

A Test of Ghiselli's "Hobo Syndrome"

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This paper has not undergone formal review or approval of the faculty of the ILR School. It is intended to make the results of Center research, conferences, and projects available to others interested in human resource management in preliminary form to encourage discussion and suggestions.

Abstract

Ghiselli (1974) observed that some workers possess internal impulses to migrate from one job to another irrespective of better alternatives or other apparently rational motives.

Ghiselli labeled this tendency the "hobo syndrome." The present study tested the validity of the hobo syndrome using a national longitudinal sample of young workers. Results of event history analyses indicated support for the hypothesis that turnover depends on the number of times an individual has left his or her job in the past. Implications of the results are discussed.

A Test of Ghiselli's "Hobo Syndrome"

Some time ago, Ghiselli (1974) provided a series of observations about past and future research in industrial/organizational psychology. These observations were based on his experience as a pioneering researcher in the field, and were meant to serve as a guide regarding some concepts and variables future researchers ought to consider. One such concept suggested by Ghiselli was the "hobo syndrome," or the tendency for workers to engage in job hopping behavior. The validity of this hypothesis has not been directly substantiated, however. The purpose of the present study is to test Ghiselli's hypothesis using a recent methodological technique, event history analysis.

The Meaning of the "Hobo Syndrome"

Ghiselli's (1974) hypothesis of a hobo syndrome was inductive, born from his many years of formal interviews and informal conversations with workers. He defined the hobo syndrome as "... the periodic itch to move from a job in one place to some other job in some other place" (p. 81). Ghiselli argued that this Wunderlust derived from instinctive impulses, writing:

This urge to move seems not to result from organized, logical thought, but rather would appear more akin to raw, surging, internal impulses, perhaps not unlike those that cause birds to migrate. Floaters regularly provide socially acceptable explanations for their peripatetic activity, but under careful examination these explanations turn out to be little more than rationalizations. The simple fact is that after being in one place for a matter of months, or perhaps a year or so, depending on the strength and periodicity of this itch, the individual is impelled to pack up and move to another place and another job (p. 81).

The concept of the hobo syndrome suggests that workers most likely to leave their current job are those who have demonstrated signs of the hobo syndrome by leaving jobs often in the past.

A similar observation regarding the hobo tendencies of some workers was reached by Viega (1981), although he did not explicitly label the behavior he observed. In a study of the career movements of managers, Viega found that some managers changed jobs a great deal in their careers, but these changes apparently were not due to desires for higher compensation or job dissatisfaction. This lead Viega (1981) to ponder, "Although mobile managers are more restless and driven than the others, it is not clear why" (p. 34). He later concluded, "Mobile managers give every indication that they march to the beat of a different drummer--for many, mobility is in their blood ... To the extent that mobility is an instinct, [organizations] will have to contend with some managers who are unwilling to stay put long" (p. 38). Viega's data and conclusions are strikingly similar to those reached by Ghiselli (1974) regarding the desire of many workers to move for apparently instinctive reasons.

The plausibility of Ghiselli's (1974) hypothesis is bolstered by research from other, related literatures. In the absenteeism literature a number of researchers have suggested that absence proneness, or the tendency for workers' past absences to be predictive of future absence, is a relevant construct (Garrison & Muchinsky, 1977). In fact, research supports the proposition that prior absence predicts future absence (Breugh, 1981; Clegg, 1983; Harrison & Hulin, 1989; Ivancevich, 1985; Keller, 1983; Morgan & Herman, 1976).

In the labor economics literature, research has demonstrated that the greater the number of spells of unemployment, the greater the probability that an individual will be unemployed at a later point in time (Heckman & Borjas, 1980). As pointed out by Heckman and Borjas (1980), this cycle of unemployment may occur because past unemployment leads to a loss of skills during unemployment. As alternate explanation, one that is more consistent with Ghiselli's (1974) hypothesis, is that past unemployment may reflect inherent characteristics (e.g., traits, preferences) that precipitate future occurrences of unemployment. With respect to worker mobility, Blumen, Kogan, and McCarthy (1955) found that dividing workers into "stayers" versus "movers" significantly

improved the fit of their Markov model of inter-industry mobility. Although differences in mobility among workers have been recognized in the labor economics literature, typically mobility tendencies have been treated as residuals without further investigation (Granovetter, 1986).

Ghiselli's (1974) hypothesis, and these related streams of research, are supportive of an often-cited maxim in industrial/organizational psychology, "The best predictor of future behavior is past behavior." In fact, this is one of the principal assumptions underlying the use of biographical information to select workers (Mael, 1991; Owens, 1976). Research has shown that biodata is predictive of employee behaviors such as turnover (Schmitt, Gooding, Noe, & Kirsch, 1984). Thus, consistent with Ghiselli's (1974) hypothesis and these supporting streams of research, it is hypothesized that the number of times individuals have left their jobs in the past will significantly influence the probability that they will leave their present job.

A necessary condition for a test of any hypothesis is that extraneous influences which may provide alternative explanations of the results be controlled experimentally or statistically (James, 1991). This is particularly important in the context of the present study since there are a number of potential explanations of the link between past and present quits that are competing alternatives to the concept of the hobo syndrome. For example, some individuals may exhibit a pattern of turnover behavior not due to a desire to job hop per se, but because they have a greater number of labor market alternatives. Those who are highly educated, or in favorable labor markets, may quit their jobs more often because more alternatives are available. Accordingly, when estimating the effect of past turnover on present turnover, it is important to control for education and labor market conditions.

In addition to education and labor market conditions, several other relevant control variables were taken into account. The selection of these variables was based on Mobley's (1982) review of past turnover research, which suggested a number of potential influences on turnover. These variables were job satisfaction (Carsten & Spector, 1987), age (Porter

& Steers, 1973), experience (Mobley, 1982), wage rates (Dalton & Todor, 1979), marital status and alternative sources of income (Muchinsky & Tuttle, 1979), the industry in which the individual works (Price, 1977), and whether the worker is employed in a rural versus urban area (Parsons, 1977). Because past research has suggested that these variables affect turnover, their influence was controlled for in the analysis to reduce omitted variable problems.

The Importance of Survival Analysis to Turnover Research

Peters and Sheridan (1988) argued that despite a wealth of research, the turnover literature has provided few recommendations for managing employee turnover. According to Peters and Sheridan (1988), one reason for this situation is that past research designs often have been inherently flawed, which has led to a diminished ability to integrate findings across studies. The principal limitation in past turnover research is that most studies have been cross-sectional in nature, and thus have not incorporated employee flows in to and out of the organization in the analysis.

Specifically, turnover research has often failed to consider several important factors related to employee movement. First, turnover increases with the length of the measurement window used in a particular study. As the measurement window widens, the base rate of turnover generally increases as well (Peters & Sheridan, 1988). For example, over an infinite amount of time, 100% of all job incumbents would be expected to terminate. The arbitrary choice of the length of the measurement window generates inconsistency across studies because the base rate of turnover substantially affects its correlation with other variables. Thus, inconsistent results with respect to turnover may be due to an artifact of the interval over which turnover is assessed.

A second problem in turnover research generated by typical cross-sectional designs is that of right censoring, or the fact that the choice of when to terminate the study affects the results observed when relating turnover to other variables. For example, Employee A may quit the day before the study concludes, and Employee B may quit the day after the

study concludes, yet only one of these employees is counted as having left the organization. This produces inconsistency across studies because if a study concludes at a particular date, yet a large group of employees happen to quit shortly after the study ends and turnover is measured, this obviously affects the results observed.

Furthermore, traditional turnover designs treat terminations the day the study begins (Time 1) as the same as the day the study concludes (Time 2). As noted by Peters and Sheridan (1988), this is a weak assumption. It is likely that predictor variables measured at Time 1 have a stronger effect on individuals who terminate closer to Time 1 than on those who terminate at Time 2. Failing to analyze when individuals leave their jobs also wastes information on why some leave soon after joining an organization while others leave at a later point in time.

Finally, left censoring can also be a problem, where the sample consists of only those workers who are employed at the beginning of the study, regardless of their hire dates (Peters & Sheridan, 1988). As a result, cross-sectional designs result in samples consisting of workers who have survived long enough to be included in the study. Consequently, the tenure distribution of the sample may be skewed, and this distribution will vary as a function of when the study commences. Thus, the choice of when to commence a study affects the results observed when predicting turnover from other variables.

As pointed out by Morita, Lee, and Mowday (1989) and Peters and Sheridan (1988), a solution to these problems is event history analysis (or in the present context, survival analysis). Survival analysis is a general term for statistical techniques in which changes in states over time are modeled (Allison, 1984; Tuma & Hannan, 1984). These techniques focus on the states an individual is in and was in, the length of time spent in these states, and the rates of movement from state to state (Harrison & Hulin, 1989).

Although it has typically been employed in the biomedical life sciences, survival analysis adapts easily to organizational behavior phenomena, such as absenteeism and

turnover. Consequently, survival analysis has recently appeared in the organizational literature (e.g., Fichman, 1988; Gerhart, 1990; Harrison & Hulin, 1989; Morita et al., 1989). Because cross-sectional turnover research ignores how long it takes for turnover to occur, survival analysis obviates base rate problems and censoring of observations by recasting the analysis in terms of survival time on the job. Furthermore, cross-sectional research assumes that the relationship between predictor and criterion variables is stable over time. As Tuma and Hannan (1984) point out, unless one uses longitudinal data, this assumption is untested, and, when analyzing turnover, is often tenuous (Peters & Sheridan, 1988). Thus, survival analysis is dynamic in that it deals with multiple waves of turnover data and tracks the time intervals between job changes and the rates of survival across these time intervals. This makes it well suited to deal with the problems in traditional research designs reviewed earlier, and to test the validity of Ghiselli's (1974) hypothesis of a hobo syndrome.

Method

Data Source and Sample

The data analyzed in this study were collected as part of the National Longitudinal Surveys Youth Cohort (NLSY), from 1979 through 1988. For the purposes of this investigation, the Work History, Current Population Survey, and Key Variables tapes were merged. The sample size for the NLSY is $N = 12,686$.

As of 1988, age of the respondents ranged from 23 to 32 years; the average age was equal to 27.2 years ($SD = 2.3$ years). Average level of respondent education was 12.9 years ($SD = 2.4$ years); education ranged from 0 to 20 years. Job tenure in the respondent's first job in 1988 ranged from 1 week to the full year; the average respondent worked at their first job an average of 34.5 weeks in 1988 ($SD = 11.9$ weeks). As measured on a 1 (very low) to 6 (very high) scale, the average unemployment level for respondents in 1988 was 2.5 ($SD = 0.73$). Average hourly wage rate in 1988 was \$8.64 ($SD = \4.59). In 1988, 51% of respondents were married and the average annual family income was \$28,090

($SD = \$19,791$). As rated on a 1 to 4 scale, average level of respondent job satisfaction was 3.27 ($SD = 0.73$). In 1988, 79% of respondents lived in urban versus rural areas. From the period of 1979 to 1987, the average respondent had quit 2.32 jobs ($SD = 2.77$ jobs); this figure ranged from no quits to 19 quits. In 1988, 26.0% of individuals quit their jobs.

Measures

Voluntary turnover. As many as 5 job changes were tracked each year during the observation period (1979-1988). Voluntary turnover was coded as 1 if the employee left his or her job voluntarily. Employees not leaving their job were coded as 0. Involuntary separations (laid off, fired, program ended, or plant closed) also were coded as 0 because these did not represent voluntary separations.

Number of past quits. For the logit analysis (see below), number of past quits was measured by summing the total number of times an individual had voluntarily exited a job between 1979 and 1987. The level of past quits was then used as a predictor of voluntary job turnover in 1988. For the survival analysis, the number of past quits was measured by recording each voluntary job change that occurred during the entire study period. Each successive voluntary job exit become an event that was accumulated throughout the study.

Control variables. Education (highest grade completed as of May 1 of each survey year), tenure (total length of experience measured in weeks at each job), unemployment rate (1=very low to 6=very high), marital status (1=married, 0=otherwise), hourly wage rate, age, rural versus urban residence (1=urban, 0=rural), job satisfaction (1=very low to 6=very high), family income measured in dollars, and 11 dummy variables representing the industry characterizing each job in which the respondent worked (the base cell was the entertainment and recreation services industry) were assessed through specific interview questions. The dummy variables representing the industries were effect coded.

For the survival analysis data set, four additional variables were used: (1) date beginning employment on a particular job; (2) date of stopping employment on the job; (3) the spell or duration of employment in each job; and (4) status of the employee (1=the

employee left his or her job voluntarily and 0 otherwise). These were measured by specific questions as part of the NLSY surveys.

Analyses

Because logistic regression is recommended when analyzing dichotomous dependent variables such as turnover (Huselid & Day, 1991), and in order to facilitate comparisons with the survival analysis results, a logistic regression was calculated by regressing whether the respondent left a job in 1988 on the number of past turnovers and the control variables. With respect to the event history analysis, because it is computationally very demanding, we could not use the full sample in the survival analysis. Therefore, the largest possible (12%) random sample was drawn from the complete sample. Examination of descriptive statistics from this random sample revealed almost identical results to those for the full sample reported above. For the survival analysis, the standard one-person, one-record data set (the person data set) was transformed to a one-person, multiple period data set (the person-period data set). As a result, the data set was inflated to 6,836 observations. It should be noted that the NLSY only measured job satisfaction once each year rather than at every job change; therefore it could not be included in the event history analyses.

Results

Logistic Regression Results

The logistic regression results are presented in Table 1. The fit statistics from the maximum likelihood estimation were as follows: $\chi^2 = 1,025.2$ with 21 degrees of freedom ($p < .01$), and -2 log likelihood ratio = 7,125.9 ($p < .01$). These statistics suggest that the model provides a good fit to the data (Aldrich & Nelson, 1984).

Insert Table 1 About Here

The logistic regression results indicate strong support for the hobo syndrome hypothesis. Specifically, past turnover was a significant predictor of future turnover ($\beta = +.214$, $p < .01$), controlling for other factors that might influence turnover such as job satisfaction, labor market conditions, and human capital characteristics. Translating the logit value back into a probability value provides the increased probability of an individual quitting his or her present job as a result of quitting a certain number of jobs in the past. Performing this translation indicates that a 1 standard deviation increase in the number of past quits results in a 28% increase in the probability of quitting the present job.

The results also indicate that older and more experienced workers were less likely to quit than younger and less experienced workers. Married individuals and those earning higher wage rates were less likely to quit than unmarried individuals and those earning lower wage rates. Also, with the exception of the mining and the agriculture, forestry, and fishing industries, all industry variables were positive and significant, indicating that workers in these industries were significantly more likely to leave their jobs than the average worker. Workers in the mining industry were significantly less likely than average to quit.

Survival Analysis Results

Survival analysis utilizes the survivor and hazard functions (Singer & Willet, 1991). When studying voluntary turnover, the survivor function represents the probability that a randomly selected employee has not left his/her job by time t . One way of representing the survival rate is a life table, which depicts duration of employment over time intervals. Table 2 illustrates the estimated life table. Based on Cutler and Ederer's (1958) method, the proportion of employees surviving (P_j) was defined as the cumulative portion of observations surviving to the time at the beginning of each of the 57.6 week intervals:

$$P_j = (1 - q_{j-1}) P_{j-1},$$

where $p_1=1$ and q_j is the number of observations which exit divided by the size of the risk set (the risk set is the number of observations minus the number of censored observations, defined as the number of stayers over each time interval, all divided by two).

 Insert Table 2 About Here

The hazard rate (λ_j), again based on Cutler and Ederer (1958), was defined as follows:

$$\lambda_j = 2q_j / [h(2 - q_j)],$$

where h is the width of the time interval and q_j is as defined above.

The profiles of both survivor and hazard rate functions are depicted in Figures 1 and 2. Examination of the survivor profile in Figure 1 reveals that the unconditional probability of staying beyond time t decreases over time. Nearly 30% of employees voluntarily left their first job over the course of the entire survey period. The hazard profile shown in Figure 2, on the other hand, reveals that the risk of being a voluntary mover decreases as the duration of the tenure at a job increases, suggesting that as individuals become more committed to and make more investments in their job, the costs of moving increase.

 Insert Figures 1 and 2 About Here

Close examination of Figure 1 demonstrates that voluntary turnover is not a normally distributed variable. Because the sample size is large and the probability of turnover is low, the binomial distribution representing turnover can be approximated by the Poisson distribution (Mendenhall, Reinmuth, Beaver, & Duhan, 1986). When one considers the Poisson distribution in a temporal framework, then the time interval between events (in this case, turnover) follows the exponential distribution (Avery & Hotz, 1984). When the survivor function follows the exponential distribution, in turn, the Weibull model

will provide a reasonable fit to the data (Fichman, 1989). Therefore, the Weibull model was estimated in the present study. Additionally, the proportional hazards model was estimated since it is the most widely used survival analysis model in psychological research, and offers the advantage of requiring no assumptions about the underlying distribution of turnover. The mathematics of these estimations are provided in the Appendix (see also Cox, 1972; Fichman, 1989; Kalbfleisch & Prentice, 1980; Morita et al., 1989).

Table 3 provides the maximum likelihood estimates for the proportional hazards model and the Weibull model. The Weibull function represents the time of survival on the job. Conversely, the proportional hazards function represents the rate of turnover over time. Thus, a significant coefficient which positively predicts survival (the Weibull function) generally would be expected to negatively influence the rate of turnover (the proportional hazards function). The table reveals that the proportional hazards and Weibull models arrive at similar estimates with respect to the variables in the analysis. Conversely, these survival analysis estimates are different from the logit results with respect to several variables (tenure, marital status, wage rate, and age). Since all of these variables are time dependent, it is not unexpected that survival analysis results for these variables are different from the logit results. The fact that the results were different in some respects reinforces the importance of using the more appropriate event history analysis in turnover research.

Insert Table 3 About Here

As with the logistic regression estimates, both the Weibull and proportional hazards function support the hypothesis of the hobo syndrome. The coefficient estimate ($+ .069$, $p < .01$) in the proportional hazards model means that each additional voluntary exit increases the log of the hazard by .69, controlling for the influence of other variables. Exponentiating the coefficient yields a value of 1.07, indicating that each additional

previous quit increases the hazard by an estimated 7%. A similar interpretation exists for the Weibull model, except that the sign of the coefficient needs to be reversed as explained above.

Figures 3 and 4 provide illustrations of the hobo syndrome for the survival and hazard functions, respectively. In both figures those individuals who had more past quits than average were classified as "movers" and those who had fewer past quits than average were classified as "stayers." Figure 3 shows that those who quit more jobs than average in the past were much less likely to survive on the job than those who quit fewer jobs than average. Figure 4 shows that the hazard (i.e., turnover) rate for "stayers" was lower than the rate for "movers." Both figures illustrate support for the hobo syndrome.

Insert Figures 3 and 4 About Here

Unobserved Heterogeneity

The models discussed thus far are based on an assumption of homogeneity of the survival distribution across individuals. This, in turn, implies the assumption that all relevant covariates have been included in the model. However, this assumption is rarely met in practice (James, 1991), and requires that all possible individual difference sources of variance are incorporated into the model. Even if the hazard rate is constant over time for any individual, differences (across individuals) in the hazard rate that are not specified in the model will function as unobserved sources of heterogeneity and cause inconsistent or biased parameter estimates and/or inferences based on inappropriate standard error estimates (Heckman & Singer, 1984; Kiefer, 1988).

A strategy to deal with the problem of unobserved heterogeneity is to explicitly include possible sources of that heterogeneity in the model. In the present study, for example, historical year when the data were recorded, and 1,529 dummy variables for each

individual could be regarded as the possible sources of heterogeneity effects. However, the inclusion of such variables in the model is inefficient and impractical.

An alternative approach is to assume that the transition rate from one state to another equals the function of the observed covariates ($\phi(z)$) multiplied by the gamma-distributed disturbance term assumed to influence the rate for the i th sample member (ϵ):

$$r(t; z) = \phi(z) \epsilon$$

If we assume that the unobserved variable, ϵ , has the gamma distribution with parameters θ and R , then the probability density function of ϵ takes the form:

$$f(\epsilon) = \theta^R \epsilon^{R-1} e^{-\theta \epsilon} / \Gamma(R),$$

where $\Gamma(R)$ is the gamma function, $\theta = \mu_\epsilon / \mu_\epsilon^2$, and $R = \mu_\epsilon^2 / \mu_\epsilon^2$.

Some statistical packages are now available that allow estimation of parameters with consideration of unobserved heterogeneity (e.g., RATE, LIMDEP). LIMDEP 6 allows estimation of the extended Weibull model where the gamma-distributed disturbance term can be included into the functional specification. Accordingly, we re-estimated the coefficient for the past turnover history variable accounting for unobserved heterogeneity. The result of this estimation confirmed the significant coefficient ($p < .01$) for past turnover history. Accounting for unobserved heterogeneity did not change the significance of the hypothesized coefficient, suggesting that confidence can be placed in the internal validity of the results.

Discussion

The present study provided support for Ghiselli's (1974) hypothesis of a "hobo syndrome." Past turnover behavior was a significant predictor of present turnover behavior; this result was quite robust to alternative methodological specifications. Furthermore, the effect of past turnover on present turnover was significant in the presence of a series of control variables derived from a review of past research. Finally, accounting for unobserved heterogeneity failed to change the significant effect of the hobo syndrome. All of this serves to increase confidence in the validity of the results.

There are several practical implications that follow from the results. One implication is that organizations wishing to control turnover might consider inquiring about the frequency of applicant job changes when making selection decisions. Presumably, those applicants who have changed jobs more frequently in the past are more likely to leave the job for which they are interviewing than those who have experienced fewer job exits in the past. Thus, one means of controlling the symptoms of the hobo syndrome may be not to select those individuals who have evidenced a consistent pattern of job hopping in the past.

The biodata literature provides some support for this supposition. For example, it is common to inquire about past job history when collecting biographical information (Mael, 1991). Furthermore, a significant correlation between biographical information and turnover has been reported in the literature (Schmitt et al., 1984). While these studies did not focus on the hobo syndrome, they do suggest that using past turnover history as a predictor in human resource selection decisions may reduce turnover.

Another implication of the present findings is that organizations concerned with controlling turnover may wish to focus their efforts on individuals who have demonstrated symptoms of the hobo syndrome on other jobs in the past. Since, according to Ghiselli (1974) and Viega (1981), frequent job changers do not seem to exhibit rational behavior, one possible means of reducing turnover would be to ask employees who have changed jobs frequently in the past to examine the reasons why they would consider leaving their current jobs. If the frequent job changers are as irrational as Ghiselli and Viega implied, attempts to help individuals examine the rationality of their actions may induce lower turnover rates.

Limitations and Contributions

The present study has several limitations that should be noted. The sample used in the present study was homogeneous with respect to age (the age range was 9 years). Thus, it is possible that the findings do not generalize to older workers. On the other hand, the

sample was quite heterogeneous in many respects other than age, which should increase confidence in the external validity of the results.

Although the results of the study suggest that Ghiselli's (1974) hypothesis of a hobo syndrome is a valid one, we cannot be fully confident about this until we better understand the psychology behind this effect. Why is it that some workers have the periodic urge to move from one job to another? The present results suggest that this Wunderlust exists, but the results are mute with respect to exactly why this motivation arises. Given the results reported here, future research examining the etiology of the hobo syndrome seems warranted. In particular, since recent research has linked affective disposition to turnover behavior (Judge, in press), this might be a useful construct for future research to consider when investigating the psychological processes underlying the hobo syndrome.

For example, Granovetter (1974, 1983) has argued that workers with a large number of prior jobs are more likely to have acquired many professional contacts and leads about alternative employment opportunities than workers who have held few previous jobs. Thus, past turnover may lead to future turnover because those who have held many jobs in the past are more able to move when they wish due to their professional contacts and "inside information" about alternative job opportunities. Our results cannot conclusively rule this explanation out, although the series of control variables such as experience and labor market alternatives, and the fact that accounting for unobserved heterogeneity did not alter the significance of the findings, should increase confidence in the interpretations we have placed in the results.

Despite these limitations, the present study has contributed to the turnover literature in several ways. First, this is the first study to directly substantiate Ghiselli's (1974) hypothesis of a hobo syndrome. The result may help us to further understand why some individuals decide to terminate their employment. Much has been learned about turnover through past research. However, rarely have researchers explained more than a small minority of the variance in turnover behavior (McEvoy & Cascio, 1985). While the

methodological reasons for this fact were reviewed earlier, much remains to be learned about the psychology of the turnover process. The present study may stimulate further research in this direction.

Also, the methodology and results of the present study reinforce the usefulness of survival analysis for turnover research. The importance of using survival analysis in turnover research has been emphasized by a number of researchers (Gerhart, 1990; Morita et al., 1989; Peters & Sheridan, 1988). However, very little research has appeared using this methodology. Furthermore, the analysis of unobserved heterogeneity is a powerful technique, yet has not been used in research in this and related areas.

In sum, the results of the present study confirmed Ghiselli's (1974) hypothesis of a "hobo syndrome." The results possess implications for practice and for future research. The research methodologies used in the present study, particularly the methods used to account for unobserved heterogeneity, also may be useful for researchers investigating turnover behavior. Hopefully, future research will continue in this direction by providing a better understanding of why the "hobo syndrome" apparently exists.

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Appendix

Computations of Survivor and Hazard Functions

The proportional hazard model takes the following form:

$$h(t) = e^{h_o(t)},$$

where $h_o(t)$ is the base line hazard rate at time t for a covariate vector o .

If one or more covariates are included in the regression, with duration data, a regression like model derived by Cox (1972) can be estimated as follows:

$$h[t; z(t)] = h_o(t) e^{\beta' z},$$

where z is a vector of covariates. Log transforming the hazard function to let it be a linear function of the covariates, the following is obtained:

$$\log h[t; z(t)] = \log[h_o(t)] + \beta' z(t).$$

For the Weibull model, the hazard function is specified as follows:

$$h(t) = \lambda p(\lambda t)^{p-1},$$

where p is the transformation of $1/\sigma$ and represents the shape parameter of the distribution, and λ is defined as the instantaneous rate of turnover at $T=t$ conditional upon survival to time t . Being cast in terms of the density of the spell durations, $f(t)$, the Weibull model takes the functional form:

$$\log T = \alpha + \beta^* z + \sigma w,$$

where τ denotes the time interval between job changes, $\alpha = -\log \lambda$, $\sigma = p^{-1}$, $\beta^* = \sigma \beta$, z is a vector of covariates, and w has a probability density function that is an extreme value distribution (Kalbfleisch & Prentice, 1980).

Table 1

Logistic Regression Results Predicting Turnover

Variable	β	SE
Job Satisfaction	0.031	0.040
Unemployment Level	-0.034	0.036
Education	0.021	0.014
Wage Rate	-0.010	0.001**
Job Tenure	-0.002	0.001**
Age	-0.048	0.014**
Past Turnover	0.214	0.012**
Married	-0.121	0.063*
Family Income	-0.001	0.001
Urban Residence	0.085	0.077
Agriculture, Forestry, & Fishery Industries	0.267	0.239
Mining Industry	-7.611	1.102**
Construction Industry	1.207	0.148**
Manufacturing Industry	0.730	0.116**
Transportation Industry	0.690	0.161**
Communication & Utilities Industries	0.890	0.113**
Finance, Insurance, & Real Estate Industries	0.821	0.153**
Business and Repair Services Industries	0.886	0.143**
Personal Services Industry	0.471	0.179**
Professional and Related Services Industries	0.854	0.116**
Public Administration Industry	0.416	0.171**
Intercept	-0.212	0.430

Note: * $p < .05$; ** $p < .01$. For the industry dummy variables, the entertainment and recreation services industry served as the excluded group.

Table 2

Estimated Life Table

Duration	Enter	Censored	At Risk	Exited	P_j	λ_j
.0.0- 57.6	6,836	2,647	5,512	3,915	1.0000	0.0191
57.6-115.2	274	185	181	67	0.2898	0.0079
115.2-172.8	22	4	20	4	0.1828	0.0039
172.8-230.4	14	0	14	2	0.1463	0.0027
230.4-288.0	12	3	10	1	0.1254	0.0017
288.0-345.6	8	0	8	0	0.1134	0.0000
345.6-403.2	8	1	7	0	0.1134	0.0000
403.2-460.8	7	3	5	0	0.1134	0.0000
460.8-518.4	4	3	2	0	0.1134	0.0000
518.4-576.0	1	1	0	0	0.1134	0.0000

Note: Number of observations=6,836; Number of observations exiting=3,989;

Number of observations censored=2,847.

Table 3

Maximum Likelihood Estimates of Event History Models

Variable	<u>Weibull Model</u>		<u>Proportional Hazards Model</u>	
	β	t	β	t
Unemployment Level	.001	-1.02	.001	1.25
Education	-.046	-0.18	.001	0.28
Wage Rate	.001	1.40	-.001	-2.60*
Job Tenure	-.001	-21.31**	.003	5.68**
Age	-.013	-3.20**	.012	2.03*
Past Turnover	-.067	-22.71**	.069	10.79**
Married	-.043	-2.06*	.120	3.17**
Family Income	.001	1.87	-.002	-2.30*
Urban Residence	.001	0.85	-.001	-1.31
Agriculture, Forestry, & Fishery Industries	.190	1.95	-.240	-2.14*
Mining Industry	.031	1.35	-.310	-1.30
Construction Industry	.055	0.80	-.007	-0.91
Manufacturing Industry	.055	1.08	-.062	-1.00
Transportation Industry	-.092	-1.27	.180	1.70
Communication & Utilities Industries	-.270	-6.77**	.300	6.77**
Finance, Insurance, & Real Estate Industries	-.100	-1.05	.099	1.07
Business and Repair Services Industries	-.160	-2.34*	.160	2.24*
Personal Services Industry	-.005	-0.08	-.009	-0.27
Professional and Related Services Industries	-.056	-0.98	.035	0.58
Public Administration Industry	.068	0.55	-.078	-0.59

Note: * $p < .05$; ** $p < .01$. For the industry dummy variables, the entertainment and recreation services industry served as the excluded group.

Figure Captions

Figure 1. Estimated survival function.

Figure 2. Estimated hazard function.

Figure 3. Survival function for stayers and movers.

Figure 4. Hazard function for stayers and movers.







