the conceptual model held stable over time.

Overall, the CFA results provided support for the job attitude measurement model. The measurement on employees' attitudes towards the organization had strong construct validity and its validity was stable across time. Thus, the employee attitudes data, which would be used in further analyses, were valid.

Survival Analysis Results

Prior to presenting the results of the survival analysis, it is important for the reader to remember two critical issues about survival analysis. First, as discussed in the introduction section of this dissertation, I examined the predictive power of 11 variables in this study. I used univariate survival models to examine the effect of each variable on employment duration. Secondly, there were two options to include participants in the survival analysis. The first way was only including employees hired during the six-year study period in the survival analysis. While this sample provided an accurate estimate of the relationship between predictors and turnover for the six-year study period, information from employees with employment duration greater than 6 years was systematically ignored in this sample. The second option was including all the employees and allowed an evaluation of the relationship between the predictors and employee duration for a greater range of employment duration data (time > 6 years). It should be noted, however, that the survival function and hazard function estimates

based on this second sample were biased, because it does not include employees who left the organization before the study period. Thus, to have a more accurate estimation of the survival and hazard function, the present study only included employees hired during the six-year study period. The results from the univariate survival analyses were presented in Table 6. Interpretation and explanation of the results were addressed in the following section.

As presented on Table 5, the first column was the estimated parameters for the associations between predictors and turnover risk. The second and their columns demonstrated the significant levels of the association: Standard error and Chi-square. The last column was hazard ratio, representing the percentage difference in turnover risk associated with a one-unit difference in the value of the predictor. The results shown on Table 6 suggested that there were significant association between all the predictors and employment duration ($p < .0001$). Among the predicting variables, age, employee attitudes towards the organization, employee annual pay rates, promotion, and their intention to quit and job satisfaction had strong impacts on turnover risk. There were a significant but moderate association between employees' employment duration and their performance ratings, their gender, and their local economical conditions.

Hypothesis 1a. As discussed previously, hypothesis 1a predicted that female employees will be more like to leave the organization than male employees. The results of the univariate survival analysis supported hypothesis 1a. The univariate survival model for gender and turnover examined the survival functions and the hazard functions. The estimate parameter for the relationship

Table 5. Univariate Survival Models Predicting Employment Duration

	Parameter Estimate	Standard Error	Chi-Square	Hazard Ratio
Gender	-0.10	0.01	55.38***	0.90
Age	-2.08	0.03	5958.21***	0.12
Performance Rating	-0.34	0.02	568.01***	0.71
Annual Pay Rate	-0.97	0.02	3237.41***	0.38
Promotion	-0.81	0.01	3101.22***	0.44
Employee Attitudes	-1.06	0.01	9523.20***	0.35
Job Satisfaction	-0.43	0.02	457.21***	0.47
Intention to Quit	1.47	0.02	7277.71***	1.77
Local Unemployment Rate	-0.13	0.01	975.61***	0.88
Local Household Income	-0.10	0.01	215.06***	0.90

Note. All the continuous predictors were standardized prior to analysis. *** $p < .0001$. All the variables were standardized before conducting the survival analyses.

between gender and turnover was $-.10$ ($\chi^2(1) = 55.38; p < .0001$). The result indicated that, with only this single predictor in the survival model, there was a substantial impact of gender on turnover risk. Since female was coded as 1 and male was coded as 2, the results show females were more likely to quit than males. The hazard ratio of gender based on the new-hiring sample was .90. Specifically, the turnover risk for females was 10 % higher than for males (see Figure 7 and Figure 8).

Figures 7 and 8 show that, males had a higher survival rate and lower hazard rate than females over the 6 year study period. More specifically, from Figure 7, we can also see that 50% of males quit after 4 years whereas 50% of females quit over 5 years. From Figure 8, we can see that employees face the highest turnover risk during their first three years in the organization. Thus, the hypothesis 1a was supported by the survival analysis results.

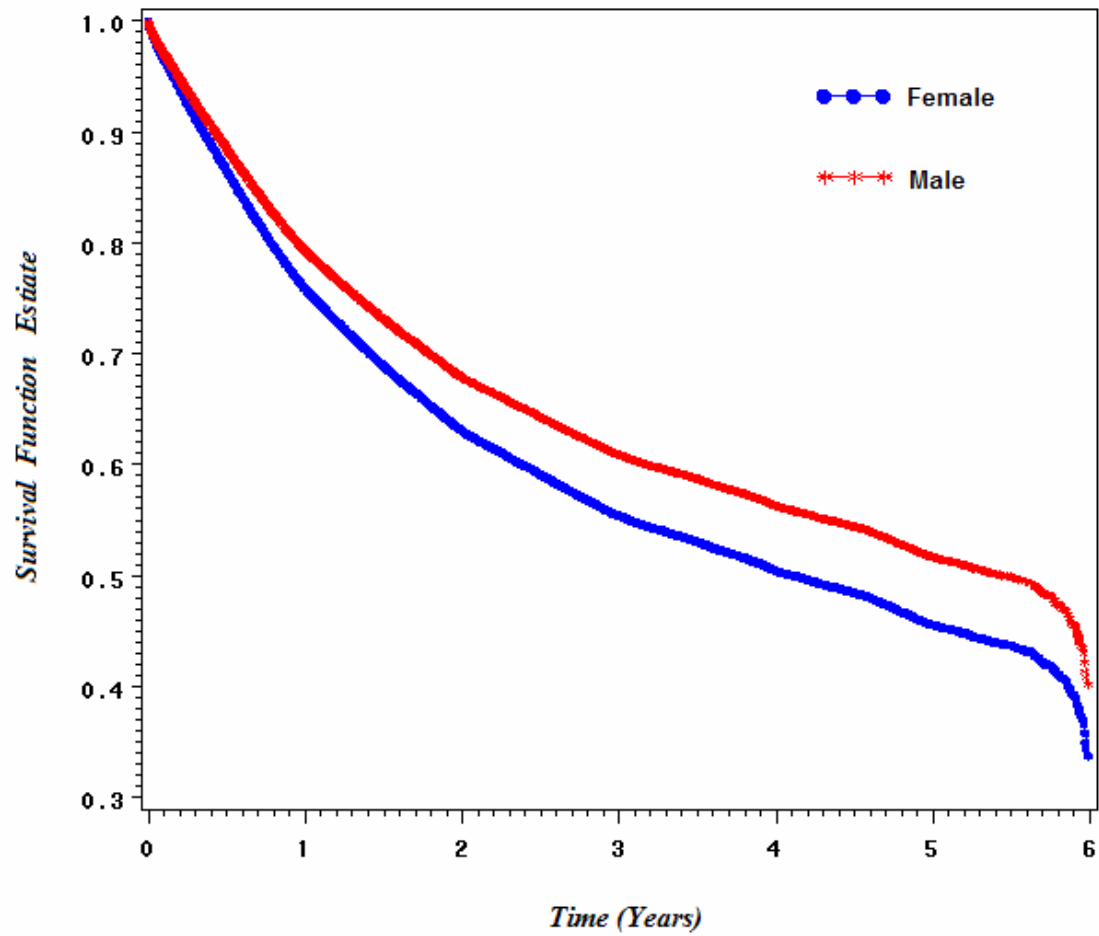


Figure 7. Univariate survival function estimate by gender

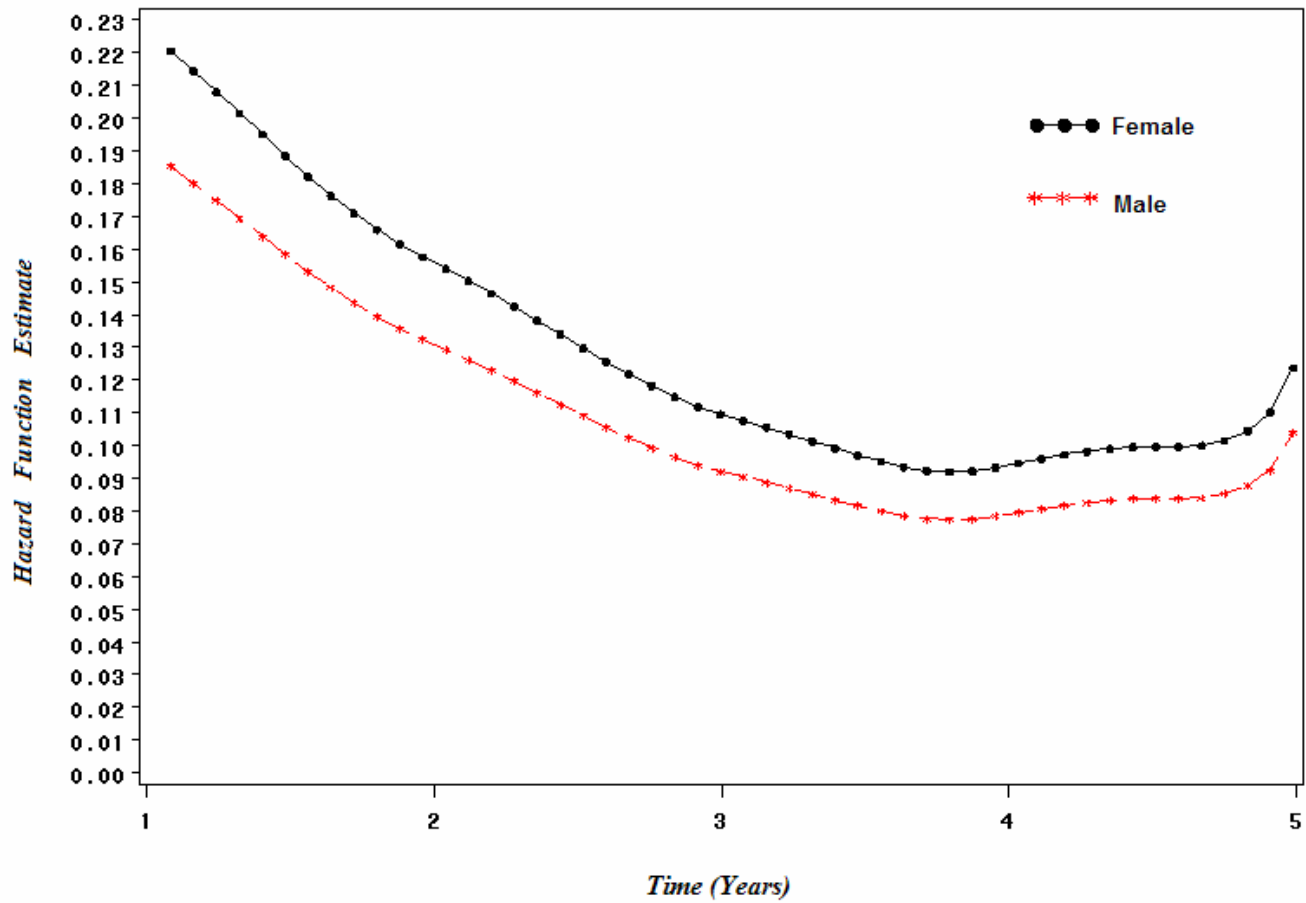


Figure 8. Univariate hazard function estimate by gender

Hypothesis 1b. As addressed previously, hypothesis 1b predicted that older employees will be less likely to quit than younger employees. The results of the univariate survival analysis supported this hypothesis. Although employee age is changing over the length of the study period, I treated age as a static variable by only using employee's age at hire. Since the rate of change in age is a constant for employees in my study, the rate of change in age provides no meaningful explanatory variance in the survival analysis. Thus, the only meaningful age difference between employees was the age at hire.

With age as the only predictor in the survival model, a significant negative relationship between age and employee turnover was found. The estimate parameter for the relationship between age and turnover was -2.08 ($\chi^2(1) = 5958.21; p < .0001$). The hazard ratios were $.12$. In other words, a one standardized deviation increase in age resulted in an 88% decrease in turnover risk.

To further demonstrate the differences between employees of different ages, I categorized age into two levels: younger employees (age < 38) versus older employees (age ≥ 38). The survival and hazard curves for younger employees and older employees are shown in Figure 9 and Figure 10. These figures show that younger employees tend to have a higher turnover risk than do older employees.

As demonstrated on Figure 9, for employees younger than 38 years old, approximately 50% leave the organization after 3.5 years of employment. However, approximately 50% of the employees 38 years or older would not leave

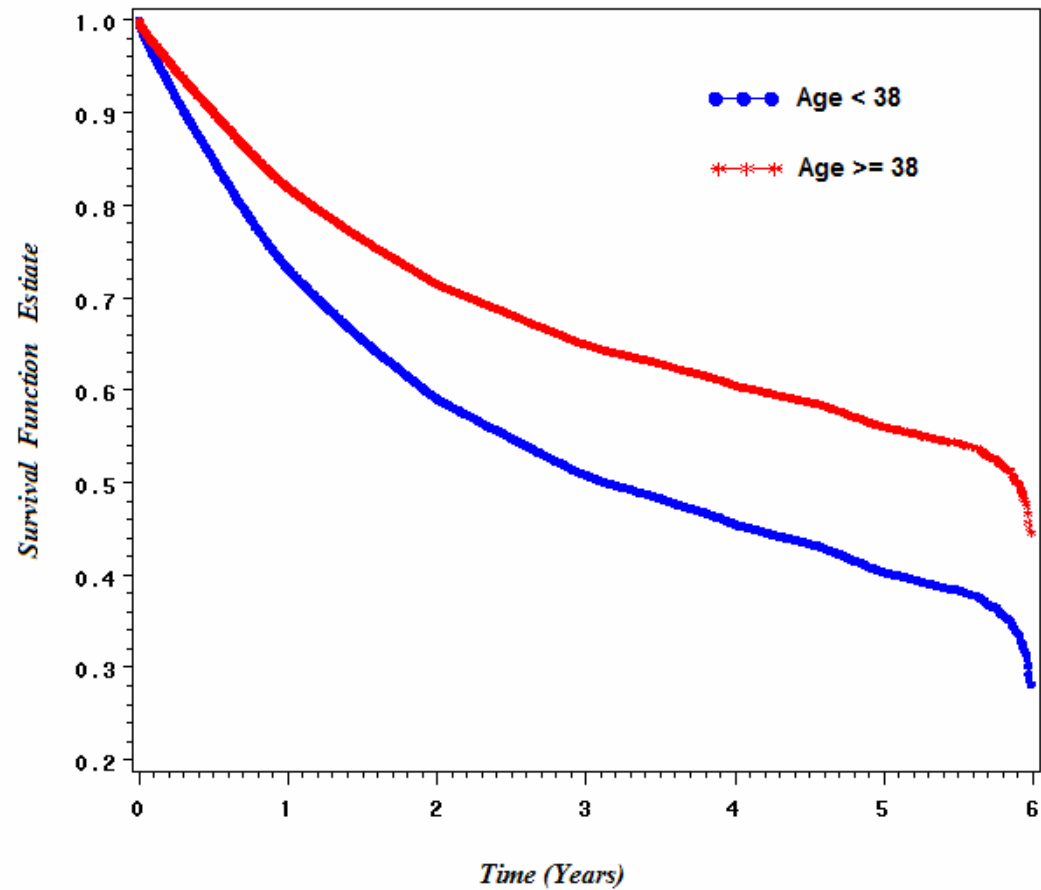


Figure 9. Univariate survival function estimate by age

Note: Employees were split into two groups according to the median age (38 years old): (1) employees older than 38 years and (2) employees younger than 38 years.

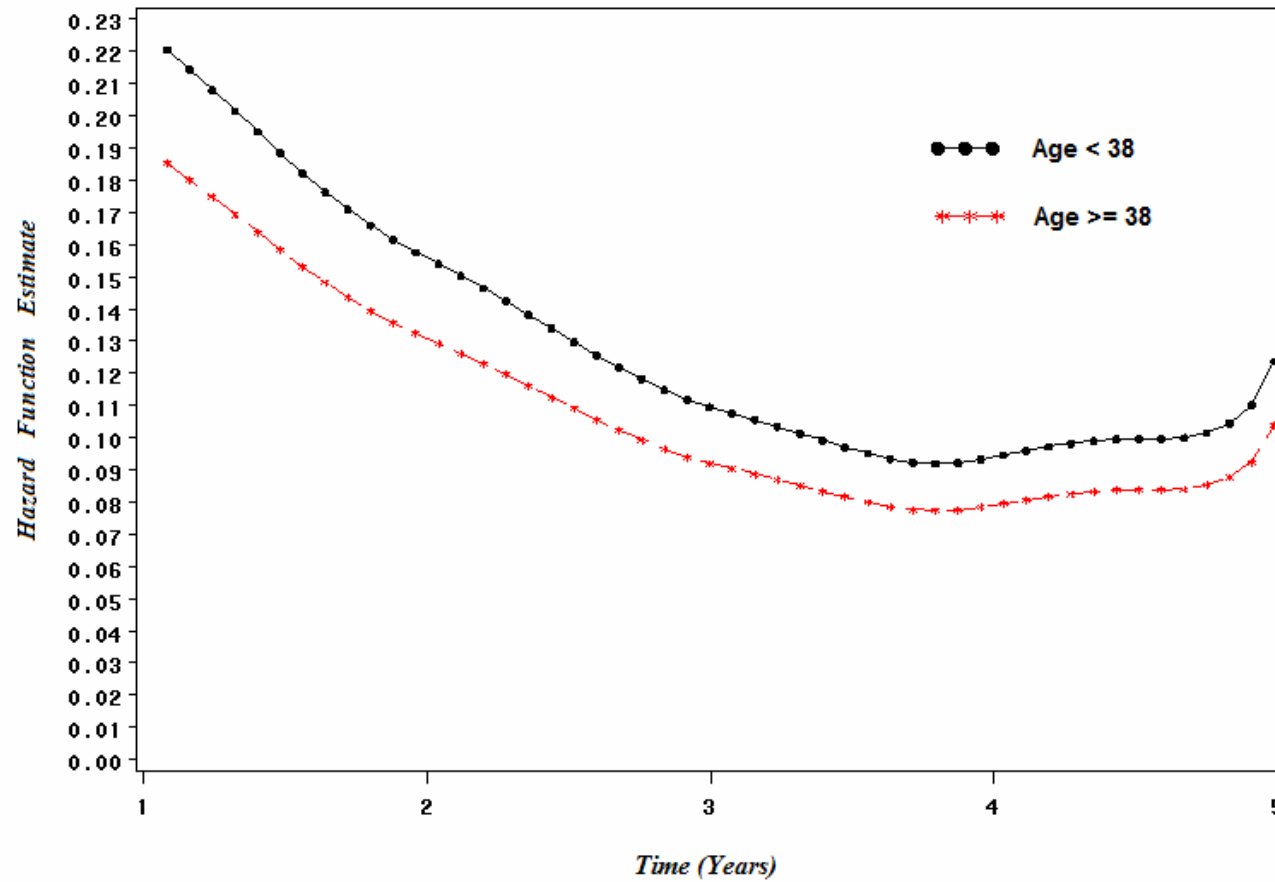


Figure 10. Univariate hazard function estimate by age

Note: Employees were split into two groups according to the median age (38 years old): (1) employees older than 38 years and (2) employees younger than 38 years.

the organization during the six-year study period. It should be noted, although younger employees had a greater likelihood of leaving than did older employees, both groups exhibited the same change pattern in the hazard function across time (see Figure 10). As a conclusion, hypothesis 1b was supported by the results.

Hypothesis 2a. As discussed previously, I performed separate analyses with job performance. In one set of analyses, job performance was treated as a stable trait (i.e., an individual's performance was averaged over time). In the second set of analysis, a latent growth model was applied to determine whether change in job performance corresponded with changes in turnover risk over time. To evaluate hypothesis 2a, the first set of analyses were conducted.

Hypothesis 2a stated that there was a curvi-linear relationship between performance ratings and turnover behaviors. That is, median level performers will have longer tenure than either high or low performers. However, the results did not support the curvi-linear argument. A linear relationship between performance ratings and turnover was found from the results. The estimated parameter for the relationship between age and turnover was -0.34 ($\chi^2(1) = 568.01; p < .0001$). The hazard ratios were .71. In other words, one unit increase in employee job performance ratings results in a 29% decrease in their turnover risk. More specifically, employees rated, on average, as *Needs Improvement* had a 29% higher turnover risk than employees rated, on average, as *Meets Expectations*. *These employees had a 29% higher turnover risk than did employees rated, on average, as Exceeds Expectations*. The survival and hazard curves for employees with different performance ratings were presented in Figure 11 and Figure 12.

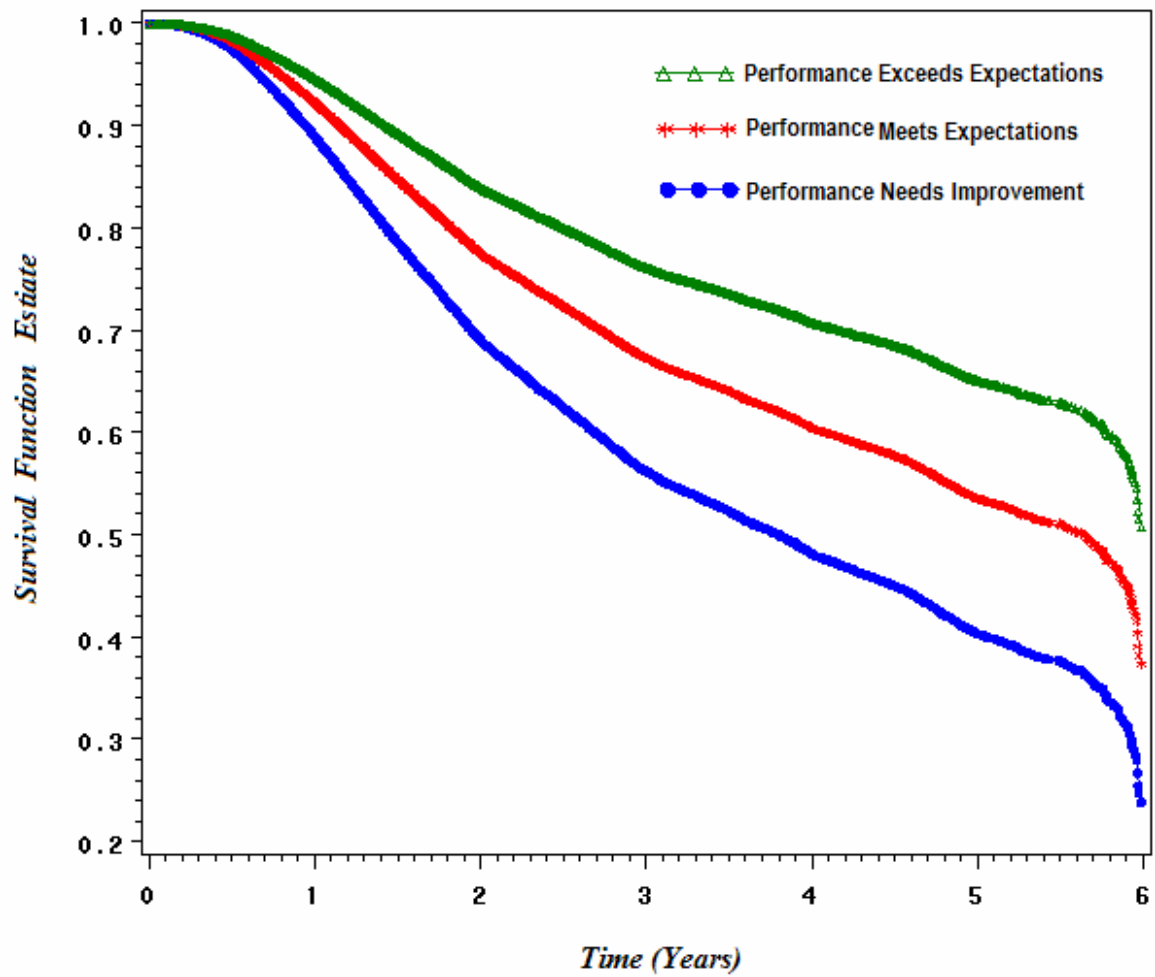


Figure 11. Univariate survival function estimate by performance rating

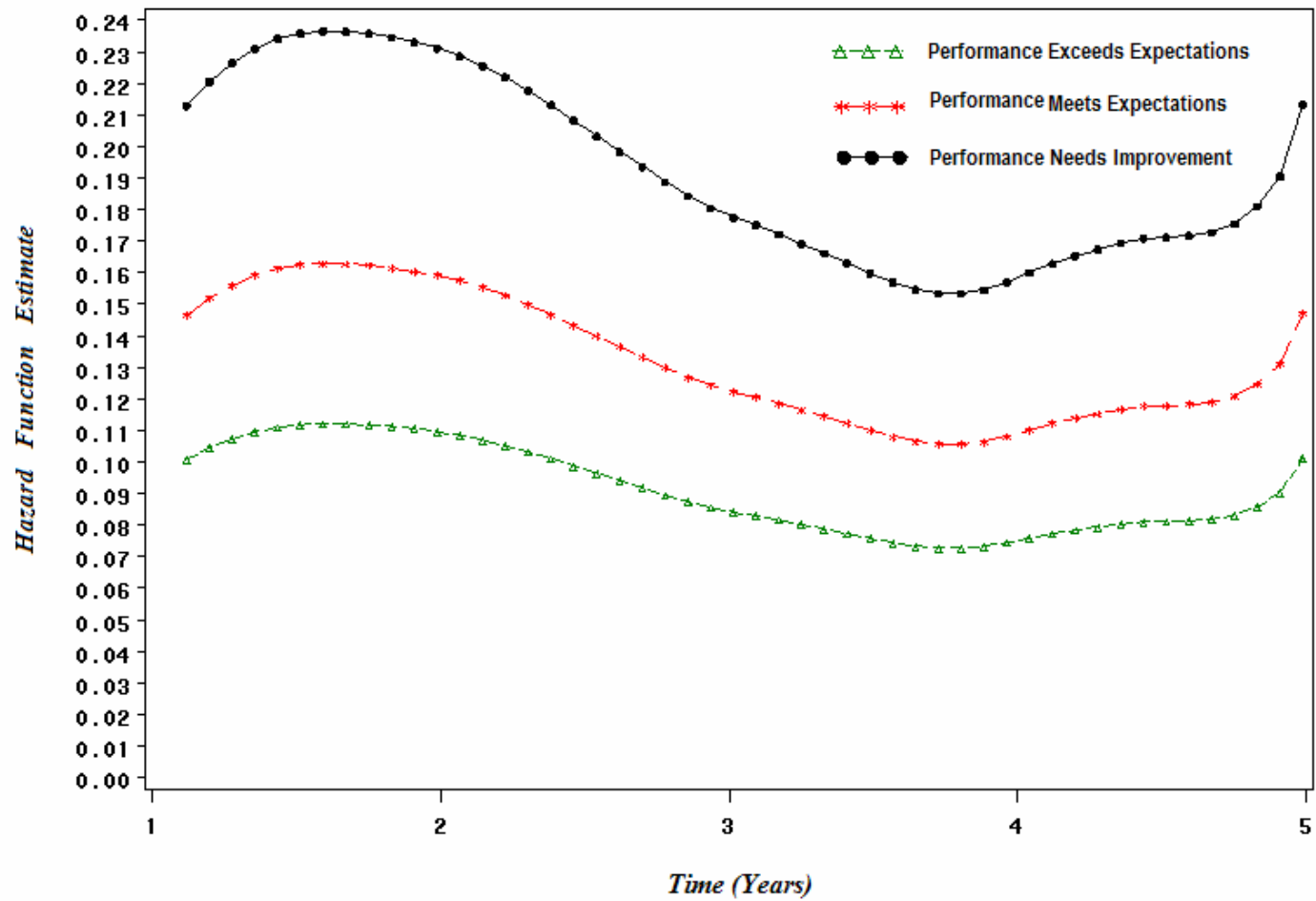


Figure 12. Univariate hazard function estimate by performance rating

The same relationship between performance ratings and turnover risk can be seen in the survival function and the hazard function figures. As demonstrated on Figure 11, approximately 50% of the low performers quit by 3.5 years, whereas approximately 50% of the median performers left the organization by 5.5 years. Finally, approximately 60% of the high performers remained with the organization by the end of the sixth year of the study. As demonstrated on Figure 12, the turnover risk for employees of different performance levels held stable over time. Higher performers always had lower turnover risk than did median or lower level performers. Thus, the hypothesis 2a was not supported by the survival analysis results. A linear, instead of a curvi-linear, relationship between performance ratings and turnover risk was found in the present study.

Hypothesis 3a. Compensation was also treated as a longitudinal variable. Hypothesis 3a focused on the different survival patterns of employees with different pay levels and Hypothesis 3b focused on the relationship between the changing trajectories of compensation and turnover behaviors. Thus, following the approach that I took previously, in the survival analysis, I used the average level of compensation across the study's time period to test hypothesis 3a. In the later analysis – the latent growth modeling analysis, I would test whether change in compensation over the years was related to change in turnover risk.

Hypothesis 3a predicted a negative relationship between employees' annual pay rates and their turnover risk. The results from the univariate model supported this hypothesis. The estimated parameter was $-.97$ ($\chi^2(1) = 3237.41; p < .0001$), which indicated that annual pay rates had significant negative impact on

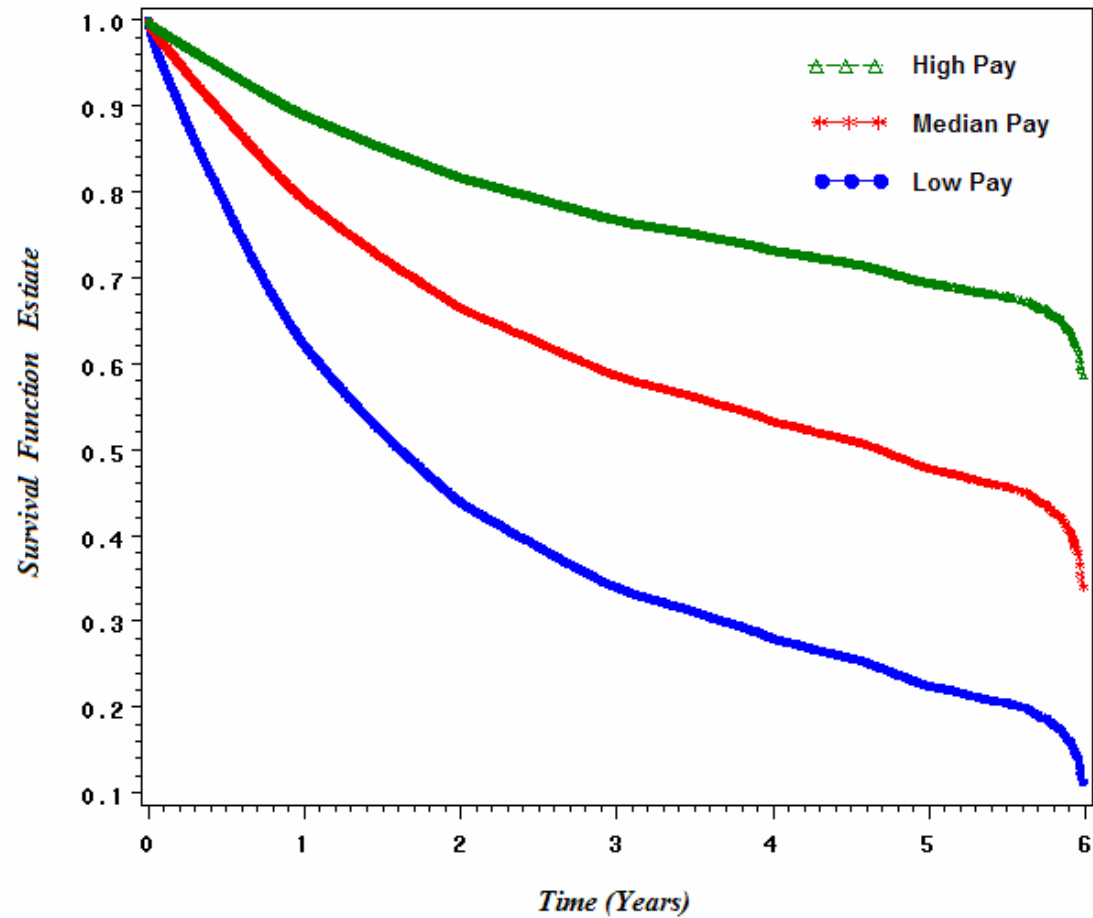


Figure 13. Univariate survival function estimate by compensation level

Note: Employees were split into three groups according to their pay: a) “Employee with High Pay” (Annual pay rate \geq 75 percentile), b) “Employee with Median Pay” (Annual pay rate between 75 percentile and 25 percentile), and c) “Employee with Low Pay” (Annual pay rate \leq 25 percentile).

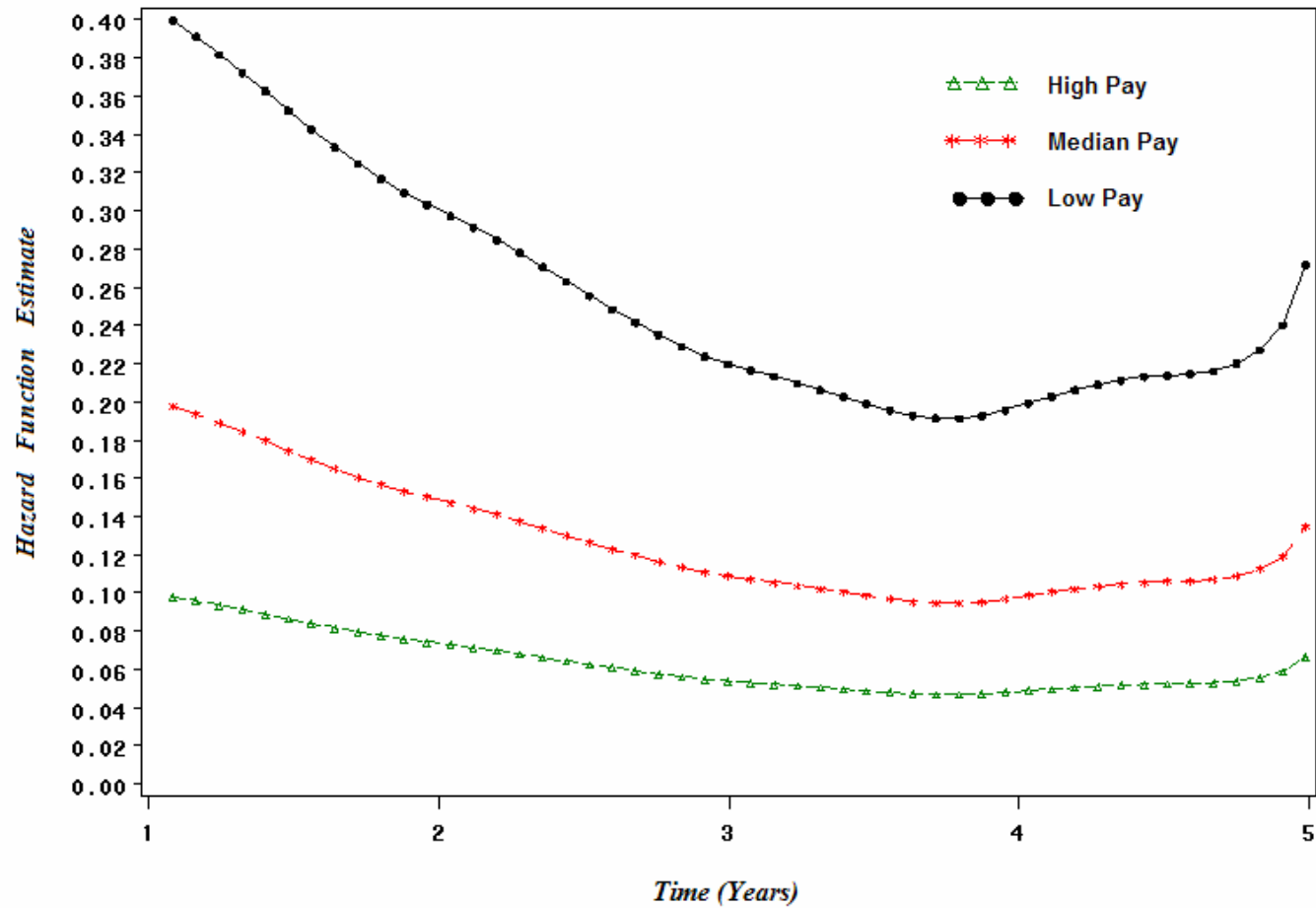


Figure 14. Univariate survival function estimate by compensation level

Note: Employees were split into three groups according to their pay: a) “Employee with High Pay” (Annual pay rate \geq 75 percentile), b) “Employee with Median Pay” (Annual pay rate between 75 percentile and 25 percentile), and c) “Employee with Low Pay” (Annual pay rate \leq 25 percentile).

turnover risk. The hazard ratios were .43. That is, one standardized deviation increase in pay decreased the turnover risk by 50% to 60%. To illustrate the effect of compensation on the survival and hazard function, I trichotomized the data by employee average annual pay. The high pay group was defined as employees in the top quartile of pay. The low pay group was defined as employees in the bottom quartile of pay. The mid-range pay group was defined as employees in the middle two quartiles of pay. The survival and hazard curves for employees with different pay rates were presented on Figure 13 and Figure 14.

As demonstrated on Figure 13, approximately 50% of the low pay group quit after 1.5 years of employment. For the median pay group, 50% quit after 4.5 years. Finally, for the high pay group, only 35% left over the 6 year period of the study. From Figure 14, we could see that the risk of turnover for different performers held stable across the six years. And higher performance always had lower risk to quit than median and low performers. Thus, hypothesis 3a was supported by the results.

Hypothesis 4. Promotion was hypothesized to be related to employment duration. Specifically, promotions would extend employees' employment duration. As discussed previously, the total number of promotions during the six-year study period was used as the value of promotion. The results from univariate survival model indicated a substantial impact of promotion on employment duration. The estimate parameter for the relationship between promotion and turnover risk was -0.81 ($\chi^2 (1) = 3101.22; p < .0001$). The hazard ratios from the

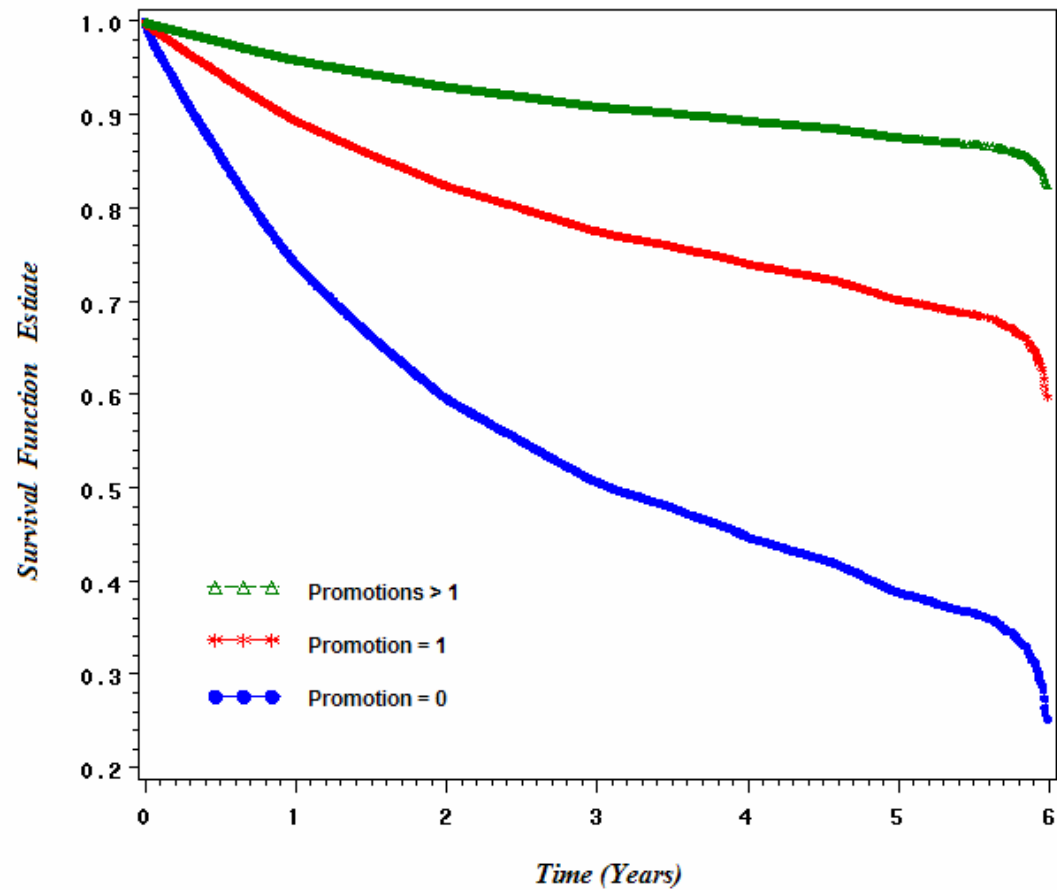


Figure 15. Univariate survival function estimate by promotion

Note: Employees were split into three groups based on the times of promotion in the study period: (1) employees with more than 1 time of promotion, (2) employees with 1 time of promotion, and (3) employees with no promotion.

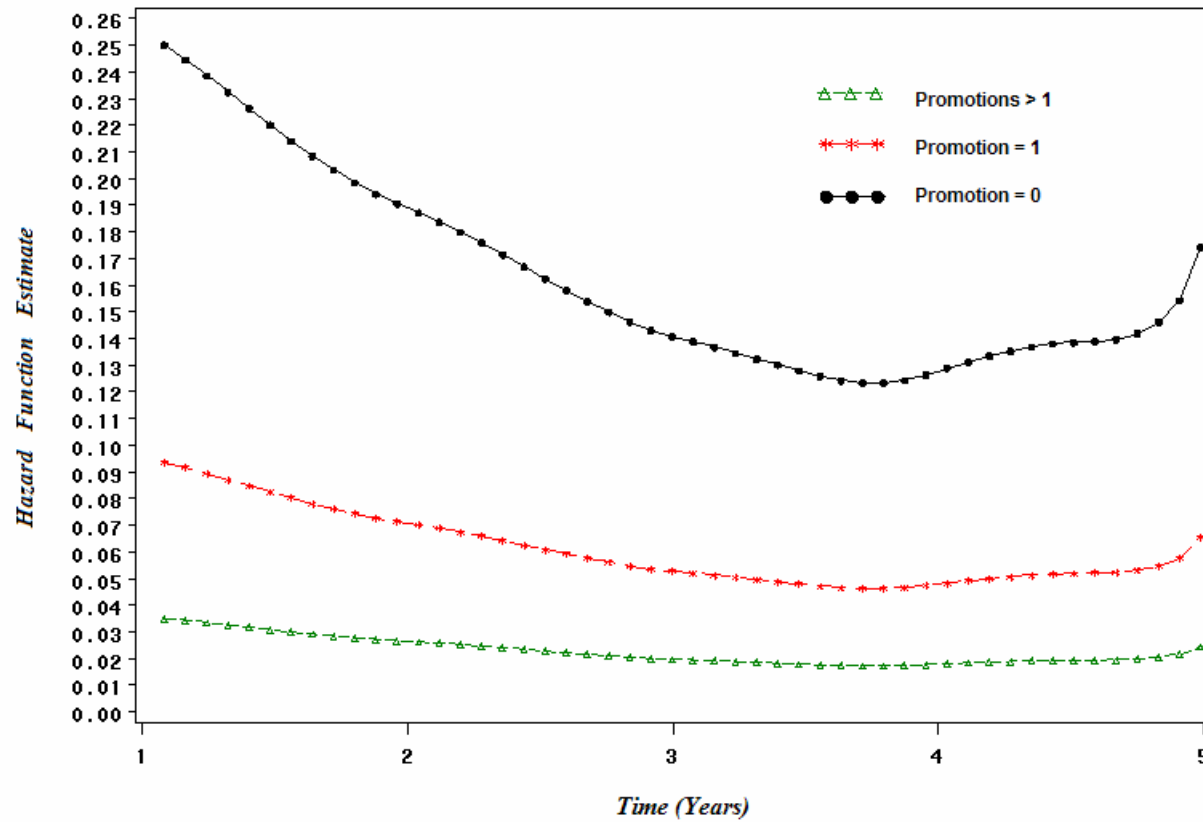


Figure 16. Univariate hazard function estimate by promotion

Note: Employees were split into three groups based on the times of promotion in the study period: (1) employees with more than 1 time of promotion, (2) employees with 1 time of promotion, and (3) employees with no promotion.

univariate model were .44, which indicated that each instant of promotion would reduce employees' turnover risk by about 50% to 60%.

The survival and hazard curves for employees with different promotion rates were presented on Figure 15 to Figure 16. As can be seen in Figure 15, about 50% of the employees who did not have a single promotion during the six-year study period would quit within 3 years of employment. Employees who received at least one promotion stayed with the organization throughout the entire study period. As demonstrated as Figure 16, the hazard function also show that employees without promotion had much higher risk to leave than employees with one time or multiple times of promotion. Overall, the hypothesis 4 was supported.

Hypothesis 5.1a. Employees' attitudes towards the organization were obtained from employee surveys across years in this study. This enabled me to analyze the survey data as a longitudinal variable. Following my procedure, however, I averaged survey scores across years in this initial stage to evaluate hypothesis 5.1.a., because this hypothesis focused on the different survival functions between employees with different attitudes towards the organization.

The results from the univariate survival model indicated that employees' attitudes towards their organization had a significant impact on their employment duration. The estimated parameter between attitudes and turnover risk was -1.06 ($\chi^2(1) = 9523.20; p < .0001$). The hazard ratio from the univariate model was .35, which indicated that one standardized deviation increase in employees' attitudes about their organization resulted in a 65% decrease in their turnover risk.

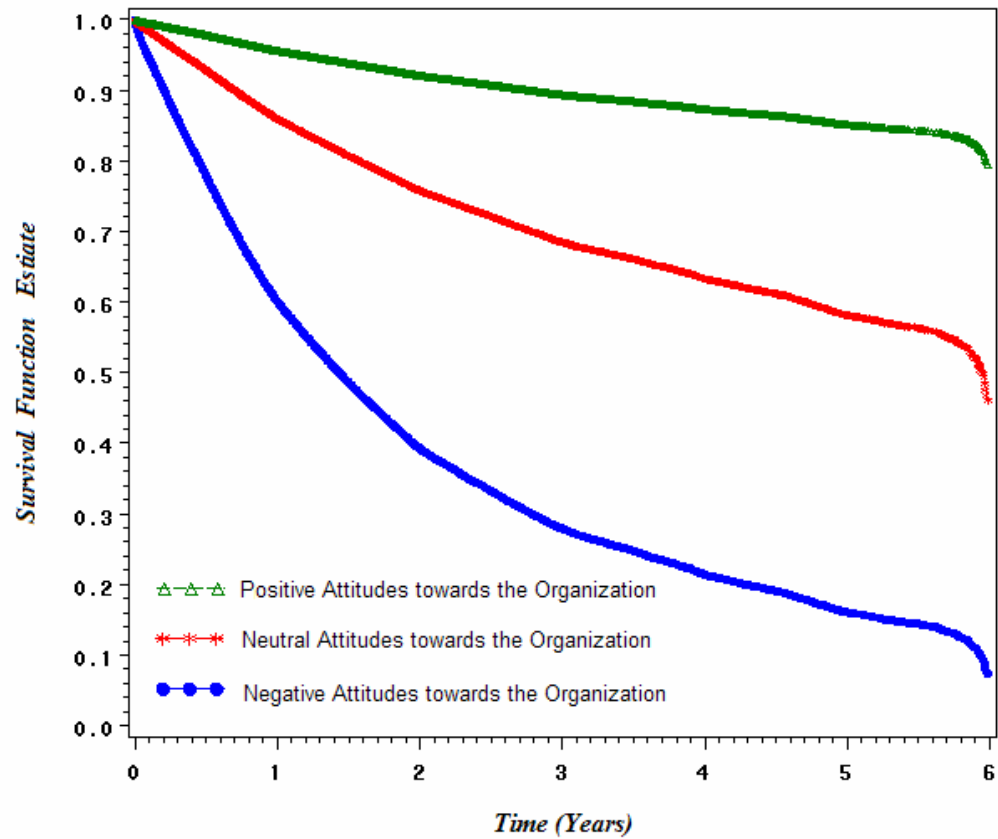


Figure 17. Univariate survival function estimate by employees' attitudes

Note: Employees were split into three groups according to their attitudes: a) "Employee with Positive Attitudes" (Attitudes scores ≥ 75 percentile), b) "Employee with Neutral Attitudes" (Attitudes score between 75 percentile and 25 percentile), and c) "Employee with negative Attitudes" (Attitudes score ≤ 25 percentile).

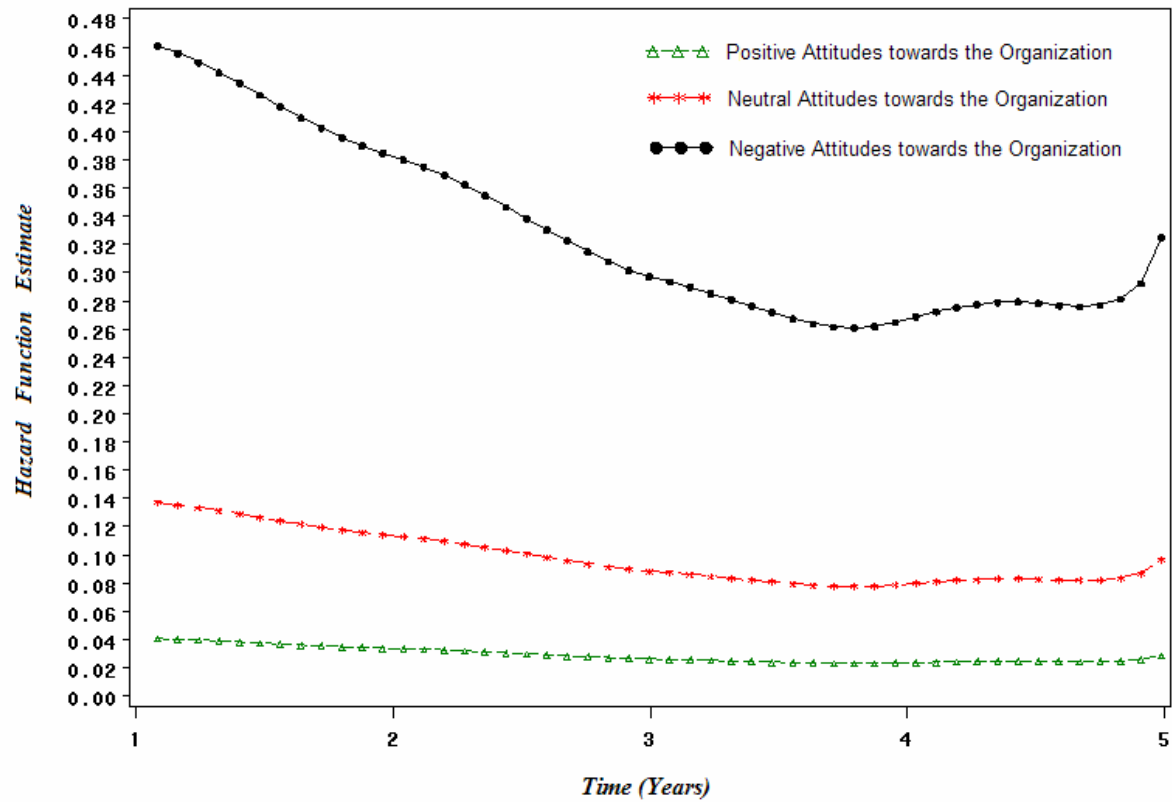


Figure 18. Univariate hazard function estimate by employees' attitudes

Note: Employees were split into three groups according to their attitudes: a) "Employee with Positive Attitudes" (Attitudes scores ≥ 75 percentile), b) "Employee with Neutral Attitudes" (Attitudes score between 75 percentile and 25 percentile), and c) "Employee with negative Attitudes" (Attitudes score ≤ 25 percentile).

To have a clearer display of the relationship between employee attitudes and survival function, employees were split into three groups according to their attitudes: a) “Employee with Positive Attitudes, b) “Employee with Neutral Attitudes”, and c) “Employee with negative Attitudes” (see Figure 17 and Figure 18). As demonstrated on Figure 17, approximately 60% of the employees with low job satisfaction leave the organization before the end of two years of employment. The turnover risk was 22% and 9% for employees with neutral and positive levels of job satisfaction, respectively. From Figure 18, we could see that the turnover risk for employees with negative overall attitudes was much higher than other employees. The turnover risk for employees with positive and neutral overall attitudes were similar and stable over time Overall, the hypothesis 5.1.a was supported.

Hypothesis 5.2a. This hypothesis predicted that employees with different job satisfaction would have different employment duration. Specifically, employees with higher job satisfaction would have longer employment tenure than employees with lower job satisfaction. As same as the discussed approach, the average scores of job satisfaction across years were used to test this hypothesis.

The results from the univariate survival model indicated a significant negative association between employees’ job satisfaction and their turnover risk. The association parameter between satisfaction and turnover risk estimated by the univariate survival model -0.43 ($\chi^2(1) = 457.21; p < .0001$). The hazard ratios from

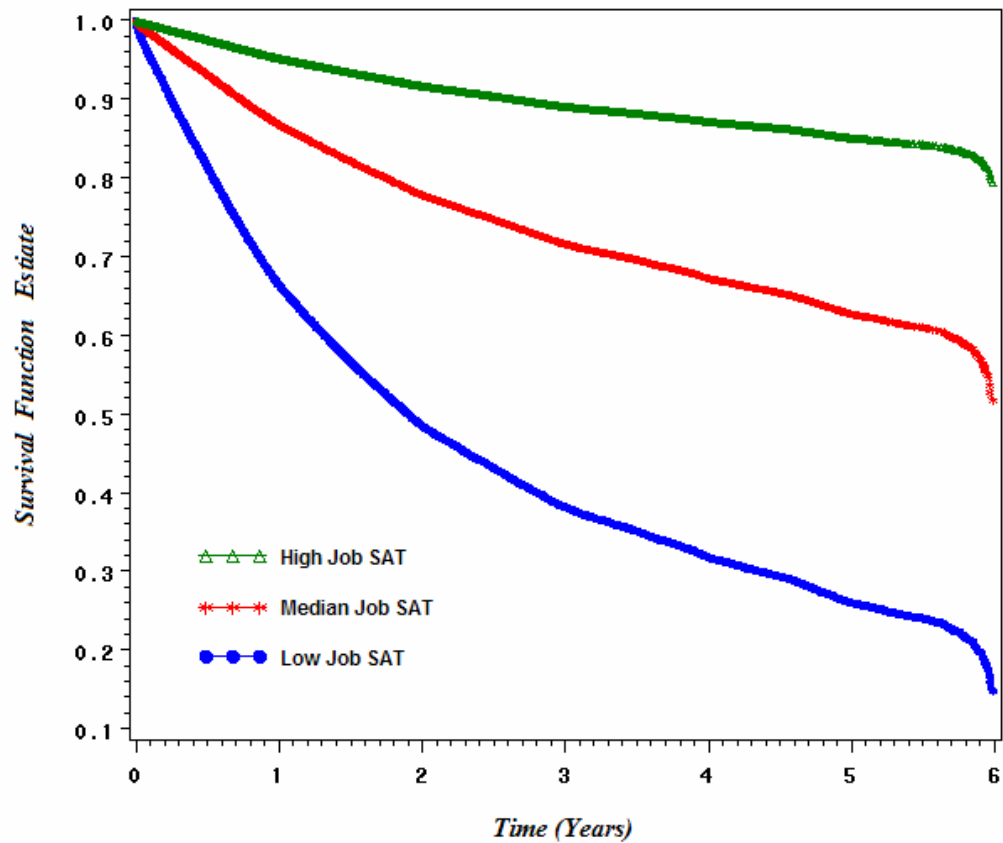


Figure 19. Univariate survival function estimate by job satisfaction

Note: Employees were split into three groups according to their job SAT: a) “Employee with High Job SAT” (Job satisfaction scores \geq 75 percentile), b) “Employee with Median Job SAT” (Job satisfaction scores between 75 percentile and 25 percentile), and c) “Employee with Low Job SAT” (Job satisfaction scores \leq 25 percentile).

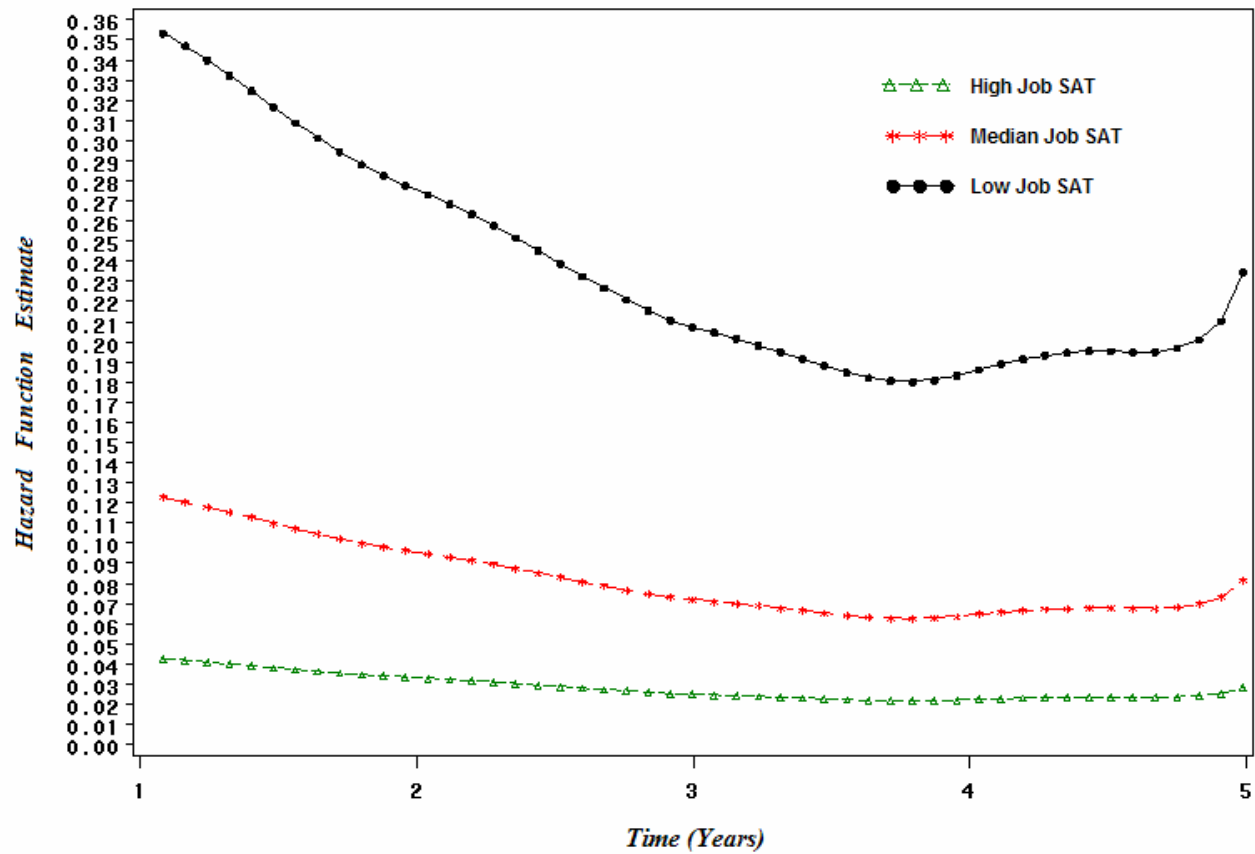


Figure 20. Univariate hazard function estimate by overall satisfaction

Note: Employees were split into three groups according to their job SAT: a) “Employee with High Job SAT” (Job satisfaction scores ≥ 75 percentile), b) “Employee with Median Job SAT” (Job satisfaction scores between 75 percentile and 25 percentile), and c) “Employee with Low Job SAT” (Job satisfaction scores ≤ 25 percentile).

the univariate model were 0.47. That is, one standardized deviation increase in employee job satisfaction decreased their turnover risk by about 50%.

To illustrate the survival and hazard function between employees' job satisfaction and their turnover risk, employees were split into three groups according to their job satisfaction: a) "Employee with High Job SAT", b) "Employee with Median Job SAT", and c) "Employee with Low Job SAT" (see Figure 19 and Figure 20).

As demonstrated on Figure 19, less than 4 percent of the employees with high job satisfaction left the organization, about 40% of the employees with median job satisfaction would leave the organization, and approximately 85% of the employees with low job satisfaction would quit throughout the six-year study period. From Figure 20, we could see that the turnover risk for employees with median job satisfaction were similar to the highly satisfied employees. The effect of satisfaction was seen for the low satisfaction group. Approximately 50% of these employees would leave the organization within two-year of employment. Thus, the hypothesis 5.2.a was supported.

Hypothesis 5.3a. Following the exact same analysis process for job satisfaction, the results of the survival analysis for employees' intention to quit revealed that intention to quit was strongly associated with employment duration. The results from the univariate survival model indicated a significant positive association between employees' intention to quit and their employment duration. The estimated association parameter between intention to quit and turnover risk was 1.47 ($\chi^2(1) = 7277.71; p < .0001$). The hazard ratio from the univariate model

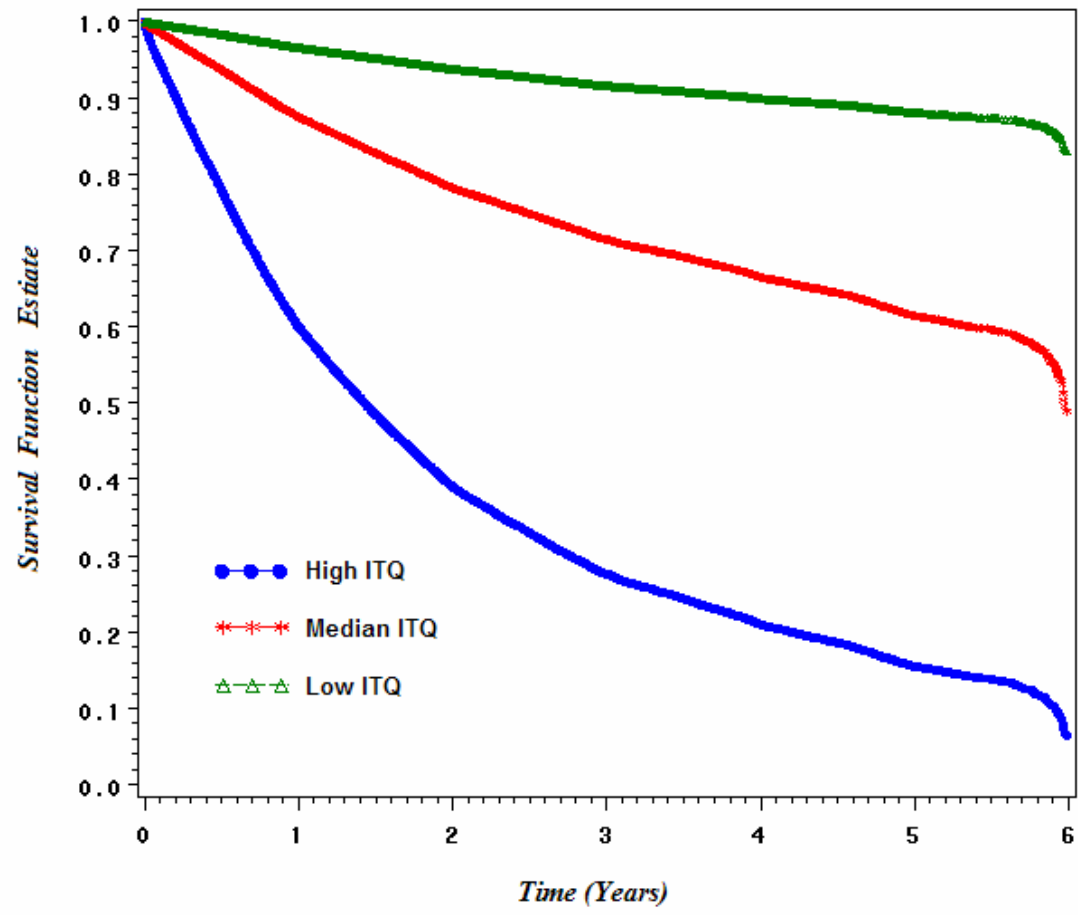


Figure 21. Univariate survival function estimate by intention to quit

Note: Employees were split into three groups according to their ITQ scores: a) “Employee with High ITQ” (ITQ scores \geq 75 percentile), b) “Employee with Median ITQ” (ITQ scores between 75 percentile and 25 percentile), and c) “Employee with Low ITQ” (ITQ scores \leq 25 percentile).

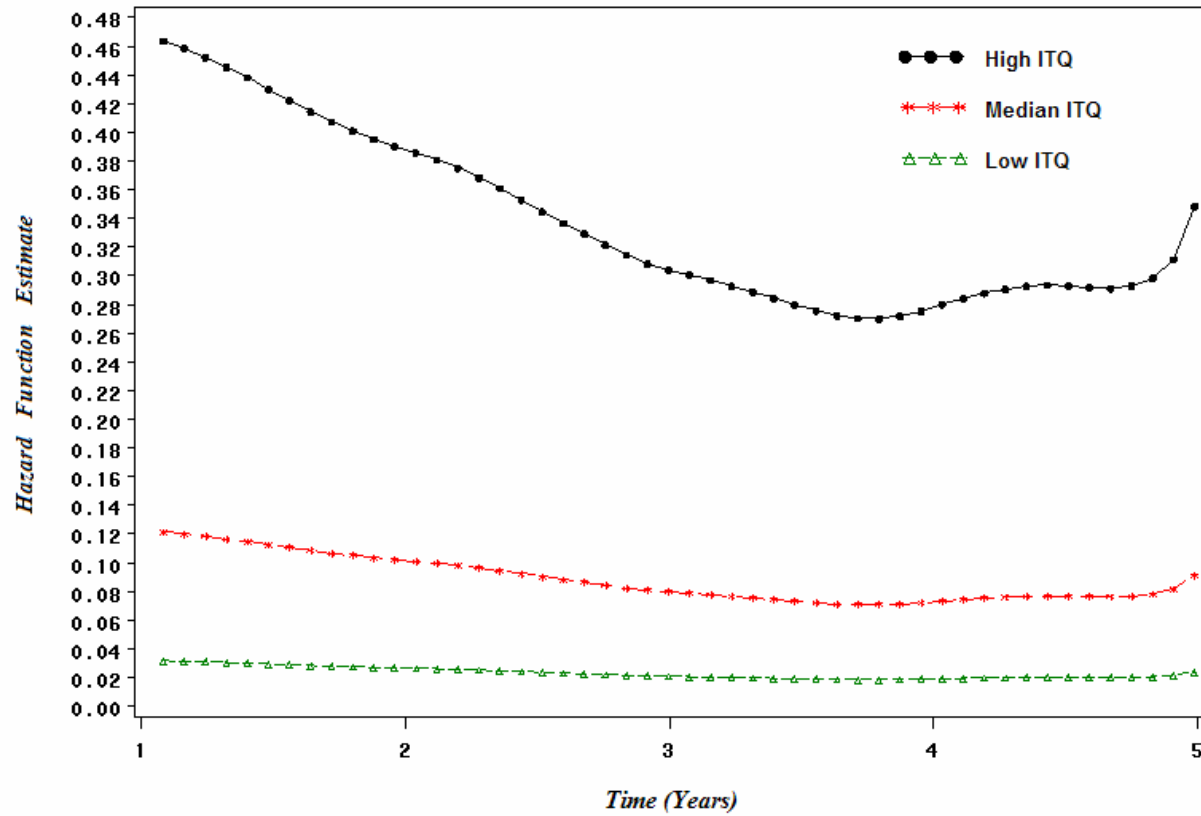


Figure 22. Univariate hazard function estimate by intention to quit

Note: Employees were split into three groups according to their ITQ scores: a) “Employee with High ITQ” (ITQ scores \geq 75 percentile), b) “Employee with Median ITQ” (ITQ scores between 75 percentile and 25 percentile), and c) “Employee with Low ITQ” (ITQ scores \leq 25 percentile).

was 1.77. That is, one standardized deviation increase in employee intention to quit increased their turnover risk by about 77%.

To have a clearer display of the relationship between employee intention to quit and survival function, employees were split into three groups according to their intention to quit (ITQ) scores: a) “Employee with High ITQ”, b) “Employee with Median ITQ”, and c) “Employee with Low ITQ” (see Figure 21 and Figure 22). As demonstrated by Figure 21, about 40% of the employment with high intention would quit during the first year and 60% of them would quit during the second year. But only 2% of the employees with low intention to quit would leave the organization in the first year employment and 5% of them would leave during the second year. For employees with median intention to quit, approximately 5% of them would leave in the first year and about 15% of them would quit during the second year of employment. From Figure 22, the hazard function estimates were telling the same story. Employees with high intention to quit had much higher risk to leave the organization than the other two groups of individuals. Thus, the hypothesis 5.3.a was supported.

Hypothesis 6a. This hypothesis predicted that local unemployment rate would affect employees’ employment duration. Employees living in high local unemployment rate area would be like to have longer employment duration than employees living in low local unemployment rate area. Following the same procedure, the averaged local unemployment rates across years were used to evaluate hypothesis 6a.

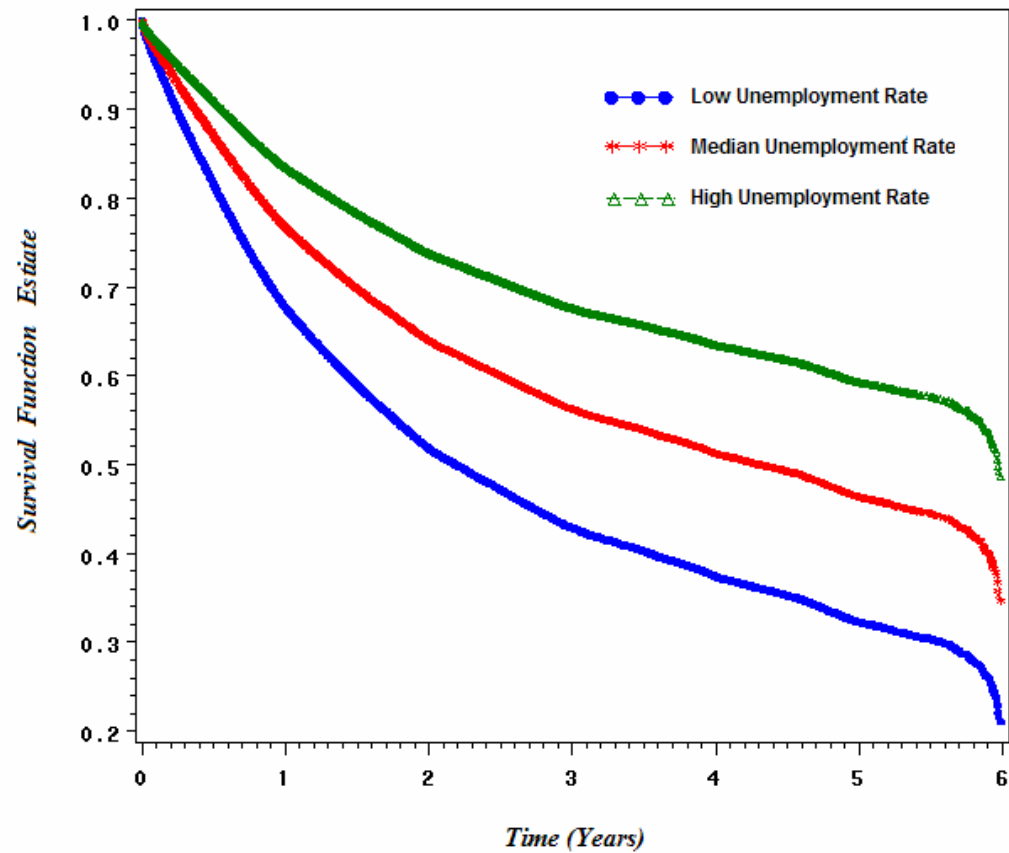


Figure 23. Univariate survival function estimate by unemployment rate

Note: Employees were split into three groups based on the employment rate where they live: a) “Employee living in an area with High Unemployment Rate” (Local Unemployment Rate \geq 75 percentile), b) “Employee living in an area with Median Unemployment Rate” (Local Unemployment Rate between 75 percentile and 25 percentile), and c) “Employee living in an area with Low Unemployment Rate” (Local Unemployment Rate \leq 25 percentile).

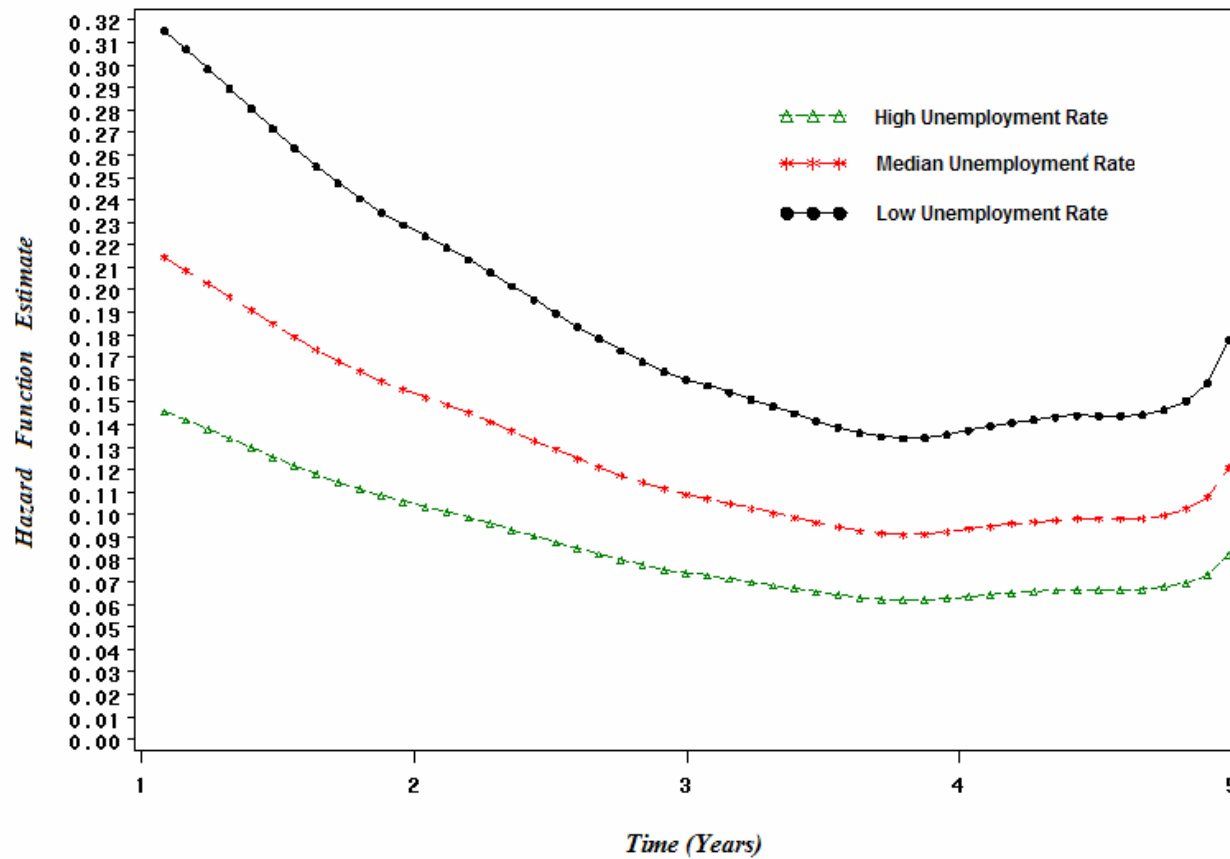


Figure 24. Univariate hazard function estimate by unemployment rate

Note: Employees were split into three groups based on the employment rate where they live: a) “Employee living in an area with High Unemployment Rate” (Local Unemployment Rate \geq 75 percentile), b) “Employee living in an area with Median Unemployment Rate” (Local Unemployment Rate between 75 percentile and 25 percentile), and c) “Employee living in an area with Low Unemployment Rate” (Local Unemployment Rate \leq 25 percentile).

The results from the univariate survival model indicated that local unemployment rates had a significant impact on employees' employment duration, although the estimated parameter was not that high $-.13 (\chi^2 (1) = 975.61; p < .0001)$. The hazard ratio from the univariate model for unemployment rates and turnover risks was .88, which indicated that one standardized deviation increase in unemployment rates resulted in a 12% decrease in their turnover risk. To have a clearer display of the relationship between local unemployment rates and employees' turnover risk, employees were split into three groups based on the employment rate where they live: a) "Employee living in an area with High Unemployment Rate", b) "Employee living in an area with Median Unemployment Rate", and c) "Employee living in an area with Low Unemployment Rate". As demonstrated on Figure 23, approximately 50% of the employees living in a low-unemployment-rate area would leave the organization around two and half years. Only 35% of the employees in a median-unemployment-rate area and 25% of the employees in a high-unemployment-rate area would quit in the same time. From Figure 24, we could also see similar results. Employees from areas with high employment rates would face much higher turnover risks than employees living in areas with low employment rates. Overall, the hypothesis 6a was supported.

Hypothesis 7a. This hypothesis predicted that local household income would affect employees' employment duration. Employees living in an area with high local household income would be more likely to have longer employment

duration than employees from a low-income-area. Following the same procedure, the averaged local household income across years was used to test hypothesis 7a.

The results from the univariate survival model a weak but statistically significant association between local household income and employees' employment duration. The estimated parameter from the univariate survival model between local economical situation and employees' turnover risk was $-.10$ ($\chi^2 (1) = 215.06; p < .0001$). The hazard ratio was $.90$, which indicated that one standardized deviation increase in local household income would result in a 10% decrease in their turnover risk. Following the same trichotomizing rule, employees were split into three groups based on the local economical condition where they live: a) "Employee living in an area with High Household Income"; b) "Employee living in an area with Median High Household Income", and c) "Employee living in an area with Low High Household Income" (see Figure 25 and Figure 26). As demonstrated on Figure 25 and Figure 26, employees living in high-household-income areas would be more likely to have higher employment duration and lower turnover risks than ones living in low-household-income areas, although the differences were not that big. Overall, the hypothesis 8.a was supported in a moderate way.

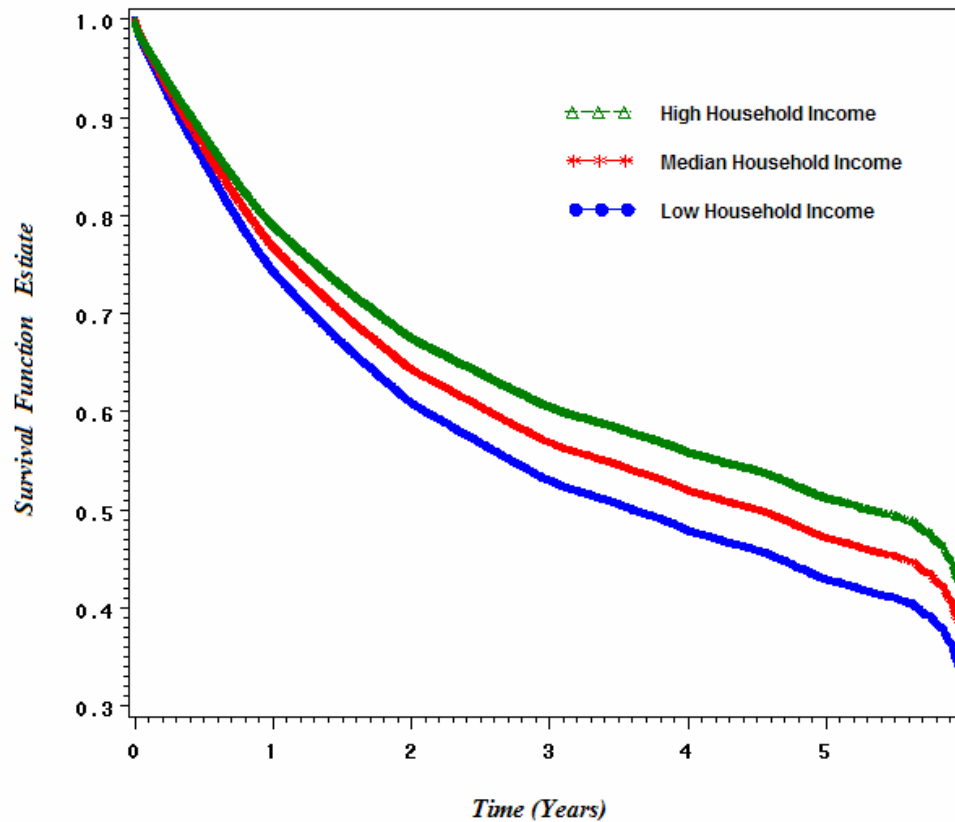


Figure 25. Univariate survival function estimate by household income

Note: Employees were split into three groups based on the local house hold income where they live: a) “Employee living in an area with High Household Income” (Local Household Income \geq 75 percentile), b) “Employee living in an area with Median High Household Income” (Local Household Income between 75 percentile and 25 percentile), and c) “Employee living in an area with Low High Household Income” (Local Household Income \leq 25 percentile).

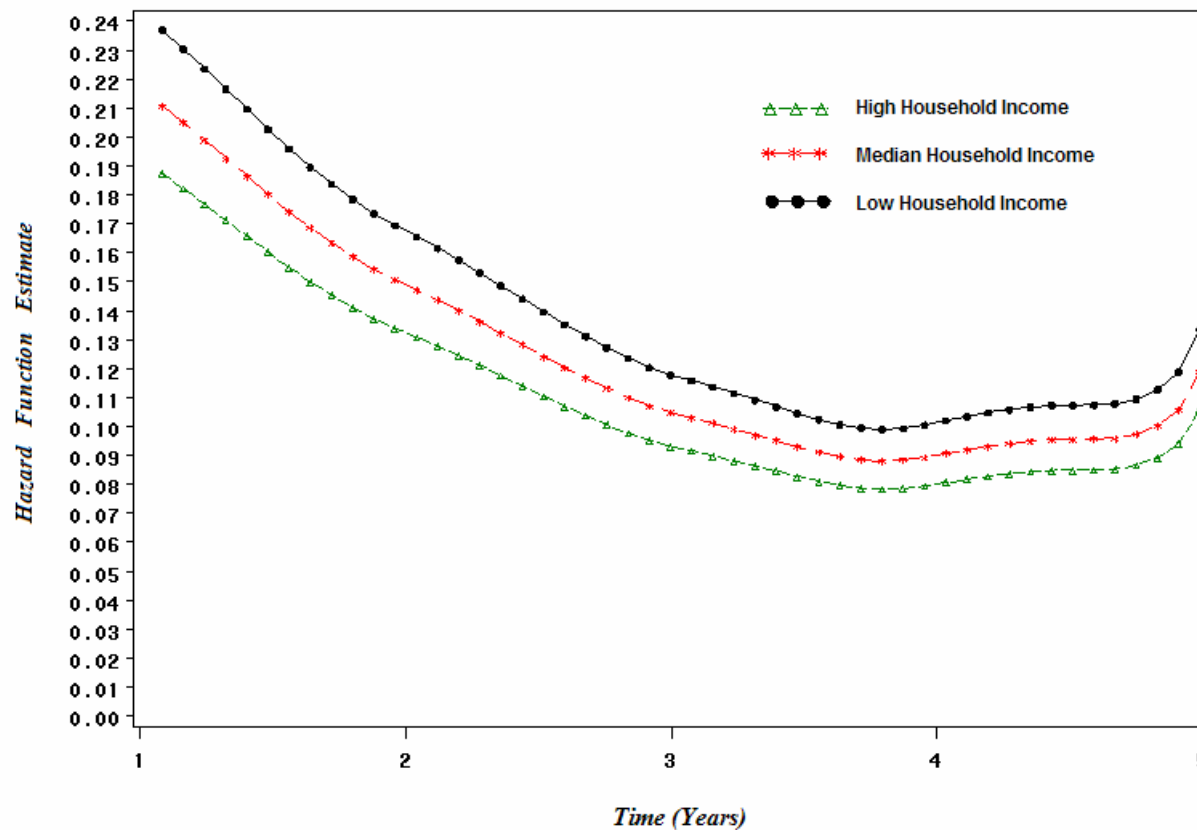


Figure 26. Univariate hazard function estimate by household income

Note: Employees were split into three groups based on the local house hold income where they live: a) “Employee living in an area with High Household Income” (Local Household Income \geq 75 percentile), b) “Employee living in an area with Median High Household Income” (Local Household Income between 75 percentile and 25 percentile), and c) “Employee living in an area with Low High Household Income” (Local Household Income \leq 25 percentile).

Latent Growth Modeling (LGM) Analysis Results

As discussed previously, a few predictor variables were conceptually considered as longitudinal in nature. That is, changes in these variables over time were believed to be associated with changes in turnover over time. These longitudinal variables were job performance, compensation, job attitudes, job satisfaction, intention to quit, local unemployment rate, and local household income. Latent growth modeling (LGM) was used in the present study to evaluate if the change patterns for these variables differed for leavers and stayers.

There were three issues related to the LGM analysis that had to be considered before evaluating the support for my hypotheses. The first issue centered on sample size limitations of current LGM analysis programs. The restriction of SAS statistical program limited me to 10,000 participants for this analysis. Thus, I randomly selected 10,000 participants for my LGM analyses. It should be noted that I repeated random sampling five times and repeated the LGM analyses for each random sample. My results were similar across these different random samples.

The second issue was still related to the actual individuals who had been included in the LGM analyses. When I conducted survival analyses, only the employees who had been hired during the six-year study period were included in the analyses. It was due to the restriction of the requirement of survival model. However, there was no such restriction of LGM analyses. To take the best use of the existing data, I included all the employees (employees who were hired before the study period and those who were hired during the study period). To be parallel

with the survival analysis, I also conducted LGM analyses based on the new hire sample. The results from the new hire sample were very close to the full sample. Thus, the LGM results reported below were based on the full sample.

The second issue concerned the multi-level results provided by LGM analysis. The present study focused on whether there were differences between stayers and leavers on the trend line of the longitudinal variables over time. This question is only answered by the Level 2 tests provided by LGM analysis. Thus, I only present Level 2 results in this dissertation (see Table 6).

The first four columns of Table 6 show the LGM Level 2 results for the intercept. The column labeled γ_{00} indicates whether there were intra-individual differences for the longitudinal variable under investigation at the initial time point of the study - Year 1. The column labeled γ_{01} indicates the mean value differences between stayers and leavers on each longitudinal variable at the initial time point of the study. In other words, this column provides evidence for whether stayers were initially different from leavers for each longitudinal variable. For example, the significant value for the γ_{01} (leavers) on *annual pay rate* referred that leavers had different levels of compensation than stayers did at organizational entry.

The results shown on Table 6 suggested that leavers had significantly lower compensation levels and lower general attitudes toward the organization than stayers did at time of entering the organization. Leavers also had significantly higher levels of intention to quit than stayers at the first year of employment. It was also found that the Year 1 local unemployment rate for

leavers was significantly lower than the Year 1 local unemployment rate for stayers.

On Table 6, the second four columns demonstrated whether the slope of each variable was changed with time. The column labeled γ_{10} provides information about the rate of change in each variable. The column labeled γ_{11} answered the question on whether stayers and leavers differed on the slopes of those predicting variables. The values on Table 6 for γ_{10} indicated that there was significant change over time on all the longitudinal variables except for employees' performance ratings. That is, compensation levels, job attitudes, and even local economical conditions were found to change over time. However, employees' performance ratings were found to be stable across the six-year study period. The γ_{11} column indicates whether stayers and leavers had different trajectories. It was found that leavers and stayers differed in terms of their rate of change in compensation, their attitudes towards the organization, and their intention to quit.

Hypothesis 2b. Hypothesis 2b proposed that employees who turned over and those who stayed with the organization would have different growth trajectories in their performance ratings over time. Specifically, it predicted that the slope of performance ratings for stayers would be more positive than those for leavers. As shown in Table 6, this hypothesis was not supported by the LGM results.

The estimated parameters on the initial status of employees' performance ratings ($\gamma_{00} = 2.32, p < .0001$; $\gamma_{01} = 0.04, p = n.s.$) indicated that employees did

significantly differ in terms of their Year 1 performance ratings, but leavers and stayers did not significantly differ in terms of Year 1 performance. The LGM results showed that there were no significant changes in performance ratings over time and that stayers and leavers did not differ in terms of their change in performance ratings ($\gamma_{10} = 0.00, p = n.s.$; $\gamma_{11} = 0.04, p = n.s.$) across this study's six-year study period. The performance trajectories for stayers and leavers are plotted on Figure 27. Overall, hypothesis 2b was not supported by the LGM results.

Table 6. Parameter Estimates for Univariate Latent Growth Models

Variables	Initial Status		Slopes		Model Fit Statistics		
	γ_{00} (Intercept)	γ_{01} (leavers)	γ_{10} (time)	γ_{11} (time*leavers)	Deviance	AIC	BIC
Performance Rating	2.32***	-0.04	0.00	-0.01	20,170.5	20,186.5	20,233.5
Annual Pay Rate	0.03**	-0.17***	0.04***	-0.03***	3,792.0	3,776.0	3,729.0
Employee Attitudes	-0.82***	-0.15***	0.46***	-0.10**	25,152.6	25,166.6	25,205.5
Job Satisfaction	-0.19***	-0.05	0.04***	-0.01	16,879.4	16,895.4	16,942.4
Intention to Quit	-0.81***	0.20***	0.51***	0.18***	28,062.9	28,076.9	28,115.8
Local Unemployment Rate	2.93***	-0.38**	0.41***	-0.02	18,142.3	18,158.3	18,198.7

Note. n = 10,000. Except *performance rating* and *local unemployment rate*, all other variables were standardized prior to analysis. *** $p < .0001$; ** $p < .001$; * $p < .01$. The results of local household income could not be converged.

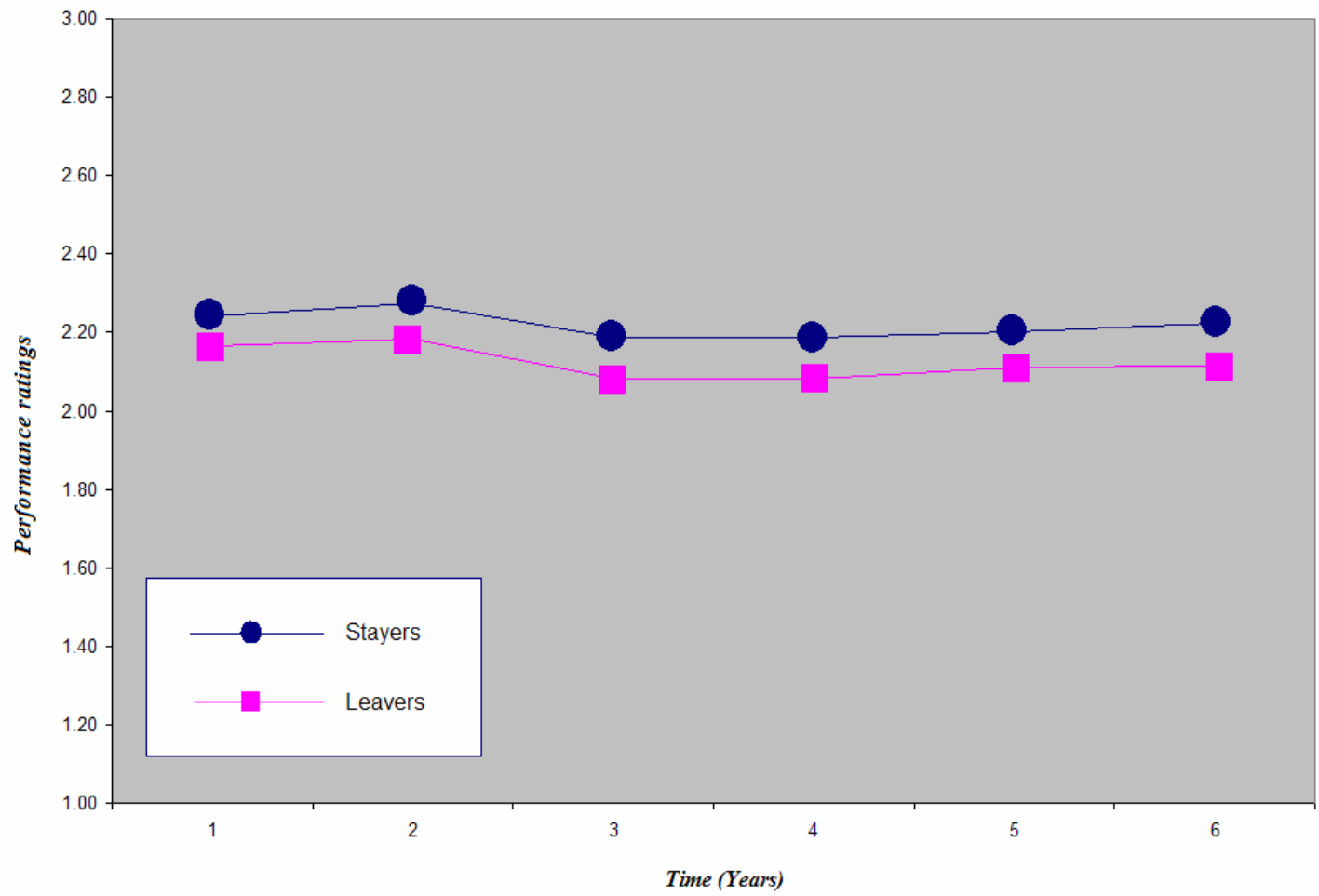


Figure 27. Latent growth modeling (LGM) graphical results for performance ratings

Hypothesis 3b. Hypothesis 3b predicted that employees who left the organization and those who stayed would have different compensation growth trajectories; furthermore, the rate of change in pay for stayers would be more positive than the rate of change in pay for leavers. As shown in Table 6, the estimated parameters on the initial status of employees' annual pay rate ($\gamma_{00} = 0.03, p < .0001$; $\gamma_{01} = 0.17, p = n.s.$) indicated that employees differed in terms of their compensation levels but that stayers and leavers did not significantly differ in terms of their initial pay levels. The results of the changing trajectories of employees' pay rates ($\gamma_{10} = 0.04, p < .0001$; $\gamma_{11} = -0.03, p < .0001$) indicated that employees' compensation were changing with time during the six-year study period and the changing slopes between stayers and leavers were significantly different. The graphical representation of the results was portrayed in Figure 28. Overall, hypothesis 3b was supported.

Hypothesis 5.1b. Hypothesis 5.1b predicted that the difference between stayers and leavers in terms of the changing patterns of their attitudes towards the organization. It was specifically proposed that stayers would exhibit a more positive change in their attitudes over time than would leavers. This hypothesis was strongly supported by the LGM results.

As shown in Table 6, the estimated parameters on the Year 1 difference among employees' attitudes towards the organization was quite substantial ($\gamma_{00} = 0.82, p < .0001$) and employees who stayed with

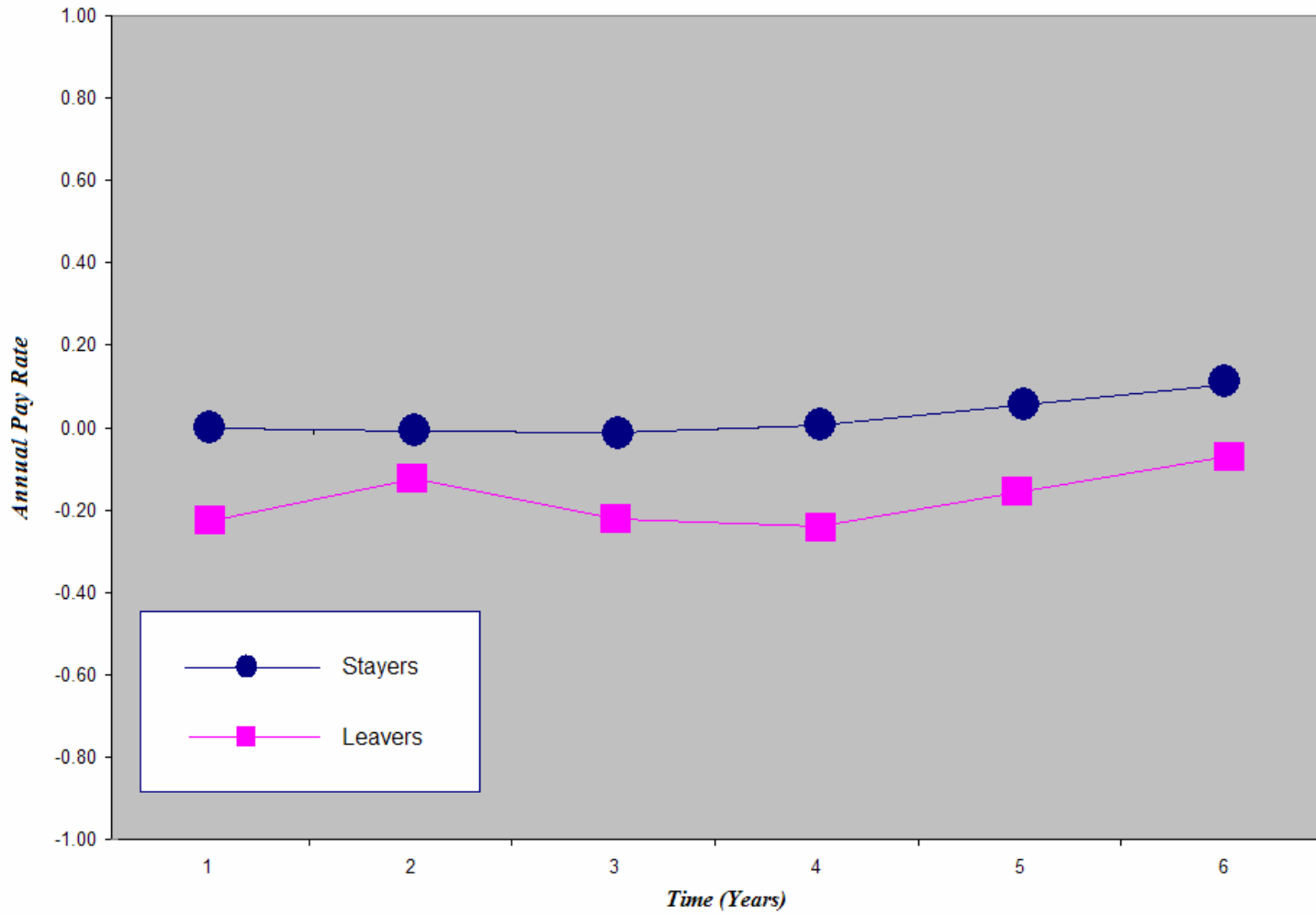


Figure 28. Latent growth modeling (LGM) graphical results for annual pay rates

the organization reported more initial positive attitudes than those who left ($\gamma_{01} = .15, p < .0001$). Further, the change in attitudes was significantly different from zero ($\gamma_{10} = 0.46, p < .0001$). Figure 29 shows these results and reveals that stayers tended to exhibit a more positive change in attitudes than did leavers. Overall, the hypothesis 5.1a was supported.

Hypothesis 5.2b. This hypothesis proposed that stayers and leavers would have different changing trajectories on their job satisfaction. More precisely, employees who left the organization would exhibit a significantly greater decline in job satisfaction than would employees who stayed.

The LGM results indicated that employees were significantly differed in terms of their initial job satisfaction ($\gamma_{00} = .19, p < .0001$), however stayers and leavers did not differ initially on this variable ($\gamma_{01} = .05, p = n.s.$). Further, employees' job satisfaction changed with time ($\gamma_{10} = .04, p < .0001$), but this rate of change did not significantly differ for stayers and leavers ($\gamma_{11} = .01, p = n.s.$). Figure 30 demonstrated the trajectories of job satisfaction for leavers and stayers. From the Figure, we could see that the changing slopes between employees who quit and those who stayed were similar with each other. Thus, hypothesis 5.2b was not supported.

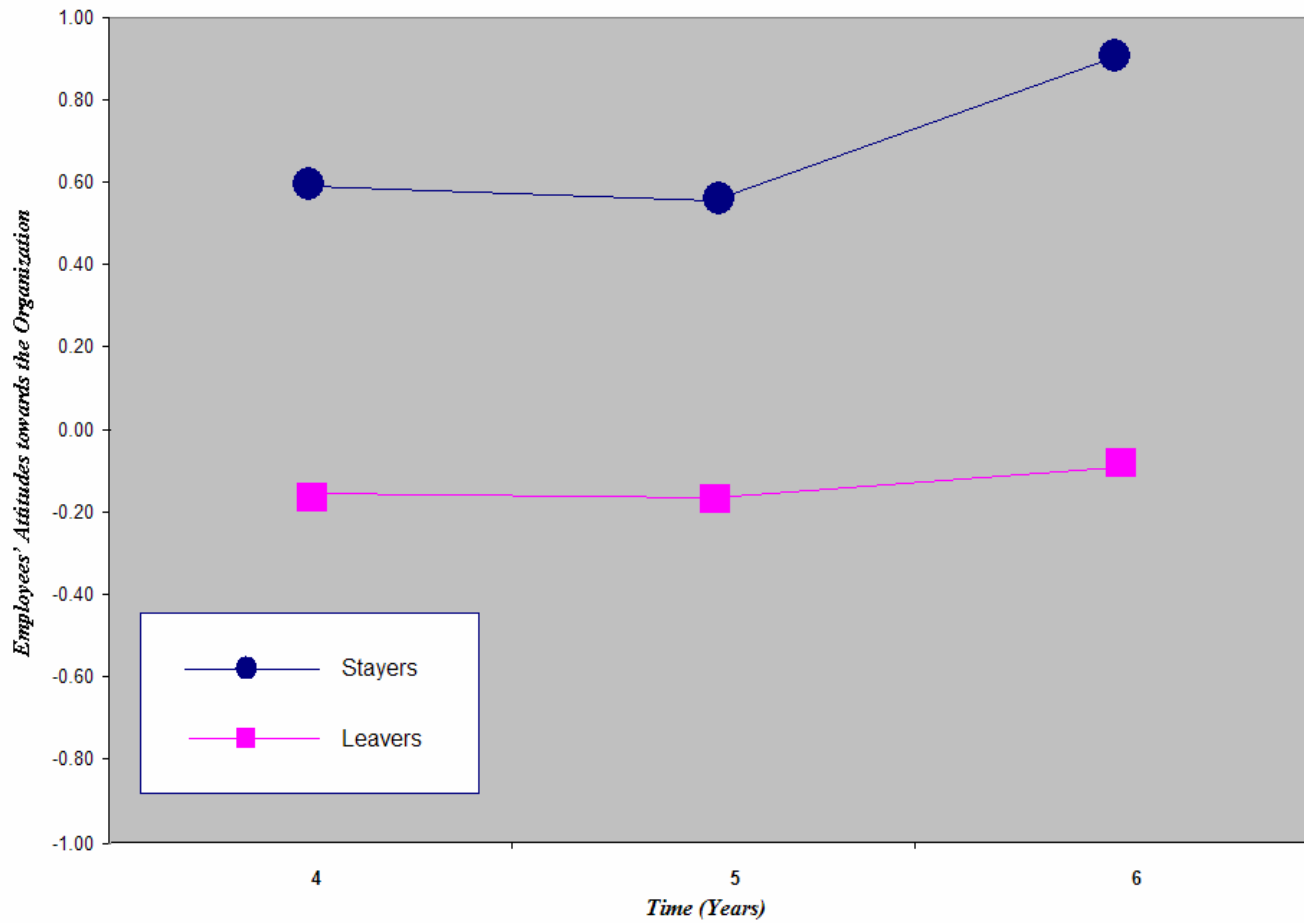


Figure 29. Latent growth modeling (LGM) graphical results for employees' attitudes towards the organization

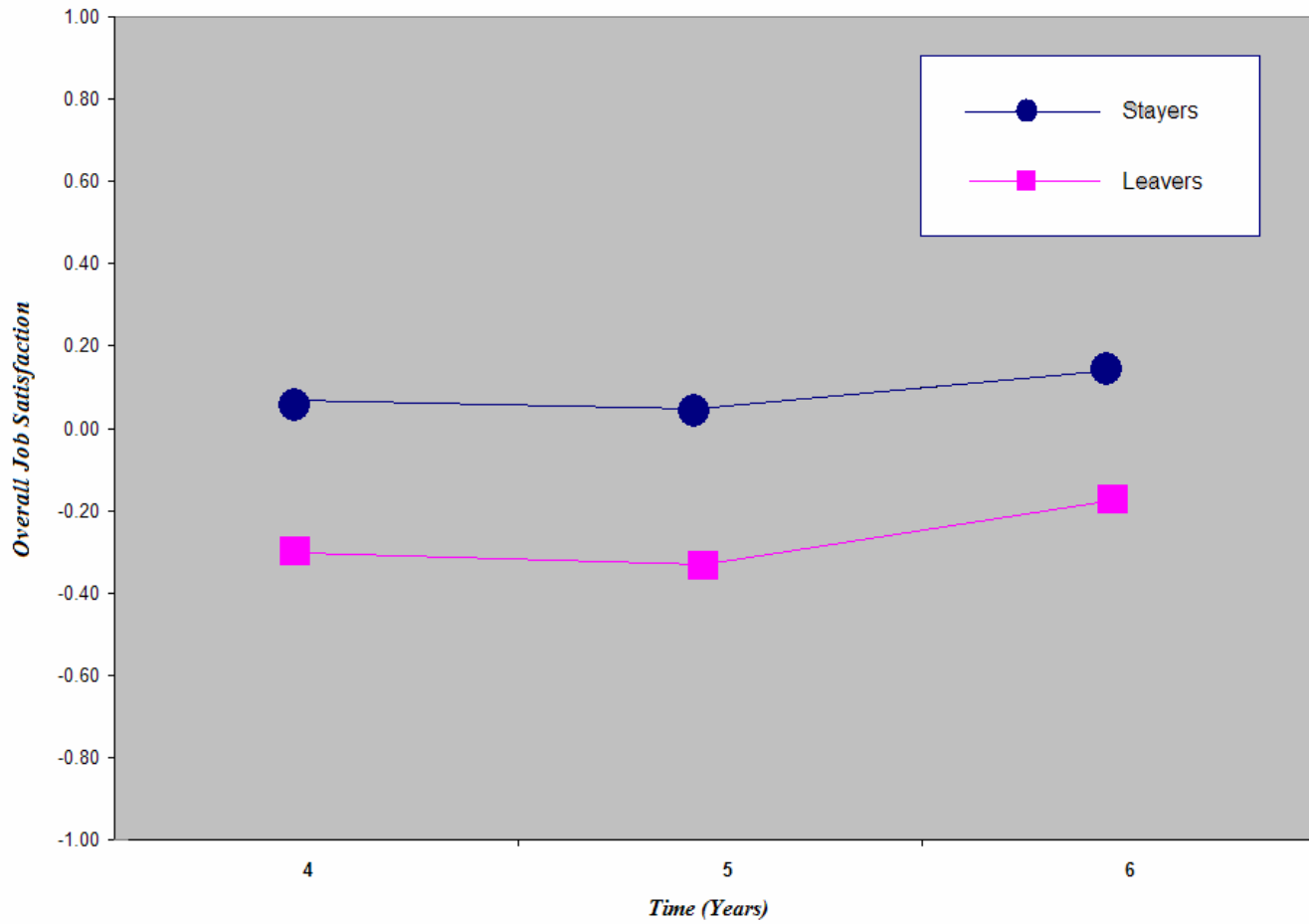


Figure 30. Latent growth modeling (LGM) graphical results for overall job satisfaction

Hypothesis 5.3b. This hypothesis proposed that employees who stayed with the organization and those who left would exhibit differences in their intentions to quit trajectories over time. More specifically, leavers would increasingly think about quitting.

As shown in Table 6, employees significantly differed in terms of their initial intention to quit ($\gamma_{00} = 0.81, p < .0001$). Further, employees who stayed with the organization had much lower initial intentions to quit than those who turned over ($\gamma_{01} = .20, p < .0001$). In terms of the rate of change in this variable, employees' intention to quit was found to significantly change over time ($\gamma_{10} = 0.51, p < .0001$) and, more importantly, the rate of change in this variable significantly differed between stayers and leavers ($\gamma_{10} = 0.18, p < .0001$). Figure 31 shows this result and it can be seen that leavers level of intention to quit over time significantly increased over time in comparison to the stayers. Stayers intention to quit trajectory actually decreased over time. Thus, hypothesis 5.3b was fully supported by the results.

Hypothesis 6b. This hypothesis proposed that the change of local unemployment over time would be different between employees who left versus those who stayed. Specifically, it was predicted that the unemployment rate slope for stayers would be more positive than the slope for leavers.

The LGM results indicated that employees differed in terms of their initial local unemployment rates ($\gamma_{00} = 2.93, p < .0001$) and that stayers came from areas with higher local unemployment-rate areas than did leavers ($\gamma_{01} = .38, p < .0001$),

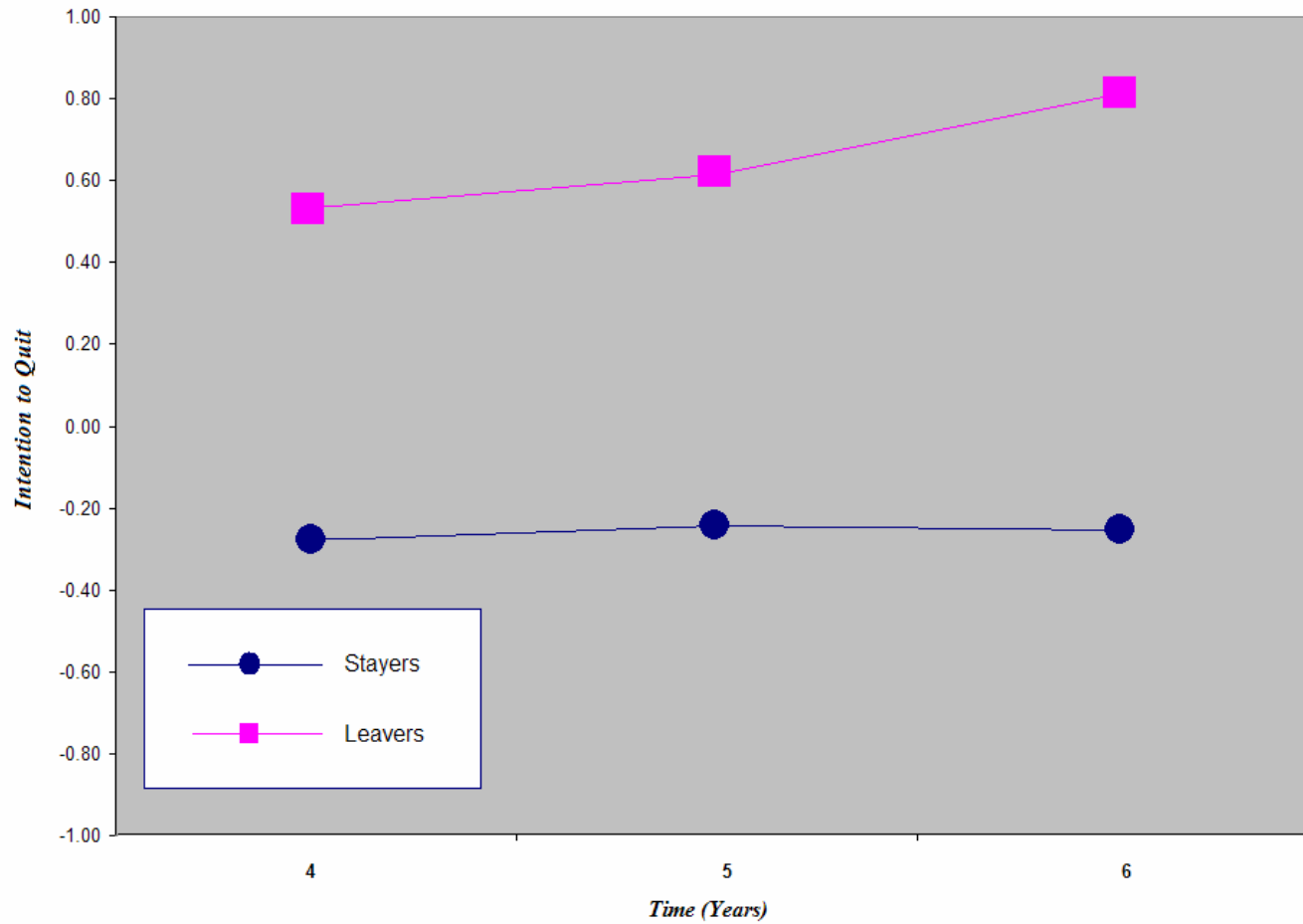


Figure 31. Latent growth modeling (LGM) graphical results for intention to quit

Table 6 also shows that the local employment rates changed over time ($\gamma_{10} = .41$, $p < .0001$). However, there were no significant differences in the rate of change of the local employment rate between stayers and leavers ($\gamma_{11} = .01$, $p = n.s.$).

Thus, hypothesis 6b was not supported by the results.

Additional Post Hoc Investigations

In the previous survival analyses, the univariate relation between each of the predictor variables and turnover risk was evaluated. The univariate survival analyses evaluated the univariate association between one predictor and turnover risk. To compare the relative strengths of the associations between each of the predictors and turnover, a multivariate survival model was applied. The multivariate model included all the predictors into the same model, which evaluated the associations between predictors and dependent variable simultaneously. The multivariate survival results were presented in Table 7, which presented the strength of the relationships between each predictor variable and turnover risk, after controlling the influence of other variables.

The results of the univariate survival model indicated a significant relationship between each of the predictors and turnover risk. The results of the multivariate survival model indicated a different story. Employees' age, performance ratings, and their local household income were found not having a significant association with the survival and hazard functions, after controlling the impact of other variables. Employees' annual pay rate, their promotion, their intention to quit, and their job satisfaction were found to have strong impact on the turnover risk. Additionally, employees' attitudes toward the organization and

Table 7. Multivariate Survival Model Predicting Employment Duration

	Parameter Estimate	Standard Error	Chi-Square	Hazard Ratio
Gender	-0.19	0.07	8.17*	0.79
Age	-0.06	0.04	1.92	0.94
Performance Rating	-0.08	0.05	2.48	0.92
Annual Pay Rate	-1.42	0.08	290.19***	0.24
Promotion	-0.56	0.05	143.50***	0.57
Employee Attitudes	-0.17	0.06	8.49*	0.84
Job Satisfaction	-0.17	0.04	22.27***	0.82
Intention to Quit	0.94	0.04	684.63***	1.61
Local Unemployment Rate	-0.10	0.03	11.11**	0.90
Local Household Income	-0.09	0.04	9.55	0.99

Note. All the continuous predictors were standardized prior to analysis.

*** $p < .0001$; ** $p < .001$; * $p < .01$. All the variables were standardized before conducting the survival analyses.

their local unemployment rates were moderately related to employees' survival and hazard function. The following section interpreted the results of the multivariate model in detail.

After controlling other variables, employees' psychological predictors were found to have significant association with turnover hazard. For example, employees' intentional to quit had the strongest impact on turnover risks. The estimated parameter for intention to quit was 0.94 ($\chi^2(10) = 684.63$; $p < .0001$) and the hazard ratio for this predictor was 1.61. Employees' job satisfaction was also found being negatively related with higher hazard function. The estimated parameter for job satisfaction was -0.17 ($\chi^2(10) = 22.27$, $p < .0001$) and the hazard ratio was 0.82. Additionally, employees' attitudes toward the organization was significantly negatively related to turnover, with the estimated parameter as -0.17 ($\chi^2(10) = 8.49$; $p < .01$) and the hazard ratio as 0.84. That is, in this model,

after controlling other variables, a 1-standard-deviation increase in intention to quit added the turnover hazard by 60% and a 1-standard-deviation increase in job satisfaction and general attitudes reduced turnover risk by 20%.

The results of the multivariate model also indicated that employees' human resource management predictors were significantly related to turnover risks. Employees' annual pay rate was the second strongest predictor among all the variables. The estimated parameter for intention to quit was -1.42 ($\chi^2(10) = 290.19; p < .0001$) and the hazard ratio for this predictor was 0.24. Promotion was also found to be associated with turnover hazard, with the estimated parameter as -0.56 ($\chi^2(10) = 143.50; p < .0001$) and the hazard ratio as 0.54. That is, a one-standard-deviation increase in employees' annual pay rate reduced turnover risk by 75% and one time increase in promotion decreased turnover hazard by 40%. However, the performance rating was shown to have no significant relationship between turnover risks when other variables were also in the survival model.

The results of the multivariate survival model show that employees' individual demographical predictors had weak associations with turnover hazard. Gender was found to be moderately related to turnover risks. The estimated parameter for gender was -0.19 ($\chi^2(10) = 8.17; p < .01$) and the hazard ratio was 0.79. It indicated that females had 20% higher turnover risk than males. However, age was found having no significant relation with turnover hazard, with the estimated parameter as -0.06 ($\chi^2(10) = 1.92; p = n.s.$) and the hazard ratio as 0.94.

Finally, external economical factors were also found to be moderately related to turnover risks. The local unemployment rate had a weak but significant

association with the hazard function. The estimated parameter was -0.10 ($\chi^2(10) = 11.11; p < .001$) and the hazard ratio was 0.90). However, the local household income was not related to turnover risks, with estimated parameter as -0.09 ($\chi^2(10) = 9.55; p = n.s.$)

Univariate Model versus Multivariate Model

The results based on the univariate survival model and the multivariate survival model told us a similar but not exactly same story (see Table 8). No matter with controlling influences from other predictors or without controlling, annual pay rate (effect size = -0.62 & -0.76), promotion (effect size = -0.56 & -0.43), and intention to quit (effect size = $+0.77$ & $+0.61$) were indicated to be strongly associated with turnover behaviors over time. Gender (effect size = -0.10 & -0.21), local unemployment rate (Effect size = -0.12 & -0.10) and local household income (effect size = -0.10 & -0.01) were shown to be weakly related to turnover risks over time. Thus, the previous predictors held a robust relationship with turnover hazard over time with or without controlling other factors. However, age and performance rating were found to be strongly related to turnover risks when other factors were not controlled, while these relationships became weak when the influence from other predictors were controlled. For instance, based on the univariate model, hazard ratio for age was 0.12 (effect size = -0.88), indicating a strong association between age and turnover risks. But, based on the multivariate model, hazard ratio for age was 0.94 (effect size = -0.06), indicating a weak relationship. The results for performance rating also

indicated that the strength of the association between performance and turnover risks became weak when other influences were taken out.

Overall, the comparison between the results based on the univariate survival model and the multivariate survival model provided more evidences about the time effect of turnover process. It indicated that the relationship between predictors and turnover risks changed over time. No matter controlling or not controlling other predictors, actual management factors and psychological indicators were found to be strongly association with turnover hazards. The association between turnover risks and demographical indicators or external economical factors became moderate or weak after controlling the influence from other predictors.

Table 8. Univariate Survival Model versus Multivariate Survival Model

	Univariate Survival Model		Multivariate Survival Model	
	Hazard Ratio	Effect Size	Hazard Ratio	Effect Size
Gender	0.90	-0.10	0.79	-0.21
Age	0.12	-0.88	0.94	-0.06
Performance Rating	0.71	-0.29	0.92	-0.08
Annual Pay Rate	0.38	-0.62	0.24	-0.76
Promotion	0.44	-0.56	0.57	-0.43
Employee Attitudes	0.35	-0.65	0.84	-0.16
Job Satisfaction	0.47	-0.53	0.82	-0.18
Intention to Quit	1.77	+0.77	1.61	+0.61
Local Unemployment Rate	0.88	-0.12	0.90	-0.10
Local Household Income	0.90	-0.10	0.99	-0.01

Note. The effect size is represented by the percentage change of turnover along with one unit change of predictors.

DISCUSSION

The importance of time and change in the prediction of turnover risks was demonstrated by the present study. By investigating how employees' turnover behaviors could be predicted by predictors and by the changing trajectories of those predictors over time, the current study enabled researchers to have a better understanding of several questions related to turnover studies, while providing suggestions for future research on this topic. The results of survival analyses indicate that psychological indicators, including employees' general attitudes towards the organization, their job satisfaction, and their intention to quit, have strong association with turnover risks over time. Management predictors, such as employees' compensation levels and their promotion history also have strong relations with turnover hazards over time. And, the results of growth modeling show that not only predictors' initial levels but also their changing patterns have strong relationships with turnover risks. Overall, survival analyses and growth modeling analyses provide an opportunity for researchers to have a better understanding of the relations between predictors and turnover longitudinally.

Contribution

As discussed previously, this study explored the prediction of turnover functions over time, using predictors from diverse resources. The present study contributes to turnover research in several ways. First, by applying the survival analysis and the LGM analysis to a six-year longitudinal data set, the present study investigated the time and change effect of predictors on turnover risks, which had been neglected by many previous turnover studies. Specifically, the

results of the survival analyses demonstrated the time effect on turnover risks. For example, from the survival function and the hazard figures, researchers could find out what was the specific turnover risk for certain employees at certain point of time. For the employees in the present study, their turnover risks were changing over time. They were facing the highest turnover hazard during their first year of employment. Additionally, the LGM analysis provided an opportunity to evaluate the relationship between the dynamic predictors and turnover risks, by several estimated parameters of the LGM analysis, such as γ_{00} , γ_{01} , γ_{10} , and γ_{11} . In the present study, all the assumed dynamic predictors, except employees' performance rating, were found to be changing with time. The dynamic patterns of employees' annual pay rate, their attitudes towards the organization, and their intention to quit were significantly related with turnover behaviors.

The second contribution of the present study was to compare the strength of predicting powers among predictor variables from different sources, including self-reported psychological predictors, actual management indicators, employees' demographics, and the external economical factors. Previous turnover research primarily used self-reported survey data for attitude to behavior turnover predictors. The current study included data from other sources besides survey data, such as actual management predictors and external economical factors into same analyses. Although a few meta-analyses (Home and Griffeth, 1995) had compared the strength of predicting power between psychological or attitudes indicators and actual event or behavior predictors, those comparison was not conducted on the exactly same samples. The present study allowed researchers to

have a more accurate evaluation of the predicting strength from different predictors on the same sample.

Because of the second contribution, the present study allowed researchers to examine the importance of the psychological predictors in terms of their associations with turnover risks. As addressed previously, the results of the survival analyses and the LGM analyses revealed the powerful role of psychological predictors in predicting turnover risks. Indeed, based on the univariate survival model, employee attitudes toward the organization, their intention to quit, and their job satisfaction were all significantly associated with the survival and hazard function over time ($p < .0001$). Even after controlling the influence from other predictors, such as demographics, management predictors, and external economical factors, those three psychological indicators were still shown to have significant relation with turnover risks. Intention to quit was the strongest predictor among all variables, with one of the highest hazard ratios ($p < .0001$). Employees' attitudes about the organization and their job satisfaction were also significantly related to turnover hazard. The LGM analyses also indicated that, except job satisfaction, the other two psychological predictors had an impact on employees' turnover risks.

Furthermore, the present study also allowed researchers to assess the influence of employees' actual compensation and actual promotion on the turnover hazard. Previous turnover studies on compensation had primarily focused on whether dissatisfaction with salary and pay strongly underlie turnover (Gomes-Meija & Balkin, 1992; Milkovich & Newman, 1993). Not many studies

had evaluated whether actual compensation would be related to turnover. This could be the reason for very little direct support on the relationship between compensation and turnover. The current research indicated that employees' actual compensation was one of the strongest predictors among all the variables. Indeed, no matter based on the univariate or the multivariate survival model, employees' annual pay rate was significantly associated with their survival and hazard function over time ($p < .0001$). The LGM analyses also indicated that the changing patterns of employment compensation were different for leavers and stayers. Previous meta-analyses on promotion and turnover risks had shown that, although satisfaction about promotion and perceived opportunities for promotion moderately predicted turnover, actual promotion strongly predicted turnover (Hom & Griffeth, 1995). The current study supported the previous results. For both univariate and multivariate survival analyses, the actual promotion was proved to be significantly related to turnover.

Additionally, the present study also allowed researchers to assess the impact of employees' demographics and the external economical situations on the turnover decisions. Previous studies had shown that those predictors were significantly related to turnover risks. The results of the univariate survival model supported this view. However, the multivariate survival analyses indicated that, after controlling the influence of other predictors, demographics and economical factors had no relations or moderate relations with turnover risks. Indeed, gender and local unemployment rate were found to be moderately associated with turnover hazards ($p < .01$ and $p < .001$, respectively). Age and local household

income were not found to be related to turnover risks after controlling influences from other predictors.

The results of the present study also contribute to the understanding of the dynamic nature of turnover predictors. As discussed previously, the LGM provided researchers an opportunity to evaluate whether a variable was changing with time. The estimated parameter - γ_{10} - was used to examine whether the studying variable was predicted by time. In the hypothesis section, it had been proposed that several predictors were dynamic and they were changing over time. For example, employees' job performance, their annual pay rate, and their attitudes were proposed to fluctuate over time. The results revealed that employees' compensation and attitudes increase or decrease with time. However, employees' job performance was found to be stable over time.

Future directions and Limitations

By including predictors from multiple sources, this longitudinal study helped to stimulate future research in several research directions. First, our findings suggested the need for more empirical examinations of the dynamic nature of predictors. For example, the assumption that performance was stable had been debated for many years. From the early theoretical work to the current empirical studies, it had been indicated that the stability assumption of job performance was false and performance was changing over time (Deadrick, Bennett, & Russell, 1997; Ghiselli (1956); Hanges, Schneider, & Niles, 1990; Hofmann, Jacobs, & Gerras, 1992; Ployhart & Hakel, 1998; Wernimont and Campbell (1968). However, in this study, job performance was found to be stable

over time. That is, for most of the employees, their performance ratings kept in the same level during the six-year study period. The results of this study seemed conflict with the previous instability assumption of performance. However, it had to notice an important issues related to performance ratings in this study before making the conclusion. There were three categories of the performance ratings: a) Exceeds expectations, b) Meets expectations, and c) Needs improvements. Figure 32 demonstrated the percentages of each category over six years. This figure indicated that, in every year, over 70% of the employees having their performance ratings as “Meets expectations”. About 25% of the employees were rated as “Exceeds expectations”. And, only 5% employees were categorized as “Needs improvement”. The percentages of these three types of ratings were stable across years. One of the reasons leading a stable performance could be the limitation of the three categories. Because these categories did not have enough distinguish power to rate employees’ performance, there were no enough variances in performance to reveal its’ instability nature. Thus, future study on performance and turnover could continue on the dynamic nature of performance as a turnover antecedent. Specifically, more accurate performance rating scale should be applied to have a better understanding of the dynamic nature of performance and turnover risks.

Another area for future research was to understand the turnover hazard of employees whose employment duration was higher than six years. In the present study, due to the restriction of the six-year study period, the relations between predictors and turnover were only evaluated during six years. Previous meta-

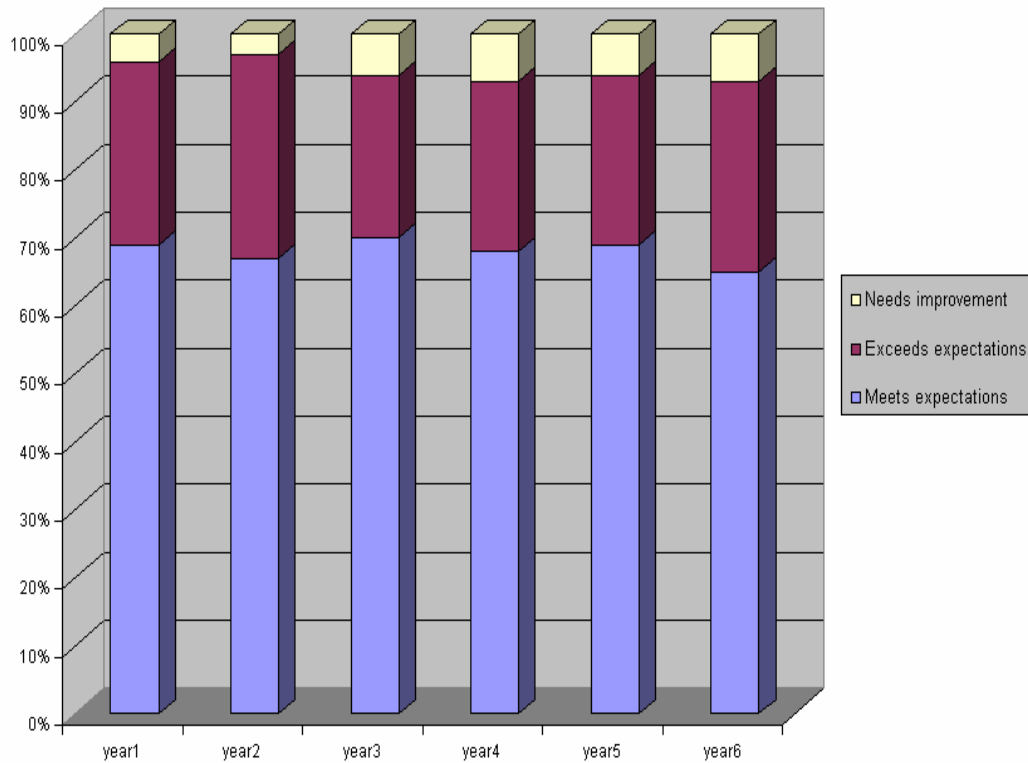


Figure 32. Performance Ratings Splitting by Categories

analyses had shown that employees' tenure was related to their turnover behaviors (Hom & Griffeth, 1995). That is, the longer employees' employment duration was, the lower turnover risk employees would have. Thus, turnover hazards would be influenced by time. However, this study only examined the relations between predictors and turnover risks within six years. What would the relation be if employees had longer employment duration? This study left the question unsolved. I conducted the survival analyses on all the employees, including the employees who hired during the six-year study period and those who hired before the beginning of the study period. These analyses allowed to evaluate the relationship between the predictors and employment duration for a greater range (time > 6 years).

It should be noted, however, that the hazard functions based on all the employees in the present study were biased, because it did not include employees who left the organization before the study period. Thus, the results of survival analyses were weighted more on the employees who had already been in the organization for over six years. The results of the univariate and multivariate survival analyses based on all the employees were presented on table 8. The results based on all the employees were telling a similar story with the previous results. Besides that, the results provided information about the survival and hazard function beyond the six-year study period.

Table 8. Univariate and Multivariate Survival Model Predicting Employment Duration (with all the employees)

	Univariate Survival Model		Multivariate Survival Model	
	Chi-Square	Hazard Ratio	Chi-Square	Hazard Ratio
Gender	55.38***	0.90	8.17	0.79
Age	5958.21***	0.12	1.92	0.94
Performance Rating	568.11***	0.71	2.48	0.92
Annual Pay Rate	3237.42***	0.38	290.19***	0.24
Promotion	3101.23***	0.45	143.50***	0.57
Job Attitudes	9523.21***	0.35	8.49*	0.84
Job Satisfaction	457.21***	1.53	22.27***	1.18
Intention to Quit	7277.71***	0.23	684.62***	0.39
Local Unemployment Rate	251.56***	0.91	11.11	1.10
Local Household Income	194.56***	0.95	9.05	1.01

Note. All the continuous predictors were standardized prior to analysis. *** $p < .0001$. Full sample included all the employees in the organization ($n = 95,859$).

For example, the estimated survival and hazard functions by employees' attitudes towards their organization were demonstrated by Figure 33 and Figure 34. According to Figure 33, it could be seen that, during the first five-year employment, about 55% of the employees with negative attitudes, about 20% of

the employees with neutral attitudes, and about 5% of the employees with positive attitudes, would leave the organization. The changing patterns of the hazard function for employees with different attitudes were different, too. During the thirty years employment period, employees with negative attitudes always had higher hazard risks than other employees. Their turnover hazards varied the most. Those employees were facing the highest risk to quit during the first ten years and the last ten years.

Two final caveats must be considered regarding the results of this study. First, the psychological predictors and the attitude indicators were collected once a year. That is, one wave of data was used to present employees' psychological conditions across the whole year. Thus, no matter when the employees left the organization during the year, those turnover behaviors were predicted by the one set of data collected in the summer. The interval between the time to collect psychological variables and the time of actual turnover behaviors ranged from one month to twelve months. This could affect the relation between those predictors and turnover risks. For example, the relationship between employees' job satisfaction and turnover risks with three-month interval might be different from the relationship between those two variables with twelve-month interval. To have a better understanding of the relationship between psychological predictors and turnover hazards over time, monthly collected data would be better than the yearly one. Thus, future studies focusing on the interval of the data collections of

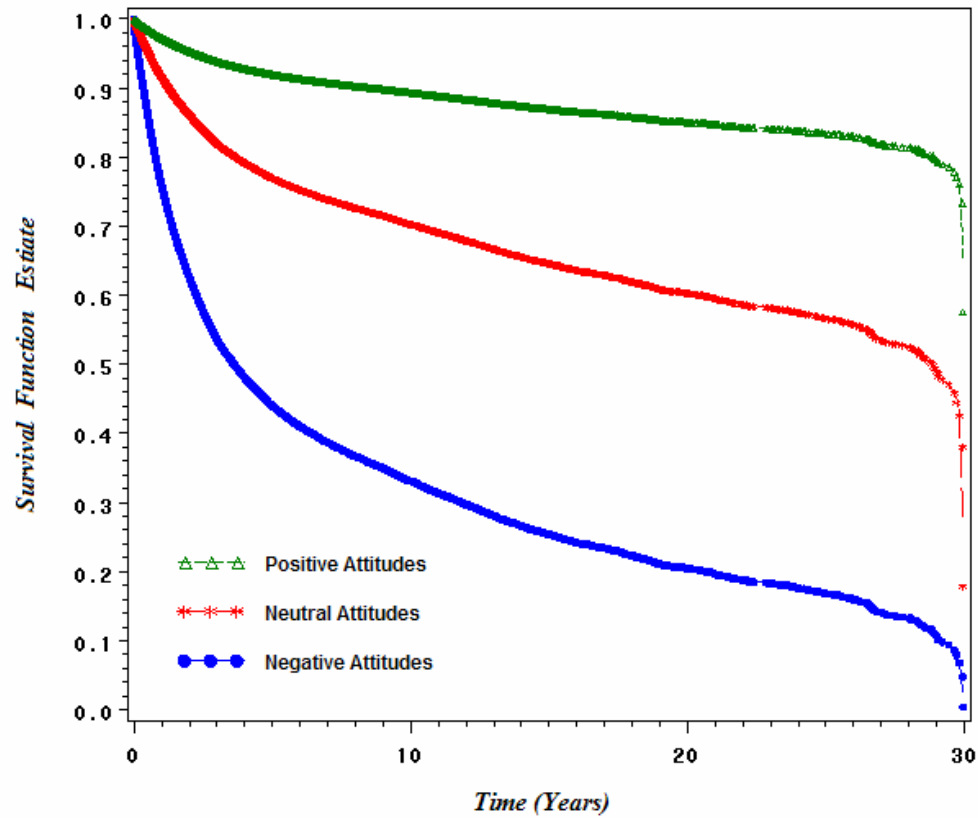


Figure 33. Survival function estimate by employee attitudes towards the organization (with all employees)

Note: Employees were split into three groups according to their attitudes: a) “Positive Attitudes” (Attitudes scores \geq 75 percentile), b) “Neutral Attitudes” (Attitudes score between 75 percentile and 25 percentile), and c) “Negative Attitudes” (Attitudes score \leq 25 percentile).

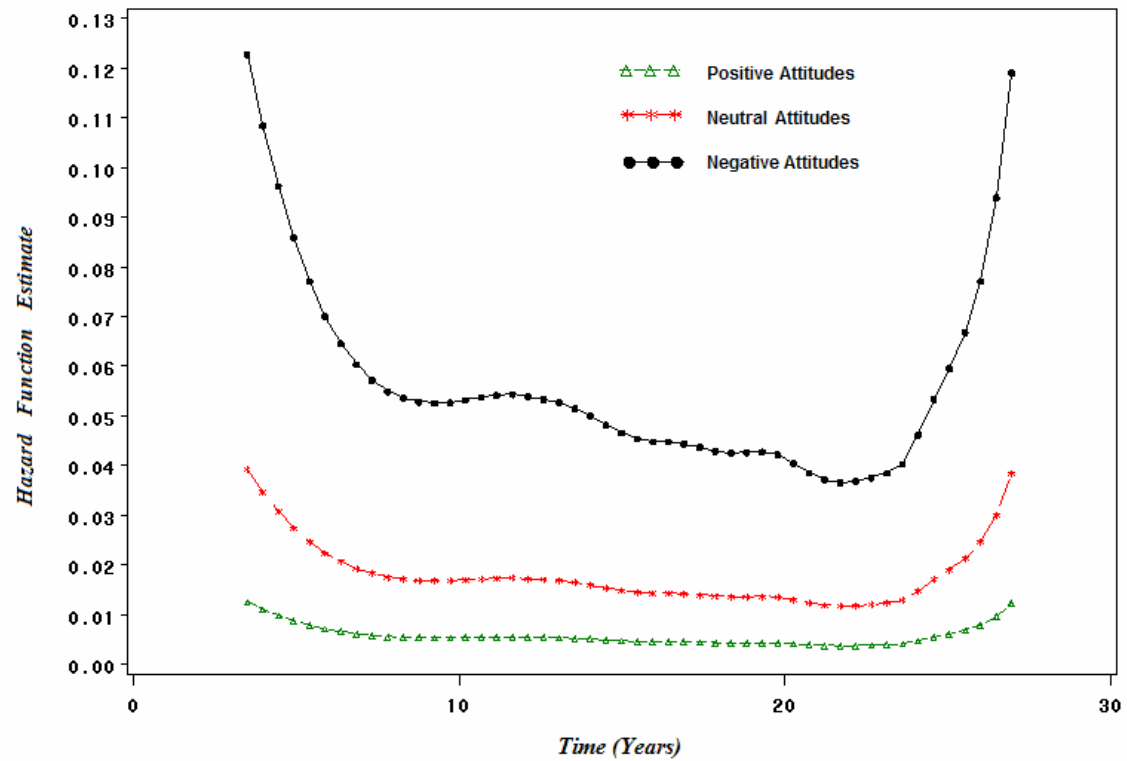


Figure 34. Hazard function estimate by employee attitudes towards the organization (with all employees)

Note: Employees were split into three groups according to their attitudes: a) “Employee with Positive Attitudes” (Attitudes scores ≥ 75 percentile), b) “Employee with Neutral Attitudes” (Attitudes score between 75 percentile and 25 percentile), and c) “Employee with negative Attitudes” (Attitudes score ≤ 25 percentile).

predictors and actual outcomes would benefit our understanding of the dynamic process of turnover.

Second, although the study involved a much more diverse sample than many turnover studies, which varied from higher level top managers to the lower job level contractors. Also, the job families included administrative supportive, business operations, clinical and pharmaceutical, customer service and claims, healthcare operations, sales and marketing, and technology. But, all the participants were from one organization. Their average salary was higher than the average pay across the whole population. Thus, they might have a different process of turnover because of the nature of this specific organization. Future research exploring the generalizability of these results to people working for other type of companies could provide a more accurate illustration of the relations between those predictors and turnover.

Appendix A. Employee Attitudes Survey

Instructions

The annual Employee Attitudes Survey will provide the company leaders with valuable information on what the organization does well and where improvements are needed in delivering services to its customers, as well as making it a better place to work.

Your responses to this questionnaire are completely anonymous.

Please place your completed questionnaire in the enclosed postage-paid return envelope, and then place it in any mailbox.

Please read each question carefully and pick the answer that best describes your opinion. Pick only one answer and shade the appropriate circle to indicate your response. If a question does not apply to you, or you don't know how to answer, skip the question or fill in the choice labeled "6 – Don't know / Not Applicable".

To what extent do you agree or disagree with each of the following statements about the COMPANY?

Indicate one answer for each statement.

1	2	3	4	5	6
Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree	Don't Know/Not Applicable

This Company has a clear sense of direction.	(1)	(2)	(3)	(4)	(5)	(6)
All in all, the changes we are making will make us a better Company.	(1)	(2)	(3)	(4)	(5)	(6)
This Company's senior management's actions are consistent with their words.	(1)	(2)	(3)	(4)	(5)	(6)
My job makes good use of my skills and abilities.	(1)	(2)	(3)	(4)	(5)	(6)
I have a clear idea of the results expected of me in my job.	(1)	(2)	(3)	(4)	(5)	(6)
This Company's senior management demonstrates that employees are important to the success of the business.	(1)	(2)	(3)	(4)	(5)	(6)
This company's senior management demonstrates that employees are important to the success of the business.	(1)	(2)	(3)	(4)	(5)	(6)
Overall, this Company is an effectively managed, well-run business.	(1)	(2)	(3)	(4)	(5)	(6)
I feel proud to work for this Company.	(1)	(2)	(3)	(4)	(5)	(6)
This company is a great place to work, compared to other organizations I know about.	(1)	(2)	(3)	(4)	(5)	(6)
I am enthusiastic about my future with this Company as a place to work and develop my skills.	(1)	(2)	(3)	(4)	(5)	(6)
My work gives me a feeling of personal accomplishment.	(1)	(2)	(3)	(4)	(5)	(6)

Considering everything, how would you rate your overall satisfaction in the Company at the present time? Indicate ONE answer:

- (1) Very Satisfied
- (2) Satisfied
- (3) Neither satisfied nor dissatisfied
- (4) Dissatisfied
- (5) Very dissatisfied

How long do you expect to continue working for this Company? Indicate ONE answer:

- (1) Less than 1 year
- (2) 1-3 years
- (3) More than 3 years to less than 5 years
- (4) More than 5 years to less than 10 years
- (5) 10 years or more
- (6) Until retirement

Appendix C. SAS Program Used for CFA of the Employee Attitudes Measurement

```

data AttitudeSurvey(TYPE=CORR);
  _type_ = 'corr';
  input _name_ $ V1 V2 V3 V4 V5 V6 V7 V8 V9 V10 V11 V12 V13 V14
V15;
  datalines;
V1 1.000
V2 0.473 1.000
V3 0.500 0.468 1.000
V4 0.275 0.298 0.233 1.000
V5 0.284 0.268 0.203 0.471 1.000
V6 0.446 0.517 0.397 0.350 0.313 1.000
V7 0.493 0.477 0.577 0.286 0.262 0.558 1.000
V8 0.589 0.463 0.601 0.283 0.247 0.428 0.535 1.000
V9 0.519 0.476 0.448 0.382 0.328 0.514 0.555 0.561 1.000
V10 0.465 0.426 0.381 0.348 0.295 0.524 0.469 0.467 0.588 1.000
V11 0.418 0.569 0.357 0.466 0.372 0.584 0.487 0.410 0.614 0.526
1.000
V12 0.306 0.338 0.252 0.754 0.512 0.393 0.323 0.304 0.460 0.399
0.530 1.000
;
RUN;

proc calis data=UHG2004 method=max edf=25000 pestim se;
  Lineqs
    V1 = X1 F1 + E1,
    V2 = X2 F1 + E2,
    V3 = X3 F1 + E3,
    V4 = X4 F2 + E4,
    V5 = X5 F2 + E5,
    V6 = X6 F3 + E6,
    V7 = X7 F3 + E7,
    V8 = X8 F4 + E8,
    V9 = X9 F4 + E9,
    V10 = X10 F4 + E10,
    V11 = X11 F4 + E11,
    V12 = X12 F4 + E12,
    F1 = X13 F5 + E13,
    F2 = X14 F5 + E14,
    F3 = X15 F5 + E15,
    F4 = X16 F5 + E16;
  Std
    F5 = 1. ,
    E1-E12 = U11-U112 ,
    E13-E16 = 4 * 1.;
  Bounds
    0. <= U11-U112;
  run;

```

Appendix C. SAS Example Program Used for Survival Analyses

```
*Univariate Survival Analysis;

*H1a: Female employees will be less likely to quit than male
employees;

Proc PHREG data = Full_Data;
  Model Employment_Duration * Turnover_Voluntary(0) = Gender;
  Run;

*Graphic Descriptions - Survival Curves;

Data IN00;
  Input Gender;
  Cards;
  1
  2
  ;

PROC PHREG Data = Full_Data noprint;
  Model Employment_Duration * Turnover_Voluntary(0) = Gender;
  Baseline Covariates = IN00 Out = Gender Survival = S1/Nonean;
Run;

Proc GPLOT Data = Gender;
  PLOT S1 * Employment_Duration = gender;
  symbol1 i= SM c=blue v= dot height=.5;
  symbol2 i= SM c=red v= star height=.5;
  Run;

*Multivariate Survival Analysis;

Proc PHREG data = Full_Data;
Model Employment_Duration * Turnover_Voluntary(0) = Gender Age
Performance Pay Promotion Attitudes JSAT ITQ Unemployment Income;
Baseline Out = overall Survival = S1/Nonean; Run;
```


Appendix D. SAS Example Program Used for Growth Modeling Analyses

*H2b: Leavers and stayers will have different growth trajectories in their performance over time;

```
Proc mixed data = Full_Data method = ml covtest;  
  class EEID;  
  model Performance = Time Turnover Time*Turnover/ solution;  
  random intercept Time / type = un subject = EEID ;  
run;
```

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