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Stepping Stones or Learning about Quality?**

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## **ABSTRACT**

### **Repeated Job Quits: Stepping Stones or Learning about Quality?\***

Despite the fact that worker quits are often associated with wage gains and higher overall job satisfaction, many workers quit once again within one or two years after changing jobs initially. Such repeated job quit behavior may arise as a stepping stone to better quality jobs (Burdett, 1978) or as a response to unexpectedly low job quality (Jovanovic, 1979). This paper tests the validity of both explanations using data from the UK labor market in order to improve our understanding of job search behavior. Results from panel estimations of job quits and job satisfaction illustrate that the labor market is characterized by elements of both explanations. More specifically, a variance decomposition shows that the stepping stone model explains 80 percent of repeated job quit behavior; the remaining 20 percent is the result of learning about job quality. Hence, workers appear to need several job quits to find their most preferred job and multiple job quits serve as a stepping stone to more satisfaction at work.

JEL Classification: J28, J62

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# 1 Introduction

As has been widely documented (see e.g. Kambourov and Manovskii (2008)), labor mobility patterns across workers exhibit a great deal of variety. Long-term employment relationships are quite common, yet some workers are involved in many job quits within a short time period (Farber (1999)). In light of recent evidence that workers usually gain in job satisfaction and obtain higher wages after a job quit (e.g. Perez and Rebollo (2005); Chi et al. (2008)), the fact that many decide to change jobs again after an initial quit raises the question whether these job changes contribute to better matching efficiency or whether they simply constitute a relocation of labor without any increase in match quality.

From a theoretical point of view, prominent explanations for changing jobs rest on the presence (or absence) of ex ante information about job quality. In this vein, at one extreme, job quality may be perfectly observable ex ante, and hence workers may decide to quit (again) if they receive a job offer which is better than their current job. This can be denoted the stepping-stone mechanism, based on the on-the-job search theory by Burdett (1978). At the other extreme, repeated job quits can be explained by the complete absence of ex ante information about job quality – the so-called learning model pioneered by Jovanovic (1979). In this model, job quality is revealed over the time spent in the job. As a result, workers may decide to leave a new job if the realized match quality turns out to be disappointing. Obviously, these two theories can be considered two ends of a continuum representing the degree to which ex ante job quality information is available. In practice, workers may decide whether to change jobs in a situation where some information about job quality is known ex ante, while some has to be learned while in the job. This paper is the first to investigate this continuum empirically, studying the extent to which repeated job quits can be explained by the stepping-stone theory versus the learning model.

In order to shed light on the relative empirical content of the two theories, this paper uses the British Household Panel Survey (BHPS), which allows me to distinguish worker-initiated job quits from other job separations. Furthermore, the panel element of the data allows to compare repeated job quits by a particular individual over time. This paper uses information

about such repeated job quits to observe how match quality evolves over time and following subsequent job changes, where information on job satisfaction is used as a measure of match quality.<sup>1</sup> If match quality improves following each job quit, then job quit behavior can be considered a stepping stone mechanism, contributing to matching efficiency. Alternatively, if the probability of a good match after a job quit appears unrelated to the quality of the previous job, job changes constitute a relocation of labor without actually improving match quality.<sup>2</sup>

This paper uses job satisfaction as a measure for workers' perceived job quality, which can be related to labor mobility decisions. A growing empirical literature on job satisfaction has shown that job satisfaction is a determinant of labor mobility; there exists a strong negative relationship with both quit intentions (e.g. Sousa-Poza and Henneberger (2004), Böckermann and Ilmakunnas (2007))<sup>3</sup> and actual quits (Freeman (1978); Akerlof et al. (1988); Clark et al. (1998); Clark and Georgellis (2004)).<sup>4</sup> In order to better understand why people may choose to quit multiple times in a short time period, it is crucial to look at job satisfaction levels after a quit has occurred, to observe whether changing jobs yields a permanent gain in job satisfaction or not. Yet, relatively little is known about the effect of quits on ex post levels of job satisfaction.

One exception is Chi et al. (2008) who focus on the effect of quits on job satisfaction. Their results illustrate that job quitters experience a permanent increase in their job satisfaction levels in the 8 years following a quit, and that job satisfaction increases up to the level of that of stayers. The increase in job satisfaction after quitting one's job can be explained by the fact that job quits are usually associated with a gain in wages (e.g. Perez and Rebollo (2005); Light (2005)), as well as higher satisfaction with non-monetary aspects of the job (Altonji and Paxson

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<sup>1</sup>Some economists are skeptical about using a self-reported satisfaction measure, because of measurement issues and difficulties in interpersonal comparisons. A recent paper by Blanchflower (2008) addresses a number of those reservations by illustrating the robust findings in the satisfaction literature and how satisfaction is related to more objectively observable measures of wellbeing (e.g. health, income).

<sup>2</sup>Note that a positive relationship may be found if only workers in the worst matches quit their job, i.e. selection effect. Then, on average, the match quality increases following a job quit. Sections 4.2 and 4.3 pay attention to this.

<sup>3</sup>Note that this follows a large psychological literature, where these effects have been investigated before.

<sup>4</sup>Actually, since current job satisfaction is assumed to represent both the worker's satisfaction with past experience and the expected happiness if he stays in this job in the future, Levy-Garboua et al. (2007) argue that the residual from a job satisfaction regression is an even better predictor for worker quits than the overall level of job satisfaction, since this residual captures the future component of job satisfaction.

(1986)). However, satisfaction does not remain at a higher level for everyone. Chi et al. (2008) provide some descriptive evidence for the absence of a long-term increase in job satisfaction for multiple time job quitters. This paper looks at what underlies the lack of long-term job satisfaction gains. Possibly, job satisfaction falls in the new job, because the match turned out to be of less quality than was expected ex ante. Alternatively, people may anticipate a new step in their career, using sequential quits as a stepping stone to more happiness at work. Such sequential search behavior is found by Neal (1999)<sup>5</sup> who shows that workers always change careers first before they search for their preferred firm to work in. Information about job satisfaction is informative here since it can show whether the mobility pattern as described by Neal (1999) is a free choice or whether specific human capital ties workers to specific sectors or occupations.

This paper investigates the relative empirical content of the stepping stone model versus the learning model in (repeated) job quits. Using the theoretical predictions from both models, a variance decomposition of job satisfaction in the new job allows me to determine the relative importance of both models. The results indicate that changing jobs improves match quality, though on average match quality turns out to be slightly lower than workers expected initially. A variance decomposition of changes in job satisfaction after a job quit illustrates that 80 percent of job quits are the result of a match improving job change, while 20 percent of the new matches turns out to be disappointing giving rise to a repeated job quit.

The structure of the paper is as follows. The next section presents a simple theoretical model which sets out possible motivations for repeated job quits. Section 3 describes the data and some stylized facts. In section 4, the results from the empirical analysis are presented; and section 5 concludes.

## 2 Theoretical model

This section presents two search models, one in which there is perfect ex ante information about job quality (based on Burdett (1978)) and one in which job quality cannot be assessed ex ante (based on Jovanovic (1979)). These models are very intuitive in illustrating the concept of

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<sup>5</sup>A more extended version of the model in Neal (1999) is shown in Pavan (2007).

match quality as perceived by the worker, which includes all kinds of aspects that may affect the quit decision, such as whether or not someone enjoys work, hours constraints, commuting time, and the effect of income support programs. For presentational simplicity the models are rather stylized (e.g. excluding worker heterogeneity and endogenous changes in match quality), but they capture the essence of the alternative mechanisms that drive worker mobility, which is the main focus of the paper.

Workers search in the labor market for their optimal job match, based on several job characteristics such as the wage, working hours, benefits, location, and working conditions. For simplicity, workers are assumed to be infinitely lived and risk neutral optimizers. If workers can perfectly observe job quality, they will accept a job offer whenever this new job is of higher quality than their current job. Hence, the current job yields a certain reservation utility and only better offers will be accepted.<sup>6</sup> However, workers' ability to assess the quality of a job may be imperfect ex ante. This implies that accepting a job offer is associated with a certain risk that the match turns out to be worse (or better) than was expected. Information about (current) job quality is revealed over time by means of quality realizations  $z_i = \mu + \epsilon_i$  which are drawn from a known common normal distribution with unknown mean  $\mu$  and known variance  $\sigma^2$  at the time of hire, where  $i = 1, 2, \dots, n$  denotes the number of realizations revealed sofar. These realizations provide information about unknown productivity on the job  $\mu$  and  $\epsilon$  represents noise in the quality signal.<sup>7</sup> Here,  $\mu$  is drawn from the actual job quality distribution which is distributed normally with known mean  $m$  and variance  $s^2$ . The worker's assessed job quality  $JS$  is equal to the conditional expected value of the true quality given all information to date,  $JS(n) = E\{\mu|z_1 \dots z_n\}$ . New job quality information arrives following a Poisson process  $\lambda$ .

The extent to which workers can assess true job quality in the search process may vary between perfect observability and a complete absence of any ex ante job information. I discuss the first of these polar cases in the next subsection.

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<sup>6</sup>For simplicity, search and mobility costs are assumed to equal zero. However, the predictions of the model are not affected when positive search costs are introduced in the model.

<sup>7</sup>Here,  $\mu$  is assumed to be exogenously given. One might argue that workers learn skills while in the job which may affect match quality. However, note that  $\mu$  represents match quality *as perceived by the worker*, and increased skills need not necessarily improve satisfaction with the job.

## 2.1 Perfect information about job quality

When there is perfect ex ante information about job quality, i.e.  $\epsilon = 0$ , workers can perfectly assess the quality  $JS$  of their current job as well as of any job offer they receive, i.e.  $z_i = \mu$  s.t.  $JS = \mu$  (cf. Burdett (1978)). Note that information regarding new job offers arrives with rate  $\lambda$  while workers are employed in their current job. Then, workers will accept a new job if they receive an alternative job offer which is of higher quality than their current job. Let  $W(JS)$  denote the value of continuing employment in the current job of a given job quality  $JS$ :

$$rW(JS) = JS + \lambda \int_0^\infty \{ \max [W(x), W(JS)] - W(JS) \} dF(x) \quad (1)$$

where  $r$  denotes the discount rate and  $F(\cdot)$  is the quality distribution of job offers. Equation (1) shows that a job change always leads to a new job that is at least as good as the previous job, i.e.  $x \geq JS$ . Furthermore, note that the value of being employed increases with the quality of the current job. Workers in low quality jobs have a higher probability of finding a better job by on-the-job search, therefore they are more likely to quit their job again. Hence, the probability that a worker quits his job given the quality of his current job equals:

$$q(JS) = \lambda[1 - F(JS)] \quad (2)$$

Because  $F(\cdot)$  is a cumulative distribution function, it is increasing in  $JS$ . As a result, equation (2) is decreasing in  $JS$ , showing that workers in poor matches are more likely to change to a better job. All in all, when match quality is perfectly observable, repeated job quits serve as a stepping stone to higher quality jobs.

## 2.2 Learning about job quality

Alternatively, there might be no ex ante information at all that allows a differential prediction concerning the quality of a given worker-job match (cf. Jovanovic (1979)). For example, workers may not know the future earnings stream or some other relevant characteristics of a job at the time of offer. This implies that changing jobs is associated with a certain risk that the match turns out to be not as good as was expected. So here, workers receive a noisy signal about

job quality  $z_i = \mu + \epsilon_i$  with  $\epsilon$  being i.i.d. normal with zero mean and variance  $\sigma^2$ . Note that positive values for  $\epsilon$  may arise for example if workers experience some good characteristics of the job (e.g. good work atmosphere) or if they acquire skills on the job. Job quality is revealed over time as new quality realizations arrive at rate  $\lambda$ . When job quality has been revealed, some workers will quit their job if job quality turns out to be disappointing.<sup>8</sup>

Given that  $\mu$  was drawn from a normal distribution with mean  $m$  and variance  $s^2$  the worker's evaluation of job quality given the past quality observations equals

$$JS(n) = E \{ \mu | z_1 \dots z_n \} = \left[ \frac{m}{s^2} + \frac{\sum_{i=1}^n z_i}{\sigma^2} \right] s^2(n) \quad (3)$$

where  $s^2(n) = 1/(s^{-2} + n\sigma^{-2})$ , following DeGroot (1970). The quality assessment next period is defined by:

$$JS(n+1) = \frac{s^2(n+1)}{s^2(n)} js(n) + \frac{1 - s^2(n+1)}{s^2(n)} [\mu + \epsilon_{n+1}] \quad (4)$$

Note that the conditional prediction of future job quality becomes increasingly more accurate with each new realization because of the law of large numbers. Given that job quality assessed next period given  $JS(n) = JS$  is normally distributed with mean  $E \{ JS(n+1) | JS(n) = JS \} = JS$ , the rational worker will use the conditional distribution of the next job quality assessment given the current quality assessment, say  $G(JS(n+1); JS, n)$ , to make predictions of future job quality to decide whether or not to quit. Each time new quality information is revealed, the worker decides to continue on the job or to try a new job. More specifically, the acceptance decision of the workers is the choice of whether or not to continue sampling job qualities from the known distribution. Note that if these quality realizations were observable at the time of hire then the original search model from section 2.1 applies. Let  $V$  represent the expected present value of future job quality of any randomly selected alternative job, i.e. the value of leaving the current job, and let  $W$  denote the value of continuing in the current job, then a worker will quit if  $V > W$  conditional on the information available on the quality in the current job. Because there is a probability that the worker will decide to quit the current job

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<sup>8</sup>Because of this Jovanovic (1979) refers to jobs as experience goods.

at some future date,  $W$  is not only a function of  $JS$  and  $n$ , but also of  $V$ . The current value of continuing in the current job equals:

$$rW(JS, n, V) = JS + \lambda \int_0^\infty \{max[V, W(y, n + 1, V)] - W(JS, n, V)\} dG(y; JS, n) \quad (5)$$

Note that this equation is similar to equation (1) except for the fact that now the quality of the new job  $V$  and the realization of the next period job quality  $W(y, n + 1, V)$  are unknown ex ante. It is assumed that all jobs are ex ante identical, so initially the quality of all jobs is perceived to equal  $JS(o) = m$ . Therefore, the value of starting in a new job is constant

$$V = W(m, 0, V) \quad (6)$$

Then, workers will quit if they *expect* the quality of the new job to exceed the quality of their current job. However, opposite to the model in the previous section, here there is a risk that after some time the match turns out to be worse (or better) than was expected ex ante due to the presence of  $\epsilon$  causing  $JS(n) \neq m$ . The quit probability can be expressed as follows:

$$q(JS, n, V) = \lambda G(V; JS, n) \quad (7)$$

Equation (7) shows that workers quit their job as soon as the quality of the current job falls below the value of starting a new job. Furthermore, workers are less likely to quit their jobs once their current job is better and once they acquire tenure (i.e. and more quality realizations have been revealed). Workers in poor jobs are more inclined to accept a new job. However, again there is a risk for ending up in a poor quality job match, and they may have to quit again to find a better job.

### 2.3 Empirical implementation

The models presented in the previous sections provide some testable predictions, which allow me to test and empirically distinguish between both models. First, both models predict that workers are more likely to quit if (assessed) job quality is lower (see equations (2) and (7)). Empirical support for this first prediction is found by investigating the effect of self-reported

job satisfaction on the quit probability. Second, even though the way in which quits react to job quality is similar in both models, the course of job quality in the new job differs. Because job quality is observable ex ante following the stepping stone approach, job quality in the new job exceeds that in the old job. Furthermore, it is assumed to be constant over time.<sup>9</sup> On the other hand, in the learning model, for workers in poor matches *expected* job quality may be higher in the new job, but there is a certain risk that revealed job quality turns out to be lower in the years after the quit due to the presence of  $\epsilon$ . Furthermore, for workers in good matches, *expected* job quality in a new job is lower in the learning model. To empirically distinguish between both explanations, the change in job satisfaction in the years after a job quit is being studied. This will provide information about whether job satisfaction is updated every year when new job quality information arrives.

The models presented in the previous sections represent both ends of a continuum of ex ante observable job quality. In reality, however, workers may search for jobs in a situation where some information about job quality might be available but not all; full information will be revealed while the worker is in the job. In the remainder of this paper testable predictions from both theoretical models will be used to investigate relative empirical content of both models. Changes in job satisfaction after a job quit has occurred provide information about the extent to which workers can observe job quality ex ante. From equation (1), according to the stepping stone model, satisfaction in a new job after a job quit is always at least as high as job satisfaction in the current job  $k$ , hence  $Cov(JS^k, JS^{k+1}) > 0$ . Alternatively, in the learning model the quality of the new job is unknown ex ante but is a random draw from the offer distribution. As a result, job satisfaction in the current job is unrelated to job satisfaction in the new job,  $Cov(JS^k, JS^{k+1}) = 0$ . As a result, the variance of job satisfaction in accepted job offers is a constant in the learning model, while it is decreasing with job satisfaction in the current job according to the stepping stone approach, i.e.  $Var_{SS}(JS^{k+1}) \leq Var_{LM}(JS^{k+1}) = Var_{LM} \forall JS^k$ . In order to calculate the expected variances  $Var_{SS}$  and  $Var_{LM}$ , I use the distribution of job satisfaction among job offers. Then,  $Var_{LM}$  is assumed

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<sup>9</sup>Here, I assume that there are no endogenous changes in match quality over time. Section 4.3 will discuss what happens if match quality does change endogenously.

to equal the variance of this distribution, while  $Var_{SS}(JS^{k+1})$  is taken to be the variance of this distribution truncated at point  $JS^k$ . The importance of both models in actual job search behavior is tested by relating actual variance in job satisfaction in accepted jobs to the variance that would be expected according to both models. The actual variance in job satisfaction in accepted job offers  $Var(JS^{k+1})$  is taken from the data and used to calculate a weight  $s$  such that  $Var(JS^{k+1}) = s * Var_{SS}(JS^{k+1}) + (1 - s) * Var_{LM}$ . Finally, this  $s$  is interpreted as the relative importance of the stepping stone model.

### 3 Data description

#### 3.1 Data

The analyses in this paper are based on information from the British Household Panel Survey (BHPS) for the period 1991-2005. The BHPS collects data annually from a representative sample of approximately 16000 individuals from 9000 households. The dataset contains extensive information that describes both the individual and the household, such as individual and spousal actual working hours, labor market position and transitions, individual and household income, and other job-related characteristics. The analyses are restricted to working-age male workers, as these workers usually have a strong labor force attachment and job changes for this group most likely serve as a means to improve their employment match.<sup>10</sup>

The wave 1 data were collected in late 1991 - early 1992, the wave 2 data were collected in late 1992 - early 1993, etc. All information on individual labor market spells that fall between two interview dates are collected in separate files. These spells can be matched to the individual records in the different waves, which may result in observing some individuals with multiple spells. For all the spells, information is available on the spell start and end date, as well as the reason for terminating the spell. Workers may report to have terminated the spell for several reasons: promoted, left for better job, made redundant, dismissed, temporary job ended, took

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<sup>10</sup>For women, job changes may serve to gradually leave the labor market for child care reasons, while job mobility after that may serve to facilitate re-entering the labor market gradually. Though interesting, these job changes may not serve to find the most productive match in the labor market. Note that some older workers may already be at the end of their job search process. However, sensitivity results indicate that the results remain unchanged when I restrict the sample to individuals who are observed in the data from early ages onwards.

retirement, stopped for health reasons, look after family, care of other person, moved away, started college/university, or left for another reason. This detailed information allows me to pin down job quit behavior. The ending of an employment spell is denoted as a quit if the worker reported to have left for a better job. About 23 percent of all employment spells end for this reason.<sup>11</sup> Note that job and worker characteristics are only observed for spells that are active on the day of the interview. Therefore, only these spells can be used in the analysis. However, the number of quits within two interviews is used to determine whether someone had quit multiple times within the survey year.

Job satisfaction is reported once a year in each wave, and follows a 1 (not satisfied at all) to 7 (completely satisfied) scale. In general, people are more likely to report high levels rather than low levels of job satisfaction (Table 1). Furthermore, Table 1 presents the distribution of self-reported job satisfaction for workers with different characteristics. Though the skewed distribution appears for all types of workers, fulltime working men and workers in poor health report slightly lower levels of job satisfaction. Finally, quitters appear to be more happy in their job than job stayers.

## 3.2 Descriptive figures

A first step in investigating job search and quit behavior involves looking at the course of job satisfaction in the years before and after the job change has occurred. Figure 1 illustrates how average job satisfaction levels differ across job quitters and job stayers. As is clear from the figure, job satisfaction not only dips in the year prior to the first quit, but is also significantly lower (compared to job stayers) in the years before. This can be a reason for workers to start looking for another job. One-time quitters obtain a significant increase in their job satisfaction at the time of the job change. Despite the fact that job satisfaction for these workers decreases slightly after the first year in the new job, a job quit implies a permanent increase in job

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<sup>11</sup>Note that the distinction between quits and layoffs is not always straightforward, as someone may report having left for a better job after being notified of an upcoming dismissal. Nevertheless, the distinction between quits and layoffs seems economically meaningful since the share of workers reporting a drop in job satisfaction after a job change (without an intervening unemployment spell) is much higher for workers who changed jobs due to layoff (32 percent) than for workers who left for a better job (18 percent).

satisfaction up to the level of job stayers.<sup>12</sup> For multiple-time quitters, the situation is slightly different in two respects. First, job satisfaction in the years before the job quit as well as the peak at the time of the job quit are lower than for one-time quitters. Possibly, repeated mobility can be explained by the fact that these workers come from relatively bad matches, and they need several job changes to catch up with workers who are satisfied with their job. This stepping stone hypothesis seems to be confirmed in Table 2, which illustrates that not only the decision to quit or not depends on job satisfaction, but also that the number of *future* quits is a decreasing function of the level of job satisfaction in the year before the first job quit. The table also illustrates the importance of multiple-quit behavior: while 76 percent of the workers does not quit at all, 35 percent of the workers who do quit are observed to quit multiple times. Second, Figure 1 shows that multiple-time quitters differ from workers who quit only once in that their level of job satisfaction falls back to a level below that of job stayers within a year after the first job quit. This might provide another explanation for their repeated job change behavior. Repeated job quits are most likely to occur within a few years after the first job quit, as is shown in Figure 2. The probability of a subsequent job quit is 16 percent in the first year after the first quit, and between 4 and 5 percent in the two years thereafter. Note from Figure 1 that after two years job satisfaction of multiple-time quitters seems to catch up again. This might be the result of a subsequent job quit: about 64 percent of all multiple-time quitters changes jobs again within two years. Figure 3 illustrates the timing of the second quit in the number of years after the first job quit (time 0). It appears that the time span between two subsequent quits is shorter the lower the level of job satisfaction in the first job.<sup>13</sup> This can be explained by the fact that the probability of receiving a job offer which is better than the current job is lower for workers who are already quite satisfied with their current job, because they have a higher reservation utility. The decline in job satisfaction might be the consequence of a poor job search. Unhappy workers may be more eager to leave their job, therefore they may concentrate more on finding (any) job than on finding a job with certain characteristics. As a

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<sup>12</sup>Note that the decline in the first year is an average decline. About 35 percent of the workers experiences a decline in job satisfaction after the first year; for 44 percent of the workers job satisfaction remains unchanged while for 20 percent it increases after the first year.

<sup>13</sup>Workers who quit again within one year seem an exception to this. However, their repeated quit decision can be explained by the relatively limited increase in job satisfaction right after the job change.

result, the probability that the match turns out to be poor may be higher. In the end, repeated job quits serve to find better matches, according to Figure 4. Workers who are very dissatisfied with their job need to change jobs several times in order to increase their job satisfaction step by step; with each quit job satisfaction reaches a higher level. Workers decide to stay in a job once they have reached a certain level of job satisfaction. All in all, the descriptive evidence in this section seems to confirm the role of the “stepping stone” hypothesis in explaining repeated job quits. However, the decline in job satisfaction after the first year in the new job points to the presence of learning.

## 4 Empirical results

### 4.1 Job-to-job quits

This section tries to find empirical support for the theoretical models presented in Section 2 by investigating the probability of quitting and whether or not this is decreasing with job satisfaction, as both the stepping stone and the learning model predict. The following logit model for job quits is estimated:

$$P(Q_{it}^k = 1) = \Lambda(JS_{t-1}^k \delta + X_{i,t-1} \beta + \alpha_i) \quad (8)$$

where  $Q$  is a dummy variable for whether a worker  $i$  quits his job  $k$  between year  $t - 1$  and year  $t$ ,  $\Lambda$  is an indicator for the logistic cumulative distribution function,  $JS^k$  refers to the level of job satisfaction in job  $k$  (with  $JS = 1, 2, \dots, 7$ ),  $X$  is a vector of worker and job characteristics and  $\alpha$  represents the individual fixed effect. The results in Panel A of Table 3 indicate that a lower job satisfaction in the current job increases the probability to quit. Furthermore, workers are more likely to quit the more hours they work, the lower their hourly wage, and if they work in a temporary job. Yet, since this paper focuses on the repeated character of job quits, panel B re-estimates the model for individuals who have quit at least once before, i.e.  $P(Q_{it}^k = 1 | \sum_{k=1}^{k-1} Q_{i\tau}^k \geq 1 \ \forall \ \tau < t)$ .<sup>14</sup> As can be seen from the table, the effects of job satisfaction on repeated quits are no different.

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<sup>14</sup>This selective sample of workers who have quit at least once will be used in the remainder of this section.

## 4.2 Job satisfaction

To date, little is known about the effect of a job quit on ex post levels of job satisfaction. However, in order to empirically distinguish the stepping stone and the learning model, workers' reported job satisfaction, which can be regarded as a measure of match quality, in the years after a quit is very informative. The stepping stone models predicts job satisfaction to increase in the year after the job quit and to remain constant thereafter. The learning model predicts an increase in job satisfaction for unhappy workers and a decrease for workers who were happy in their old job. Furthermore, the learning model allows job satisfaction to change in later years when workers learn more about the true job quality. This section investigates job satisfaction immediately after a job quit and in the years thereafter by estimating the fixed effects ordered logit model developed in Ferrer-i-Carbonell and Frijters (2004):

$$JS_{it}^* = Q_{1,t}\pi + Z_{it}\theta + \nu_i + \varepsilon_{it} \quad \text{with} \quad JS_{it} = j \Leftrightarrow JS_{it}^* \in [\gamma_{ij}, \gamma_{i,j+1}) \quad (9)$$

where  $JS_{it}^*$  is latent job satisfaction,  $JS_{it}$  is observed satisfaction,  $\gamma_{ij}$  is the individual threshold level (increasing in  $j$ ) for job satisfaction,  $Q_1$  indicates whether someone has quit his job in the past year,  $Z$  is a vector of worker and job characteristics and  $\varepsilon$  is a time-varying logit-distributed error term.<sup>15</sup> Note that job satisfaction is a rather subjective measure and individual-specific characteristics may cause some workers always to report lower satisfaction scores than others while they are in fact equally satisfied (e.g. due to a different interpretation of the satisfaction scale). The parameter  $\nu_i$  controls for such unobserved time-invariant individual effects. By introducing individual specific cut-off points  $c_i = \sum_t JS_{it}/n_i$ , where  $n$  is the number of observations per individual, Ferrer-i-Carbonell and Frijters (2004) show that the fixed effects ordered logit model can be reformulated as a fixed effects binomial logit model.<sup>16</sup> Applying Chamberlain's method removes the individual specific effects  $\nu_i$  and the individual specific thresholds  $\gamma_i$  from the likelihood specification. The fixed effects logit model is estimated over

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<sup>15</sup>Note that the timing of the explanatory variables in (8) and (9) allow that both equations are estimated separately rather than simultaneously.

<sup>16</sup>The advantage of this approach is that all observations for individuals whose satisfaction score changes at least once are included, while a common threshold implies that only those individuals are included whose satisfaction score crosses the given threshold.

observations  $y_{it}$ , where  $y_{it} = 1$  if  $JS_{it} \geq c_i$  and 0 otherwise.<sup>17</sup> The results are presented in Table 4. From Panel A it appears that job satisfaction increases substantially after a job quit.<sup>18</sup> This suggests that job quits serve to form better matches. Note however that this might also result in the learning model if only workers in the worst matches quit their job. Then, on average, match quality will increase after a job quit. As part of a sensitivity analysis, the model is re-estimated separately for workers who were unhappy in their old job (i.e.  $JS < 5$ ) and for those who were happy in their previous job (i.e.  $JS \geq 5$ ) (not presented in the table). For the former, the learning model would predict a positive coefficient for the quit dummy, while it would predict a negative coefficient for the latter. The results 1.280\*\* and 0.467\*\*, for happy and unhappy workers respectively, support the stepping stone approach. Furthermore, note that people will only decide to quit if they expect to experience a gain in job satisfaction. Therefore, the results should be interpreted as the average gain in job satisfaction for those who quit; for those who do not quit the average job satisfaction gain might be much lower. In order to take into account the repeated character of job quits, panel B includes the number of previous quits the worker has experienced so far.<sup>19</sup> The results show that changing jobs serves to find a better match, but the gain from quitting your job decreases with the number of previous quits. As a result, workers may decide to stay in their job if the gains from quitting no longer exceed the mobility costs.<sup>20</sup>

Panel C provides information about the nature of repeated job quits by including dummy variables for the gain in job satisfaction in the first year after the quit ( $Q_1$ ), and marginal changes in this gain in the second, third and fourth year after the quit ( $\Delta Q_2$ ,  $\Delta Q_3$  and  $\Delta Q_4$  respectively, where  $\Delta Q_t = Q_t - Q_{t-1}$ ). Note that the gain from quitting one's job is rather constant across all three specifications. Furthermore, the results show that the gains from a job quit decline substantially after the first year. This might be due to learning about job quality, since job quality is predicted to remain constant following the stepping stone model. Apparently, downward adjustments of job evaluations outweigh upward adjustments and this

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<sup>17</sup>Note that the results are unchanged when  $y_{it}$  is defined as  $y_{it} = 1$  if  $JS_{it} > c_i$  and 0 otherwise.

<sup>18</sup>Including a dummy variable for other types of separations does not improve the model fit.

<sup>19</sup>The number of job quits before the start of the sample is censored. However, this is assumed to be captured by the individual fixed effect.

<sup>20</sup>Note that mobility costs were allowed to be positive in the theoretical model (section 2).

learning occurs especially in the first year. Table 5 shows that this learning pattern exists in satisfaction with several job characteristics. Also the possibilities for promotion are estimated to be lower by workers in the second year than in the first year after the quit. Since it is not very plausible that new hires have higher promotion possibilities than workers who have been with the firm for a slightly longer period, this suggests that workers learn about the job. Furthermore, note that a similar pattern is found for life satisfaction and satisfaction with the amount of leisure time (which can be affected by the type of job), while it is absent in satisfaction with objects that are unrelated to work such as satisfaction with the partner or the house/flat someone is currently living in. Note that only the initial gain in satisfaction after a quit depends on the number of previous quits, while the decline after the first year doesn't. Sensitivity analyses (not presented in the table) illustrate that the decline after the first year is also independent of the total number of quits during the observation period as well as of the individual fixed effect obtained from the quit estimation. The latter suggests that frequent job quitters are not quitting their job frequently because the drop in job satisfaction shortly after they have started a new job is steeper than for others (i.e. person effect). All in all, the earlier finding that (repeated) job quits depend on job satisfaction in the previous job can be explained by the fact that learning causes job satisfaction to fall below a certain threshold level, and hence individuals with lower initial satisfaction are more likely to change jobs again.

### 4.3 Decomposing job satisfaction variance

The evidence thus far indicates that repeated job quit behavior is characterized both by stepping stone and learning elements. In this sub-section I will investigate the relative empirical content of the theoretical approaches by decomposing the variance in job satisfaction in newly accepted jobs. When mobility costs are assumed to be nonexistent, according to the stepping stone model workers are expected to accept any job which offers them at least the satisfaction level that they currently experience in their job. For example, a worker who is very unsatisfied in his current job ( $JS^k = 1$ ) has a low reservation utility and will accept any job offer he receives ( $JS^{k+1} = 1, \dots, 7$ ), while a rather satisfied worker ( $JS^k = 6$ ) will only accept a job offer which will yield a job satisfaction level equal to 6 or higher ( $JS^{k+1} \geq 6$ ). As a result, expected

variance in satisfaction of accepted job offers will be decreasing with the initial level of job satisfaction. Alternatively, in the learning approach the expected variance is independent of initial job satisfaction. Since job quality is unobservable ex ante, the probability of receiving a poor offer is equal to the probability of receiving a good offer, regardless of the job quality of the current job. The expected variance according to the stepping stone model and the learning model can be calculated using information about the job offer distribution. This distribution is taken to be the satisfaction distribution of new jobs accepted by labor market entrants who have just left school,<sup>21</sup> because these workers are expected to accept any job offer they receive. The distribution of accepted job offers is presented in Figure 5. It appears that workers are more likely to accept good offers than poor job offers. This is not necessarily due to the fact that they are more likely to receive a good offer, but rather to the fact that workers might receive multiple offers in a certain time interval of which they only accept the best. Given the assumption that in the learning model workers cannot select the best offer since quality is unobserved ex ante, a uniform offer distribution is assumed for the learning model.<sup>22</sup>

The offer distribution from Figure 5 is used to compute the expected mean and then the expected variance in job satisfaction according to the stepping stone model, while a uniform offer distribution is used to compute the expected variance according to the learning model. The expected variance in job satisfaction in a newly accepted job  $k$  is computed as follows:

$$\textit{Stepping stone: } \text{Var} \{E(JS^k | JS^{k-1} = R)\} = \sum_{r=R}^7 \left( JS_r^k - \frac{\sum_{r=R}^7 p_r JS_r^k}{\sum_{r=R}^7 p_r} \right)^2 \frac{p_r}{\sum_{r=R}^7 p_r} \quad (10)$$

$$\textit{Learning model: } \text{Var} \{E(JS^k | JS^{k-1} = R)\} = \sum_{r=1}^7 \left( JS_r^k - \frac{\sum_{r=1}^7 p_r JS_r^k}{\sum_{r=1}^7 p_r} \right)^2 \frac{p_r}{\sum_{r=1}^7 p_r} \quad (11)$$

where  $p_r$  represents the probability of receiving a job offer with satisfaction level equal to  $r$ , with  $R = 1 \dots 7$  and  $r = 1 \dots 7$ . Note that the variance in equation (10) is increasing in the level of job satisfaction in the old job, while that in equation (11) is independent of the old job satisfaction level. Both expected variances are shown in Figure 6. The actual variance in

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<sup>21</sup>Labor market entrants are defined as those whose main labor market position is fulltime education in one year and being employed in the next.

<sup>22</sup>Sensitivity checks will be presented later in this section.

satisfaction of accepted job offers is also presented in the figure.<sup>23</sup> Since the stepping stone model and the learning model represent both ends of a continuum, it is not surprising to find the actual variance to be in between both extreme variance predictions. Figure 7 shows that the variance in accepted job satisfaction illustrates the selectivity of job search. The variance in accepted job satisfaction after a job change resulting from a layoff is much higher than after a job quit. Workers being laid off are more likely to accept the first job offer that comes along, while job quitters can be more selective in the type of job they accept resulting in a lower variance of accepted offers. Note that workers being promoted, which is defined as a within-employer job change, experience about as much variance in new job satisfaction as job quitters, suggesting that ex ante information about job quality is not necessarily more accurate within the firm than on the market.

Table 6 presents a decomposition of the actual variance in job satisfaction among job quitters using the predictions from the stepping stone and learning model (as presented in Figure 6). In particular, it shows the share  $s$  of the variance in job satisfaction that can be explained by the stepping stone theory:<sup>24</sup>

$$s = \frac{Var - Var(LM)}{Var(SS) - Var(LM)} \quad (12)$$

where  $Var$ ,  $Var(LM)$ , and  $Var(SS)$  represent actual variance and expected variance following the learning model and stepping stone model, respectively. The share  $s$  and its standard error are obtained from a non-parametric bootstrap with 5000 replications. From Panel A it appears that about 80 percent of the job quits arises from a stepping stone motive. Note that this is more or less independent of the level of job satisfaction in the previous job. As part of a sensitivity analysis, Panel B replicates the results using an alternative accepted job offer distribution. Because labor market entrants lack any labor market experience they may receive relatively more poor job offers and hence low job offers may be over-represented in the accepted job offer distribution. Alternatively, labor market entrants may have started their job search well before the end of their studies and hence could have acted more selectively than other

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<sup>23</sup>Note that job satisfaction in the first year of the new accepted job is used here.

<sup>24</sup>Hence, 1 minus this share represents the importance of learning about job quality.

workers. Therefore, Panel B uses the distribution of accepted job offers among all workers who are observed to change jobs for the first time. The distributions do not differ much in shape, and the results in Panels A and B are more or less similar. Panel C considers some alternatives for the uniform distribution used to compute expected variance for the learning model. The first specification takes the distribution of job satisfaction in the new job for workers who were very dissatisfied in their old job. These workers should be willing to accept any job offer that comes along without awaiting potentially better job offers. Hence, this distribution can be used to compute both the expected variance according to the stepping stone and the learning model.<sup>25</sup> Note that this distribution seems to be less able to fit the actual data, since the variance for workers reporting satisfaction equal to 2 in the last job cannot be explained by either one of the models. This group of workers appears to be more selective in accepting new jobs than the stepping stone model would predict. Possibly, the poor identification is due to the low number of workers with lagged JS=1 used for identifying the offer distribution. The second specification assumes that job offers are draws from a normal distribution. The expected variance according to the learning model is computed accordingly.<sup>26</sup> The results indicate again that a majority of the job quits arises from a stepping stone motive.<sup>27</sup> The role of the stepping stone model might be overrated in Panels A to C for several reasons. First, in reality mobility costs are likely to be existent and positive. As a result, workers will only accept a new job if it yields a strictly higher utility than the current job.<sup>28</sup> As a result, variance resulting from workers accepting a new job in which they are equally satisfied as they were in the previous job will no longer be attributed to the stepping stone model but to the learning model. Though for unsatisfied workers this will happen rarely (up to 6 percent of the cases), satisfied workers are much more likely to accept a new job with similar job satisfaction rating (about 50 percent of the cases). As a result, the shares presented in Panels A to C should be considered as an upper bound. Alternatively, the importance of the stepping stone model might be misstated

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<sup>25</sup> As a result,  $\text{var}(\text{SS}) = \text{var}(\text{LM})$  for lagged JS=1, and hence  $s$  cannot be identified for these workers.

<sup>26</sup> Note that the expected variance according to the stepping stone model is computed using the baseline specification, since workers will be able to pick the best offer from a series of offers in a given time interval.

<sup>27</sup> Excluding the insignificant value for the most unhappy workers, the average share increases to about 70 percent.

<sup>28</sup> Note that in this situation job changes by workers who reported being completely satisfied in the old job ( $JS^k = 7$ ) cannot be explained by either model.

if workers have not completely learned the true job quality during the first year in the job, because Panels A to C relate job satisfaction in the old job to job satisfaction reported in the first year of the new job. Therefore, in Panel D, job satisfaction in the old job is compared to job satisfaction reported in the final year of the new job when learning is expected to be completed.<sup>29</sup> Note that the share of variance attributed to the stepping stone model is slightly lower in this specification. Apparently, the role of the stepping stone model was - on average - slightly overrated in the above Panels due to downward adjustment of job satisfaction when job quality was revealed.<sup>30</sup> Nevertheless, this lower bound of 78 percent is relatively close to the upper bound of 81 percent. Hence, the table illustrates that repeated job quits serve to improve matching efficiency rather than being a random relocation of labor resources.

Table 7 presents some sensitivity results. Panel A replicates the baseline results from the previous table. In Panel B a distinction is made between first time quits and repeated job quits. Note that the results are similar for both types.<sup>31</sup> Panel C differentiates between workers who quit only once and multiple time quitters. It appears that quit behavior by single time quitters is characterized by slightly more stepping stone features. This may explain why these workers quit only once. Finally, Panel D illustrates that learning is more important early in the career than among older workers. Other sensitivity checks, such as high versus low educated workers and private versus public sector workers, did not yield any significant different results and hence are not presented in the table.

In addition to being a response to a change of jobs, job satisfaction may change from one year to the other because of some exogenous variation. Think for example of a reorganization or a direct colleague leaving the firm which may affect your job satisfaction. The presence of such exogenous variation may affect the findings in Tables 6 and 7. To determine whether such variation is present, the variance in job satisfaction for job stayers is investigated by looking at changes in job satisfaction from one year to another. Figure 8 illustrates the variance in job

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<sup>29</sup>The final year is either the year before a new job quit occurs, or the last year in which the worker is observed in the sample.

<sup>30</sup>Note a positive difference for initially poor quality matches ( $JS^k = 1, \dots, 3$ ). Here, job satisfaction has been adjusted upward during the learning period.

<sup>31</sup>However, there are some small differences for workers who were initially very unsatisfied in their job. The insignificant effect is due to the relatively low number of cases among the repeated job quits.

satisfaction for stayers relative to the variance for job quitters. It appears that the variance among dissatisfied workers is much higher among stayers than among job quitters. This suggests that job quitters are able to positively select into good jobs. Hence, the difference in variance, i.e. the area between the two lines, can be seen as the gains from search and changing jobs. Furthermore, note that the ‘exogenous’ variation among job stayers is not constant across workers. Workers who are very dissatisfied with their job are more likely to experience a change in job satisfaction one year later than those that are quite satisfied already. Possibly, workers look for alternatives and firms are willing to offer different tasks or different fringe benefits to dissatisfied workers in order to retain them with the firm, while such ad hoc offers are less frequently made to workers who are satisfied already. Alternatively, it might be the case that such offers are also made to satisfied workers, and that the low variance results from their satisfaction level being close to the upper limit of the satisfaction scale. This suggests that there seems to be some stepping stone element even for job stayers. From Panel E in Table 7 it appears that this is indeed the case. This suggests that a job change is not always required to improve job satisfaction. In particular, the difference between stayers and quitters (bottom panel) indicates that there are gains from search only for those workers who are dissatisfied in their job. For those reporting being ‘not dissatisfied/not satisfied’ or a higher satisfaction level the probability of improving job satisfaction is equal if they stay in their current job and if they would change jobs.

## 5 Conclusions

This paper studies repeated job quit behavior to investigate whether such job changes contribute to better matching efficiency or whether they simply constitute a relocation of labor without any increase in match quality. Theoretical studies often adopt either the stepping stone model or the learning model as the explanatory mechanism for labor mobility. This paper is the first to investigate the relative empirical content of both models in job quit decisions. The results from an innovative variance decomposition help improve our understanding of job quit behavior, a key phenomenon determining the functioning of the labor market.

Using UK data over the period 1991-2005, the analyses in this paper show that job satisfac-

tion increases with each job quit, though at a decreasing rate. This finding is consistent with both the stepping stone and the learning model. However, expected gains from a job quit are also positive for workers who are in above-average quality matches already. This points to a stepping stone motive underlying repeated job quit behavior. On the other hand, the evidence indicates that workers learn about job quality, this learning occurring mainly in the first year of their new job. This paper is the first to quantify the relative empirical content of both models. A decomposition of variance in satisfaction in the new job shows that 80 percent of job quits arises from a stepping stone motive. This implies that repeated job quits mainly serve as a stepping stone to more happiness at work and as such may contribute to matching efficiency.

Though job quits are costly for firms in terms of hiring and training costs if they want to hire a replacement worker, firms may experience positive spillovers from job mobility as it enhances workforce flexibility which enables firms to more easily adjust their workforce to changing economic circumstances. However, the finding that job mobility improves matching efficiency implies that it may have additional positive spillovers if the rents of the better job match are being shared between the worker and the firm. As such, job quits may not only serve workers to find a better match, but may also be beneficial for firms.

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**Table 1: Job satisfaction distribution (row %)**

	Job satisfaction level							Average job satisfaction
	1	2	3	4	5	6	7	
<i>Job status</i>								
Stay	1.7	3.2	8.1	9.6	24.7	43.6	9.2	5.2
Quit	0.8	2.1	4.4	7.0	20.6	50.1	15.1	5.5
<i>Tenure</i>								
<2 years	1.7	2.9	6.9	8.8	23.1	44.4	12.3	5.3
≥2 year	1.9	3.3	8.2	10.3	24.5	42.1	9.6	5.2
<i>Working hours</i>								
<30 hours	1.1	2.3	5.5	7.8	21.2	44.0	18.2	5.5
≥30 hours	1.9	3.2	7.8	9.8	24.1	43.0	10.2	5.2
<i>Marital status</i>								
Single	1.8	3.5	7.5	9.7	23.7	42.5	11.4	5.2
Married	1.9	3.0	7.7	9.7	24.0	43.3	10.5	5.2
<i>Education level</i>								
No education	2.9	3.3	5.7	9.3	20.2	39.9	18.7	5.4
Low education	2.7	3.1	5.2	11.6	21.2	40.1	16.2	5.3
Med education	1.7	2.9	7.6	10.4	25.3	42.2	10.0	5.2
High education	1.5	3.3	8.6	8.9	24.4	45.0	8.3	5.2
<i>Health status</i>								
Poor	4.8	6.0	10.8	12.1	24.0	32.4	9.8	4.8
Fair	2.8	4.4	9.6	12.0	26.2	36.4	8.6	5.0
Good	1.5	2.7	7.1	9.1	23.5	44.8	11.2	5.3
<i>All men</i>								
	1.9	3.1	7.6	9.7	23.9	43.1	10.8	5.2

Source: BHPS.

**Table 2: Frequency of job quits, by initial level of job satisfaction (row percentages [No. of persons])**

	Total number of quits observed				Total	One-time to multiple quit rate
	0	1	2	3 or more		
<b>Job satisfaction in year before first quit*</b>						
<b>1</b>	17.7	47.1	22.1	13.2	100.0 [68]	1.3
<b>2</b>	25.4	47.4	15.6	11.6	100.0 [173]	1.7
<b>3</b>	51.4	30.7	11.3	6.5	100.0 [397]	1.7
<b>4</b>	75.2	15.3	5.1	4.4	100.0 [888]	1.6
<b>5</b>	79.2	13.6	4.2	3.0	100.0 [2084]	1.9
<b>6</b>	80.4	13.0	3.9	2.8	100.0 [2887]	1.9
<b>7</b>	77.7	14.8	3.1	4.4	100.0 [682]	2.0
<b>Total</b>	75.6 [5428]	15.7 [1130]	4.9 [354]	3.7 [267]	100.0 [7179]	1.8
<b>No. of observations</b>	20479	6071	2346	2328	31224	

\* For job stayers this refers to average job satisfaction during their (observed) working life.

Source: BHPS.

**Table 3: Quit behavior - fixed effects logit results**


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*A. Baseline*

$JS^k$	-0.336 (0.021)**
Tenure (years)	0.024 (0.020)
Tenure <sup>2</sup> (*0.1)	0.004 (0.011)
Married	-0.005 (0.101)
Log working hours (per week)	0.534 (0.109)**
Low educated	0.084 (0.388)
Medium educated	-0.007 (0.298)
High educated	0.307 (0.302)
Log gross hourly wage	-0.552 (0.089)**
Poor health	0.190 (0.168)
Good health	0.139 (0.082)*
Temporary job	0.393 (0.106)**
Industry dummies	yes
Occupation dummies	yes
Firm size dummies	yes
Year dummies	yes

$\log L = -3507.59$

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*B. Baseline - selected sample<sup>a</sup>*

$JS^k$	-0.333 (0.038)**
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$\log L = -1112.42$

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<sup>a</sup> Model includes same set of covariates as presented in Panel A.

Note: Dependent variable is dummy for quit in upcoming year. Standard errors in parentheses; a \*\* (\*) indicates that the coefficient is different from zero at a 5% (10%) level of significance. Analysis is based on 11300 and 3388 observations in Panels A and B-C, respectively.

Source: BHPS

**Table 4: Job satisfaction after a job quit - fixed effects ordered logit results**

<i>A. Baseline</i>	
$Q_1$	0.672 (0.057)**
$\log L = -11538.16$	
<i>B. Including total number of quits sofar</i>	
$Q_1$	0.739 (0.098)**
Total number of quits	0.304 (0.034)**
$Q_1$ * Total number of quits	-0.119 (0.050)**
$\log L = -11496.68$	
<i>C. Pattern in job satisfaction</i>	
$Q_1$	0.797 (0.099)**
$\Delta Q_2$	-0.495 (0.154)**
$\Delta Q_3$	0.237 (0.203)
$\Delta Q_4$	-0.376 (0.258)
Total number of quits	0.310 (0.040)**
$Q_1$ * Total number of quits	-0.138 (0.054)**
$\Delta Q_2$ * Total number of quits	0.020 (0.076)
$\Delta Q_3$ * Total number of quits	-0.033 (0.105)
$\Delta Q_4$ * Total number of quits	-0.031 (0.137)
$\log L = -11486.13$	

Note: Dependent variable is job satisfaction (1 - 7). Other explanatory variables included in the estimation are tenure and its squared value, age and its squared value, log of hours worked, log of hourly wage, and dummies for marital status, education level, industry, occupation, firm size, health, temporary job, and calendar year; standard errors in parentheses; a \*\* (\*) indicates that the coefficient is different from zero at a 5% (10%) level of significance. Analysis is based on 26694 observations

Source: BHPS.

**Table 5: Patterns in satisfaction - sensitivity results**

	$Q$	$\partial Q_2$	$\partial Q_3$	$\partial Q_4$
<i>Satisfaction with job characteristics</i>				
Satisfaction with pay	0.675 (0.058)**	-0.356 (0.079)**	-0.104 (0.104)	-0.026 (0.131)
Satisfaction with hours	0.559 (0.056)**	-0.344 (0.076)**	-0.042 (0.101)	-0.149 (0.127)
Satisfaction with work itself	0.653 (0.058)**	-0.435 (0.079)**	-0.006 (0.105)	-0.193 (0.133)
Satisfaction with job security	0.244 (0.056)**	-0.002 (0.078)	0.053 (0.105)	0.057 (0.134)
Promotion opportunities	0.231 (0.069)**	-0.244 (0.096)**	0.015 (0.129)	-0.143 (0.164)
<i>Satisfaction with life</i>				
Lifesat	0.289 (0.070)**	-0.189 (0.092)**	0.044 (0.118)	-0.166 (0.147)
Leisuresat	0.294 (0.065)**	-0.171 (0.086)**	-0.147 (0.110)	-0.017 (0.136)
<i>Other satisfaction measures</i>				
Partnersat	-0.065 (0.089)	0.072 (0.115)	-0.092 (0.143)	0.113 (0.175)
Housesat	0.058 (0.066)	-0.148 (0.087)*	0.008 (0.113)	-0.051 (0.141)

Note: Each row represents a separate analysis. Other explanatory variables included in the estimation are tenure and its squared value, age and its squared value, log of hours worked, log of hourly wage, and dummies for marital status, education level, industry, occupation, firm size, health, temporary job, and calendar year; standard errors in parentheses; a \*\* (\*) indicates that the coefficient is different from zero at a 5% (10%) level of significance.

Source: BHPS.

Table 6: Variance decomposition - proportion explained by stepping stone theory

	Job satisfaction in old job:							Average	
	1	2	3	4	5	6	7		
<b>A. Baseline</b>									
	0.726** (0.124)	0.892** (0.075)	0.824** (0.054)	0.807** (0.041)	0.837** (0.023)	0.799** (0.020)	0.793** (0.037)	<b>0.811**</b> <b>(0.024)</b>	
<b>N</b>	71	162	271	294	608	872	222		
<b>B. JS after first job quit</b>									
	0.717** (0.122)	0.863** (0.073)	0.788** (0.051)	0.796** (0.040)	0.834** (0.022)	0.801** (0.020)	0.793** (0.037)	<b>0.799**</b> <b>(0.024)</b>	
<b>C. Alternatives for Var(LM)</b>									
<i>JS among most unhappy</i>	<i>a</i>	2.797** (1.148)	0.513** (0.175)	0.558** (0.112)	0.666** (0.055)	0.584** (0.044)	0.576** (0.075)	<b>0.949**</b> <b>(0.196)</b>	
<i>Normal distribution</i>		0.419 (0.264)	0.780** (0.153)	0.661** (0.103)	0.661** (0.073)	0.727** (0.038)	0.674** (0.033)	0.627** (0.058)	<b>0.656**</b> <b>(0.048)</b>
<b>D. JS in final year of new job</b>									
	0.734** (0.131)	0.882** (0.077)	0.935** (0.041)	0.747** (0.048)	0.792** (0.026)	0.786** (0.021)	0.589** (0.064)	<b>0.781**</b> <b>(0.025)</b>	

Note: the proportion explained by the stepping stone theory is computed as follows:  $s = (Var - Var(LM)) / (Var(SS) - Var(LM))$ , where  $Var$ ,  $Var(LM)$  and  $Var(SS)$  represent actual variance and expected variance according to the learning model and the stepping stone theory, respectively. Standard errors calculated using a non-parametric bootstrap with 5000 replications are in parentheses; a \*\* (\*) indicates that the coefficient is different from zero at a 5% (10%) level of significance.  
<sup>a</sup>: Cannot be computed, since  $Var = Var(LM) = Var(SS)$  for lagged  $JS = 1$ .

Source: BHPS.

Table 7: Variance decomposition - sensitivity

	Job satisfaction in old job:							Average
	1	2	3	4	5	6	7	
<b>I. QUITTERS</b>								
<b>A. Baseline</b>	0.726** (0.124)	0.892** (0.075)	0.824** (0.054)	0.807** (0.041)	0.837** (0.023)	0.799** (0.020)	0.793** (0.037)	<b>0.811**</b> <b>(0.024)</b>
<b>B. First time vs. repeated quits</b>								
<i>First job quit</i>	0.777** (0.118)	0.864** (0.092)	0.766** (0.076)	0.789** (0.051)	0.844** (0.029)	0.789** (0.027)	0.797** (0.041)	<b>0.804**</b> <b>(0.026)</b>
<i>Repeated job quit</i>	0.450 (0.412)	0.966** (0.118)	0.932** (0.058)	0.845** (0.069)	0.828** (0.036)	0.813** (0.030)	0.783** (0.070)	<b>0.802**</b> <b>(0.063)</b>
<b>C. Single vs. multiple quits</b>								
<i>Single time job quitters</i>	0.873** (0.141)	0.925** (0.121)	0.862** (0.093)	0.742** (0.069)	0.867** (0.034)	0.810** (0.034)	0.812** (0.049)	<b>0.842**</b> <b>(0.032)</b>
<i>Multiple time job quitters</i>	0.577** (0.195)	0.872** (0.094)	0.800** (0.065)	0.854** (0.049)	0.819** (0.030)	0.792** (0.025)	0.778** (0.052)	<b>0.784**</b> <b>(0.034)</b>
<b>D. Young vs. older workers</b>								
<i>Age &lt; 30</i>	0.557** (0.270)	0.940** (0.126)	0.745** (0.097)	0.771** (0.065)	0.815** (0.036)	0.788** (0.032)	0.842** (0.040)	<b>0.800**</b> <b>(0.046)</b>
<i>Age ≥ 30</i>	0.800** (0.122)	0.870** (0.092)	0.883** (0.061)	0.835** (0.054)	0.855** (0.029)	0.808** (0.026)	0.751** (0.057)	<b>0.829**</b> <b>(0.027)</b>
<b>II. STAYERS</b>								
<b>E. Job stayers</b>	0.214** (0.040)	0.540** (0.024)	0.721** (0.012)	0.750** (0.010)	0.791** (0.006)	0.822** (0.004)	0.781** (0.010)	<b>0.660**</b> <b>(0.007)</b>
<b>Difference (A - E)</b>	0.512	0.352	0.103	0.057	0.046	-0.023	0.012	<b>0.151</b>

Note: the proportion explained by the stepping stone theory is computed as follows:  $s = (Var - Var(LM)) / (Var(SS) - Var(LM))$ , where  $Var$ ,  $Var(LM)$  and  $Var(SS)$  represent actual variance and expected variance according to the learning model and the stepping stone theory, respectively. Standard errors calculated using a non-parametric bootstrap with 5000 replications are in parentheses; a \*\* (\*) indicates that the coefficient is different from zero at a 5% (10%) level of significance.

Figure 1: Job satisfaction (JS), before and after the first job quit

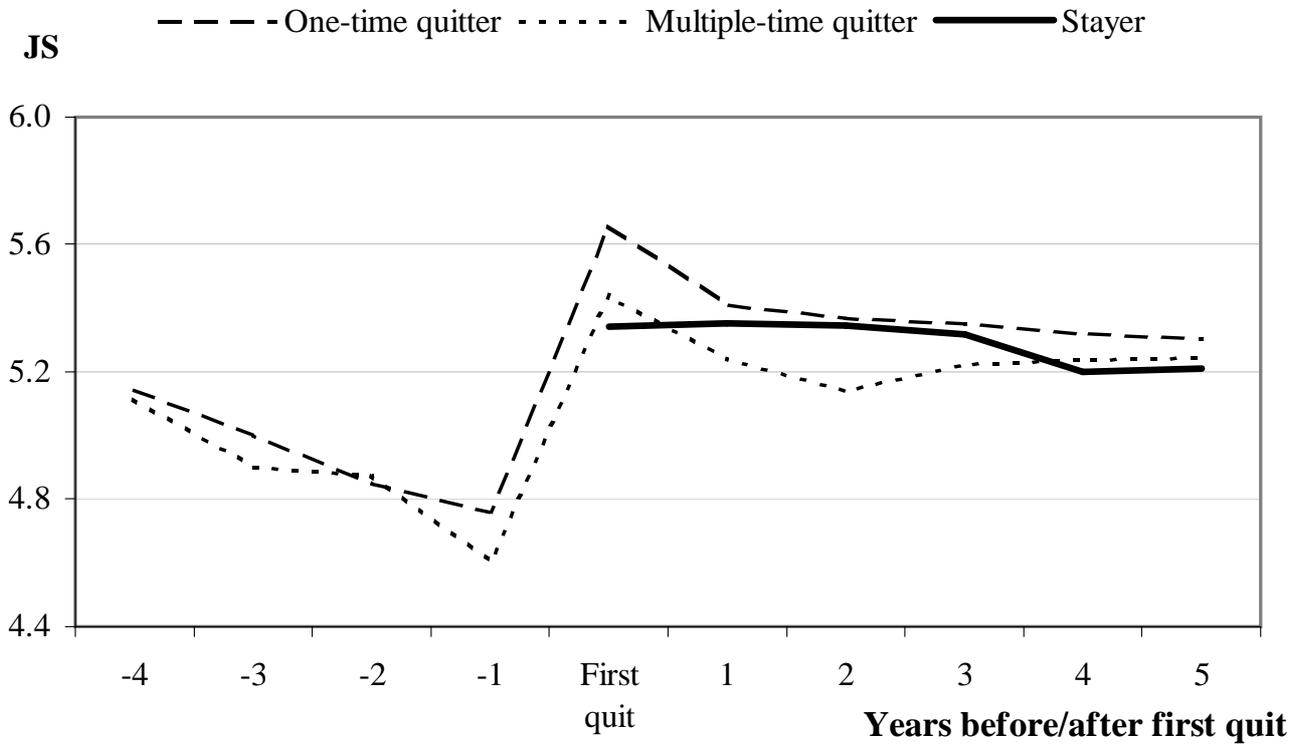
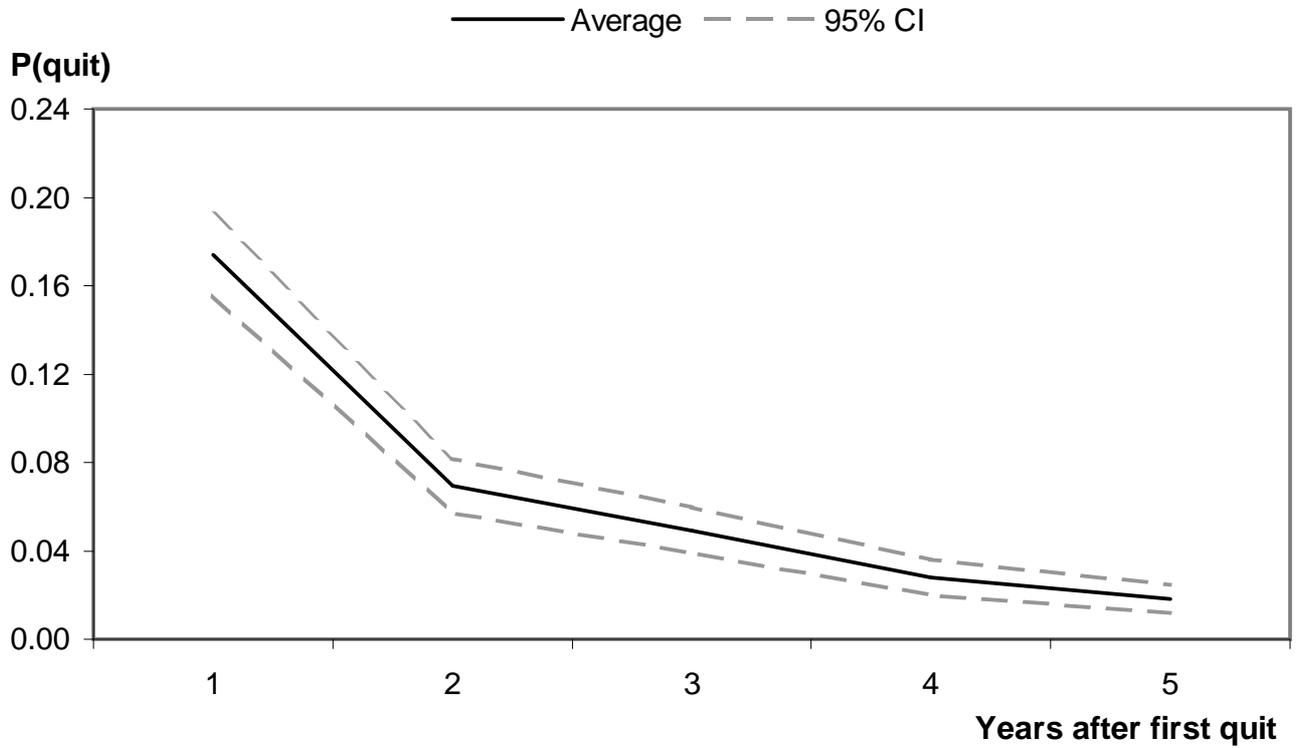
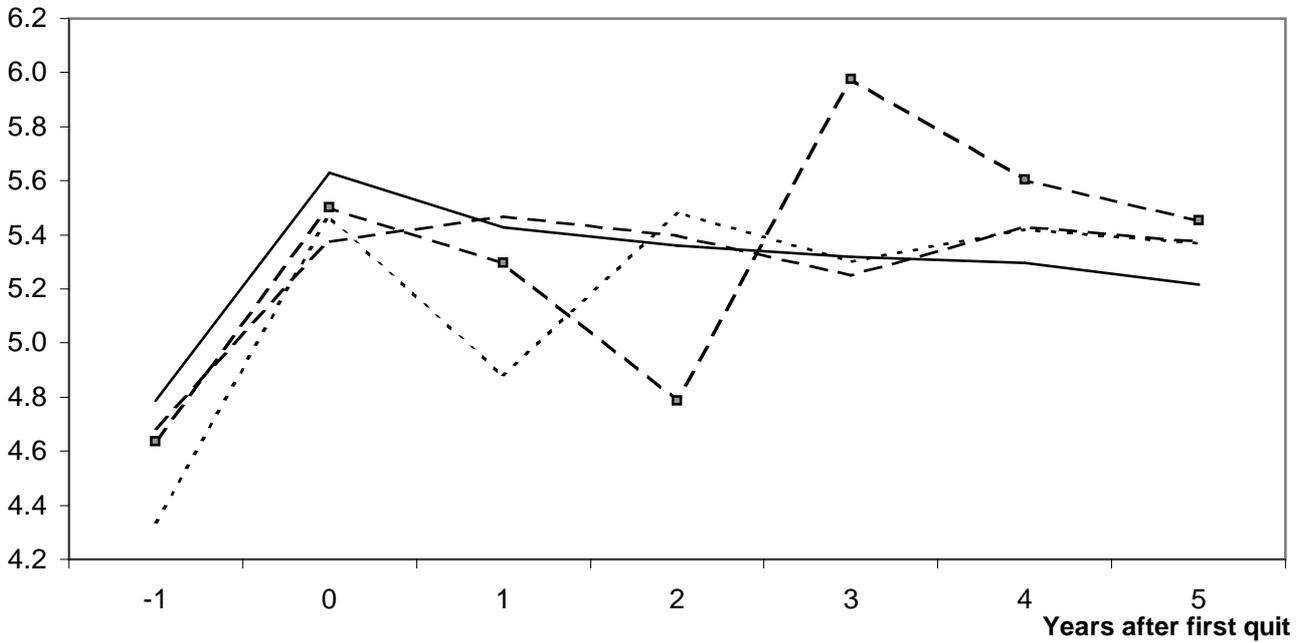


Figure 2: Average quit probability in years after the first job quit



Note: P(quit) is calculated as the probability that people quit again conditional on having quit once before.

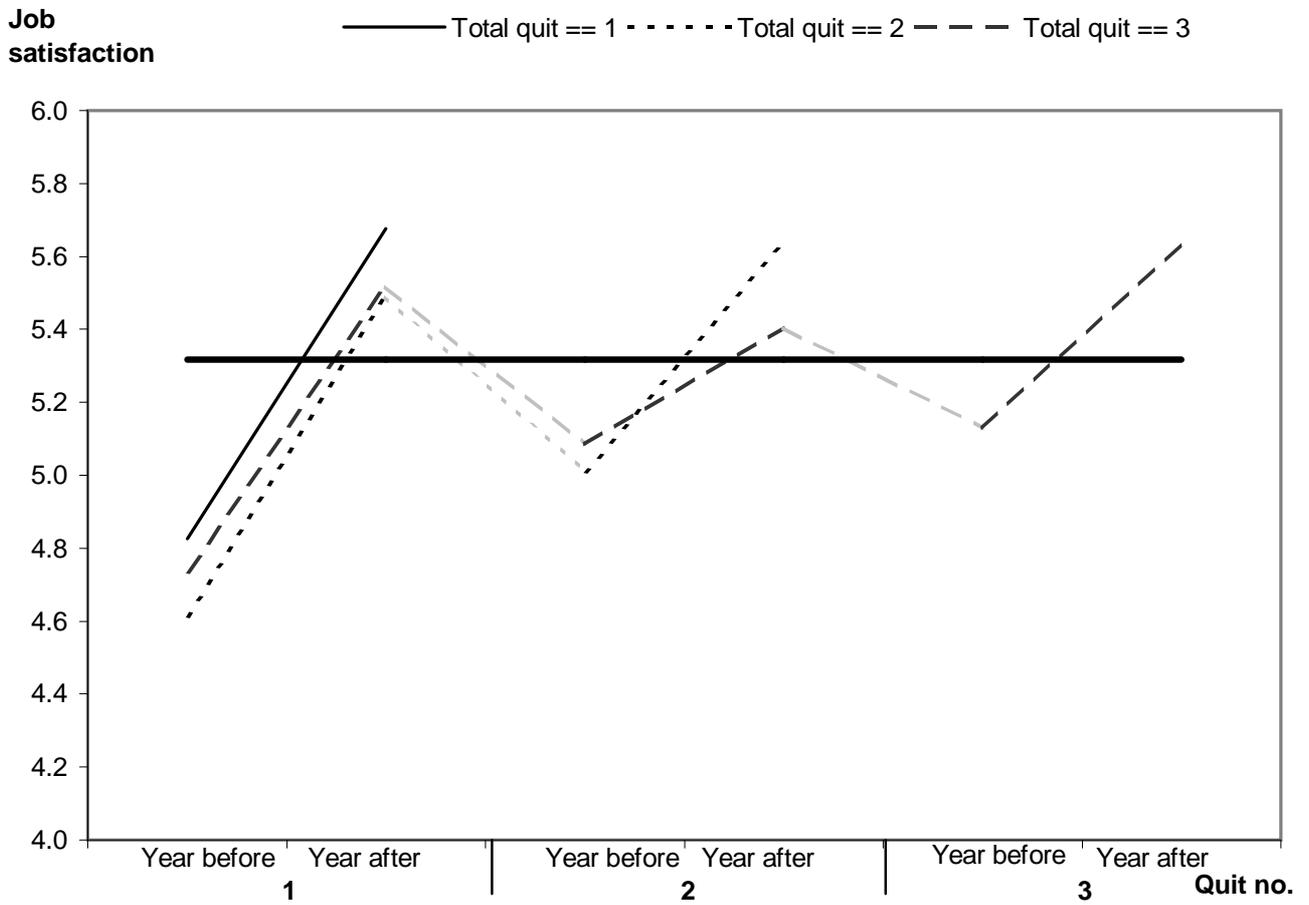
Figure 3: Job satisfaction by timing of second quit relative to first job change



No. of years after first quit after which subsequent quit occurs:

— No subsequent quit - - - 1 ····· 2 - □ - 3

Figure 4: Job satisfaction and sequential job quits



Note: 'Total quit' refers to the total number of quits experienced by an individual during the observation period.

Figure 5: Accepted job offer distribution

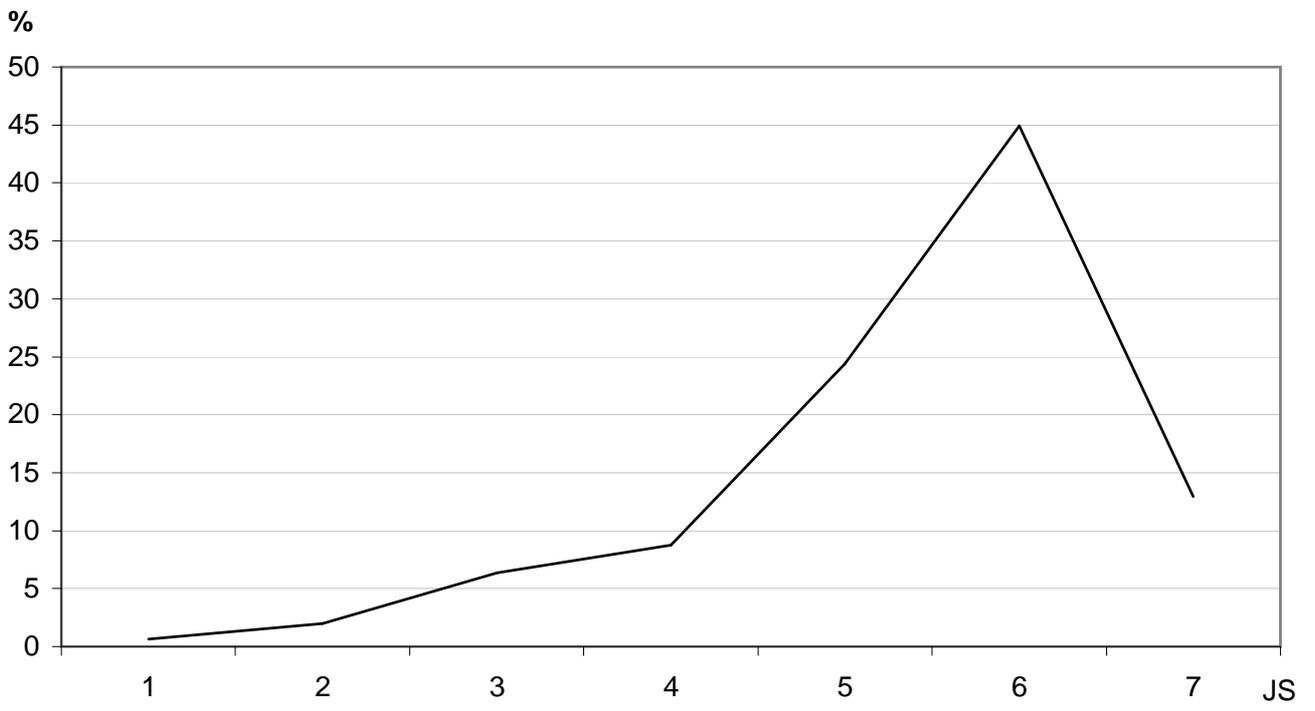


Figure 6: Variance in accepted job satisfaction

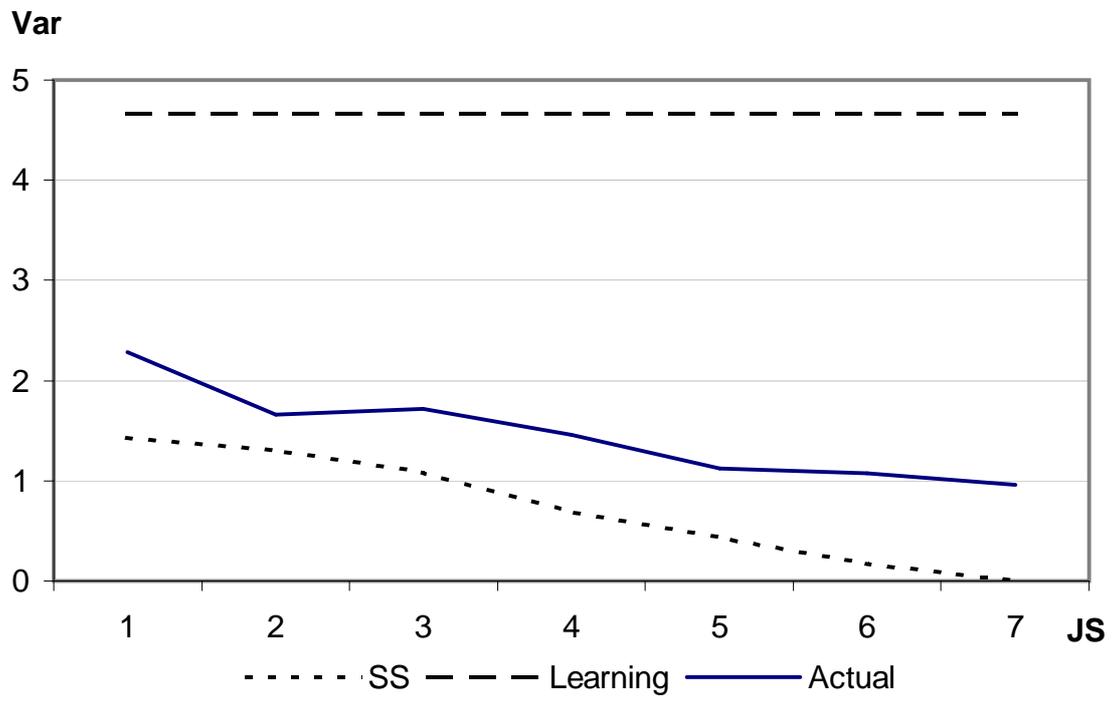


Figure 7: Variance in accepted job satisfaction following a job separation

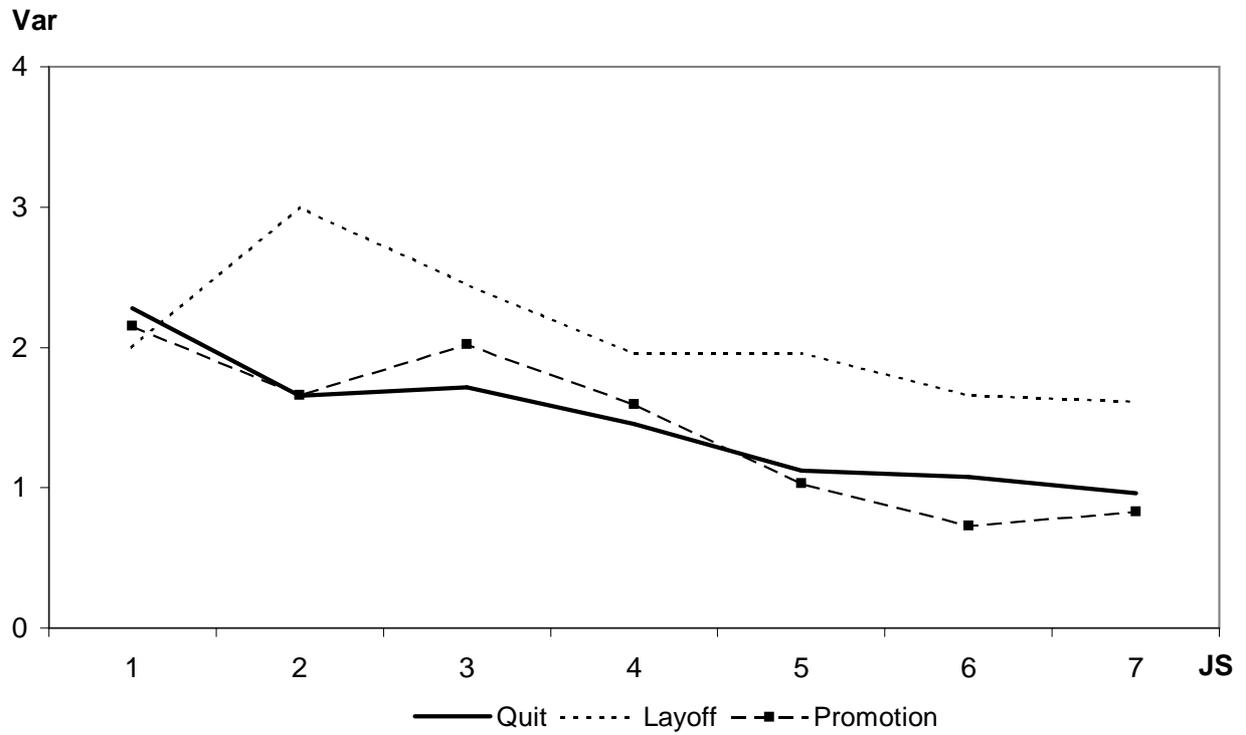


Figure 8: Variance in accepted job satisfaction - job stayers vs. quitters

