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Optimal number of job changes

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This paper estimates the individual optimal number of job changes which is derived from an earnings function where the working history affects the earnings in a direct and an indirect way. In comparison between actual and optimal number of job changes it is found that workers with a high degree of on-the-job training and unexperienced persons have underoptimal mobility behavior.

1. Introduction

Empirical studies of individual labor turnover are usually based on probit models.[1] The dependent variable is a dummy separating movers and stayers. The following or a similar decision rule to quit is used: A worker i compares his expected utilities (earnings streams) in the present job ($V(PJ_i)$) and in an alternative job ($V(AJ_i)$), and accepts the offer of the alternative job only if the utility associated with the latter is at least as great as in the first job plus the costs associated with mobility (C_i):

$$V(AJ_i) \geq V(PJ_i) + C_i . \tag{1}$$

Although this outcome may be what intuitively appealing, it is not necessarily valid. Implicitly, decision rule (1) assumes that an accepted offer is acceptable forever. The worker is allowed to move only once; the possibility of further search for higher-paying jobs is ignored. But this is the normal behavior as *Thurow* points out: "The sensible search strategy is to accept the first job offered but to keep on looking. Whenever a better job is found at a higher wage rate the sensible searcher quits the first job and takes the second."[2] With respect to this behavior, problems will not arise if

$$V(J_i^{(1)}) \leq V(J_i^{(2)}) - C_i^{(1,2)} \leq V(J_i^{(3)}) - C_i^{(2,3)} \leq \ldots \leq V(J_i^{(L)}) - C_i^{(L-1,L)}, \tag{2}$$

where $V(J_i^{(1)})$ is the expected utility of individual i in job 1 and $C_i^{(l-1,l)}$ are mobility costs if i moves from job $(l-1)$ to job l. In some cases, however, the

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[1] E.g. *Borjas / Rosen* (1980), *Bartel* (1982), *Robinson / Tomes* (1982), *Blau / Kahn* (1983), *Antel* (1985), *Shah* (1985), *Osberg / Mazany / Apostle / Clairmont* (1986).

[2] *Thurow* (1983), 194.

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isolated decision between two jobs according to rule (1) may be suboptimal. It is possible to get another wage offer after a job change that would have been preferred before changing but which is not sufficiently high to induce a second change. Furthermore, we have to consider situations in which an offer is accepted, although equation (1) does not hold. Such a decision might be appropriate if a job change induces more attractive offers later on. Examples are migration into regions with larger labor markets and higher probabilities to obtain better jobs than in the present region; moves to jobs where the contact with firms offering more attractive jobs is improved; and job changes which signal the worker's flexibility and productivity and thus may induce promotions of further offers. We focus upon the latter consideration, one that has been neglected in the economic literature on search and labor turnover. Even studies of optimal search[3] appear unaware of the problem. Assuming perfect information, all potential offers can be included within the decision rule. But in reality, there exists uncertainty about the prospective offers.

The purpose of this paper is to derive the optimal number of job moves under optimizing behavior. Our basic hypothesis is that the decision to quit the current job depends on the worker's employment history, especially on the past number of job changes. If the actual number (NOM) is smaller than the optimal number (ONOM), a worker should intensify his search and possibly accept an offer even if equation (1) does not hold. He or she should reject a utility increasing offer (equation (1)) if NOM exceeds ONOM.

The paper is organized as follows. In section 2, we give arguments that employment history measured by NOM affects earnings in direct and indirect ways. We present a basic earnings model from which alternative optimal mobility functions are derived. The empirical investigation – data, specification, estimation problems, results and interpretation – follows in section 3.

2. Some theoretical aspects and the model

2.1 Effects of turnover on earnings

Some arguments suggest that earnings depend on working history as measured by the number of jobs, although most empirical investigations of earnings functions neglect this aspect.[4] First, some economists interpret mobility costs as investment human capital.[5] Individuals with different amounts of investment have to be compensated according to their costs. Second, the

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[3] *Morgan / Manning* (1985).

[4] Exceptions are *Borjas / Mincer* (1978), *Bartel* (1980), *Mincer / Jovanovic* (1981), *Hübler* (1984).

[5] See, for example, *Fein* (1965).

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number of jobs is a screening device for firms. In general, employees are risk-adverse. Risk-lovers are scarce. Workers who change jobs, though returns are uncertain, signal such a characteristic. Third, movers possess better information about their abilities and suitable jobs in the sense of job-shopping and job-matching[6] than stayers. Fourth, the number of jobs is a proxy for the offers. We can assume that the most able employees are attracted away from their jobs earlier than other workers.[7]

These arguments support the hypothesis of a positive correlation between earnings and the number of jobs. However, a negative dependency is also possible. According to implicit contract theory, movers have inferior reputations. A job change may signify the violation of a long-term implicit contract. Firms will be prepared to hire workers with a poor reputation only if they can pay them lower wages than other employees.

If we incorporate working history, z, measured by the number of job moves into a conventional linear model of earnings functions as an independent variable, then the idea of an optimal z under maximizing behavior is useless. The greater (smaller) z, the greater (smaller) are earnings. Substituting the linear term $\beta_z z$ by non-linear terms (e.g. $c_0 z + c_1 z^2$) we obtain a nontrivial z.

Our theoretical considerations suggest that this approach makes sense. We expect opposite signs on c_0 and c_1; for example, growth of information by job-shopping decreases with the number of jobs.[8] But this is not the whole story of the effects of working history or job moves on earnings. Our hypothesis is as follows: The returns to earnings determinants vary with z. The term $c_1 z^2$ is merely a proxy for the unspecified indirect earnings effects of z. In other words, the employers evaluate identical personal characteristics differently, and this evaluation is based on working history. For their part, employees are in a better position to signal their abilities the longer and the more diversified is their working history, while firms interpret employment history as a good signal for workers' prospective behavior.

Following the idea of varying returns to earnings determinants, we have to introduce the so-called indirect effects of z on earnings by systematically varying parameters. Assume that the total individual coefficients can be divided into three components (a constant element for all individuals, a z-dependent part and a stochastic component)

$$(3) \qquad \beta_{ij} = (a_0 + a_1 z_i + \varepsilon_i) \cdot \beta_j \quad \text{and} \quad \beta_{iz} = (a_0 + a_1 z_i + \varepsilon_i) \cdot \beta_z ,$$

6 *Johnson* (1978), for example, presents a model of job shopping.
7 *Lazear* (1986) makes this assumption.
8 See *Miller* (1984).

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where $i = 1, \ldots, n$; $j = 1, \ldots, k$; a_0 and a_1 are unknown parameters, ε is a $(nx1)$ vector of disturbances, $E(\varepsilon_i) = 0$ and $E(\varepsilon_i^2) = \sigma_\varepsilon^2$. Not all earnings effects are observable and some of them are small. These variables are summarized in an error term u, where $E(u_i) = 0$ and $E(u_i^2) = (\sigma_u^2)$ and $E(u_i \varepsilon_i) = 0$. Accordingly, our earnings functions may be written

$$(4) \qquad y = (\text{diag}(a_0 + a_1 z_1 + \varepsilon_1, \ldots, a_0 + a_1 z_n + \varepsilon_n)) \cdot (X\beta + \beta_z z + u),$$

where $y \sim (nx1)$, $X \sim (nxk)$, $u \sim (nx1)$, $\beta \sim (kx1)$, $z \sim (nx1)$, $\beta_z \sim (1x1)$, $a_0 \sim (1x1)$, $a_1 \sim (1x1)$, $z_i \sim (1x1)$, $\varepsilon_i \sim (1x1)$, $i = 1, \ldots, n$. A more flexible approach is given by substituting (3) by

$$(3a) \qquad \beta_{ij} = (a_0 + a_{1j} z_i + \varepsilon_i) \cdot \beta_j \quad \text{and} \quad \beta_{iz} = (a_0 + a_{1z} z_i + \varepsilon_i) \cdot \beta_z,$$

where $j = 1, \ldots, k$. Consequently, more realistic cases may be considered, where z affects y indirectly via some but not all earnings components (some a_{1j} or a_{1z} are zero).

The decision rule for job changes in conventional models is not only based on earnings. Mobility costs (C) have also to be considered. We assume that working history also affects C. The more jobs sampled, the higher will be the total mobility costs. But the workers learn to manage job changes, so that marginal costs may be expected to fall with an increasing number of job moves. In particular, pre-move information decreases the marginal costs of search.[9] We complete our model with the following mobility cost function constructed in a similar fashion to the earnings function

$$(5) \qquad C = (\text{diag}(b_0 + b_1 z_1 + \tilde{\varepsilon}_1, \ldots, b_0 + b_1 z_n + \tilde{\varepsilon}_n)) \cdot (W\gamma + \gamma_z z + \tilde{u}),$$

where C is a $(nx1)$ vector of mobility costs, b_0, b_1 and γ_z are unknown parameters, W is a (nxl) matrix of l costs determinants, γ is a $(lx1)$ vector of unknown parameters, $\tilde{\varepsilon}_i$ is an error term, and $\tilde{u}$ is a $(nx1)$ vector of disturbances. Furthermore, we assume $E(\tilde{\varepsilon}_i) = 0$, $E(\tilde{\varepsilon}_i^2) = \sigma_{\tilde{\varepsilon}}^2$, $E(\tilde{u}_i) = 0$, $E(\tilde{u}_i^2) = \sigma_{\tilde{u}}^2$ and $E(\tilde{u}\,\tilde{\varepsilon}') = 0$.

Equation (5) can be modified in the same way as the earnings function if we substitute (3) by (3a)

$$(5a) \qquad \gamma_{ij'} = (b_0 + b_{1j'} z_i + \tilde{\varepsilon}_i) \cdot \gamma_{j'} \quad \text{and} \quad \gamma_{iz} = (b_0 + b_{1z} z_i + \tilde{\varepsilon}_i) \cdot \gamma_z,$$

where $j' = 1, \ldots, l$.

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[9] See *Herzog / Hofler / Schlottmann* (1985), 374.

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2.2 Optimal number of job moves

Equations (4) and (5) are the basis for deriving an optimal working history function. But it is not useful to calculate the expression $\partial (y - C)/\partial z$. We have instead to consider expected net earnings. Let us assume that after the job change there are no further mobility costs incurred and that all individuals work until age 65. Moreover, suppose that earnings increase uniformly with the factor $\exp(gt)$, where g is a constant rate, that may be positive or negative. This rate is a composite of the usual rate of wage growth, the conventional discount rate, the death and layoff risk, and of the probability of interrupting the working career. This definition allows us to calculate the net returns of a given working history[10]

$$(6) \qquad V(z_i) = \int_0^{65\text{-AGE}_i} y(z_i) \exp(gt)\, dt - C(z_i)$$

$$= (y(z_i) (\exp(g(65\text{-AGE}_i)) - 1)/g) - C(z_i)$$

$$=: y(z_i) \cdot F(\text{AGE}_i) - C(z_i) \qquad i = 1, \ldots, n,$$

where AGE_i is the age of the i-th person and t ist a time variable. If we calculate

$$(7) \qquad (\partial (y' F/\partial z) - (\partial (C' \iota)/\partial z) = 0,$$

where $F = (F(\text{AGE}_1), \ldots, F(\text{AGE}_n))' =: (F_1, \ldots, F_n)'$, $\iota = (1, \ldots, 1)'$, the solution for all z_i is

$$(8) \qquad z = \frac{1}{2} (b_1 \gamma_z \operatorname{diag}(1, \ldots, 1)_n - a_1 \beta_z \operatorname{diag}(F_1, \ldots, F_n))^{-1} \cdot$$

$$((a_0 \beta_z F - b_0 \gamma_z \iota) + (a_1 (\operatorname{diag}(F_1, \ldots, F_n)) X \beta - b_1 W \gamma) +$$

$$(a_1 (\operatorname{diag}(F_1, \ldots, F_n)) u + \beta_z (a_1 (\operatorname{diag}(F_1, \ldots, F_n)) \varepsilon - b_1 \tilde{u} - \gamma_z \tilde{\varepsilon}).$$

This model is nonlinear. In special cases, we obtain a linear specification ($\beta_z = 0$ or $a_1 = 0$ or $a_{1z} = 0$, if we use (3a) instead of (3)). The first case excludes the direct effects of z on y. The second case neglects all indirect effects. In the third case, the interaction of z with itself vanishes. We then have

$$(8a) \qquad z = \alpha_0 + \alpha_1 F + (\operatorname{diag}(F_1, \ldots, F_n)) X \overset{r}{\alpha}_2 + W \overset{r}{\alpha}_3 + v =: \tilde{X} \alpha + v,$$

[10] We follow *Weiss* (1984) who has presented a quit decision rule for conventional models.

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where r in X and W indicates that only a part of $X = (X^{r} \vdots \cdot)$ and $W = (W^{r} \vdots \cdot)$ interact with z, in other words, that some a_{1j} and b_{1j}, are zero. α_0 and α_1 are unknown parameters, α_2 and α_3 are $(kx1)$ and $(lx1)$ vectors of unknown coefficients, and v is a $(nx1)$ vector of disturbances. As we have emphasized that the term of z^2 is only a proxy for unspecified indirect earnings effects of z, the assumption $a_{1z} = 0$ entails little loss of information if the model is well specified.

Another way of obtaining a linear model is to use a first-order Taylor expansion as an approximation. In this case, F and all variables of matrix X and W which interact with z are included as exogenous variables in the optimal working history function.

The crucial point of (8) and (8 a) is its assumption of a uniform rate of wage growth. We argue that g depends on z, too. For reasons suggested earlier, the actual returns of earnings determinants are a function of z. Therefore, it is sensible to expand this hypothesis to prospective returns. Accordingly, we have to replace (7) by

$$\text{(9)} \qquad \partial V(z_i) / \partial z_i = \{[(\partial y_i / \partial z_i)\, g_i - (\partial g_i / \partial z_i)\, y_i] / g_i^2\} \cdot$$

$$(\exp(g_i (65\text{-AGE}_i) - 1) + (y_i / g_i)(\partial g_i / \partial z_i) \cdot$$

$$(65\text{-AGE}_i) \exp(g_i (65\text{-AGE}_i)) - (\partial C_i / \partial z_i) = 0 .$$

The resulting optimal working history function from (9) is nonlinear. An approximate linear approach is again obtained by using a first-order Taylor expansion. This means that compared with the Taylor-expansion of (8) we have nearly the same specification, although AGE is now substituted for F. We propose an alternative approach. Take (8 a) and complete this function by a function of F_i which depends on z

$$\text{(10)} \qquad F_i = ((\exp(kz_i (65\text{-AGE}_i)) - 1) / kz_i)\, \varkappa_i^* ,$$

where $g_i = kz_i$, k = const., and $\varkappa^*$ is an error term assuming $E(\varkappa_i^*) = 1$. We approximate (10) by

$$\text{(11)} \qquad \ln F_i = d_0 + d_1 z_i + d_2 Z_i \text{AGE}_i + d_3 \ln z_i + \varkappa ,$$

where d_j are unknown parameters ($j = 0, 1, 2, 3$) and $\varkappa$ is a disturbance term. We now have to estimate a nonlinear, two-equation model of (8a) and (11).

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3. Empirical investigations

3.1 Data

The information on individual working histories used in the empirical analysis is based on a 10 percent random sample of all employed persons in the state of Bremen. In November 1981, a questionnaire was sent to 26,453 employees, the purpose of which was to obtain data on schooling, job change, industry, type of work, working conditions, job stability, earnings, and personal characteristics. The sample size used in this study consists of 4,657 employees. Only those persons are included which where not unemployed far at least ten years. The purpose of this restriction is that we want to exclude dismissals. We have no information whether an individual job move is voluntary or not. But most quitters change jobs directly without intervening unemployment, while most layoffs are unemployed between jobs. We expect in accordance with *Antel* and *Mincer*[11] that the latter have a different search behavior than quitters, while *Borjas / Rosen*[12] argue that the decomposing in quits and layoffs is artifical since workers who know that a layoff is about to occur may quit and firms who know that workers are about to quit may lay them off.

All the variables used in the empirical analysis are described in Table 1 but some of them has to be explained a little bit more. In our investigation the most important variable z is measured by the answer to the question: "How many firms did you work for during your life?" (NOF = number of firms). Earnings are expressed by the natural logarithm of monthly gross income ($\ln Y$). Social background (SB) is proxied by father's occupation status. From seven categories (1 – unskilled worker, 2 – skilled worker, 3 – farmer, 4 – white collar worker, 5 – civil servant, 6 – self-employed, 7 – manager) an ordinal scale 1 - 7 is constructed where the average income of unskilled workers is the lowest and that of the managers is the highest. In one question the employees are asked: "What is your degree of management tasks?" (1 – no, 2 – small, 3 – middle, 4 – high). The answer is interpreted as the individual position in the hierarchy of the firm (HIER). Another variable measured by an ordinal scale is the degree of on-the-job training (DOJT). The answer to the question "On your job what degree of training is necessary that an average new person is fully trained and qualified? (1 – no training, 2 – longer training period, 3 – vocation requiring an apprenticeship, 4 – vocation requiring an university education) is used as a proxy for special human capital.

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[11] *Antel* (1985); *Mincer* (1986).

[12] *Borjas / Rosen* (1980).

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3.2 Specification and expected signs

We have to specify the earnings and the mobility costs function. In the human capital tradition, the logarithm of earnings is explained by schooling (S), experience (EX) and its square (EXSQ). In more recent studies,[13] the exogenous variables are supplemented by the number of years of tenure in the current firm (TEN) and square of tenure (TENSQ), or TEN and the previous experience (PEX = EX − TEN) are substituted for EX.[14] We follow the latter approach. Notable explanations of earnings-tenure profiles are the firm-specific human capital, agency, self-selection, implicit contract and segmented labor market hypotheses.[15] We add selected job and personal characteristics such as firm size (SIZE), measured by the number of employees, position in the hierarchy of the firm (HIER), working time (TIME), sex (MEN; 1 – man, 0 – otherwise), social background (SB). The direct earnings determinants (X) and the resulting sign expectations of the partial derivatives in the earnings functions are as follows

$$X = f(\underset{?}{\mathrm{NOF}}, \underset{+}{\mathrm{S}}, \underset{+}{\mathrm{TEN}}, \underset{-}{\mathrm{TENSQ}}, \underset{+}{\mathrm{PEX}}, \underset{-}{\mathrm{PEXSQ}}, \underset{(+)}{\mathrm{SIZE}}, \underset{+}{\mathrm{HIER}}, \underset{-}{\mathrm{TIME}}, \underset{+}{\mathrm{MEN}}, \underset{+}{\mathrm{SB}})\,. \tag{12}$$

Several recent empirical studies of the determinants of wages have come to the conclusion that a positive and significant correlation between SIZE and wages exists, but apparently this positive effect of firm size is statistically significant only for firms with more than 100 employees.[16] For firms with fewer than 100 employees, there is no consistent relationship between firm size and wages. The positive sign of HIER can be explained by the degree of responsibility[17] or by the rank-order tournament theory.[18] If working time is expanded the earnings also increase. Therefore, considering the definition of TIME (see Table 1) the expected sign of this variable is negative. Pay differences between men and women may be attributed to sex segregation by firm or unobserved characteristics which differ between male and female. Nepotism is one reason that we have to expect a positive correlation between SB and earnings.

[13] See, for example *Hashimoto / Raisian* (1985).

[14] See *Mincer / Jovanovic* (1981); *Holmlund* (1984).

[15] See *Arai* (1982); *Cornfield* (1982); *Hashimoto / Raisian* (1985).

[16] *Weiss / Landau* (1984) present theoretical arguments and empirical evidence for this relationship.

[17] See, for example, *Lydall* (1968).

[18] *Lazear / Rosen* (1981).

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Our earnings function has to be completed by interactions between number of firms (NOF) and other earnings factors. We introduce four interaction variables so that the implicit $\ln Y$ function is

$$\ln Y = f(\mathrm{X}, \underset{-}{\mathrm{NOF^*PEX}}, \underset{+}{\mathrm{NOF^*PEXSQ}}, \underset{-}{\mathrm{NOF^*SIZE}}, \underset{-}{\mathrm{NOF^*SB}}) . \tag{13}$$

The sign expectations of the interaction variables with respect to NOF have to be explained. A firm which recruits an employee may expect that on-the-job-training in previous jobs increases with the duration of the tenure in previous firms. But, as *Borjas* has argued, "the proportion of time spent in training activities will probably decline as time elapses within a particular job. The reasons for this, of course, relative to the fact that given jobs of finite duration in a person's life cycle, the returns are greater to earlier than to later investments and the costs of investment are likely to increase over time".[19] Accordingly, we can guess that the returns to PEX decrease and that to PEXSQ increase with NOF.

Usually, large firms invest more than small and medium sized firms in specific human capital. Therefore, they are more interested in longer tenure in order to realize profits on these investments. Tenure correlates positively with firm size.[20] If firms expect an employee to have short tenure, they will consequently invest less in him. Assuming workers participate in costs and returns to investments,[21] workers with short expected tenure will receive nearly the same wage in all firms due to training effects. But the earnings effect with long expected tenure is greater in large firms than in small firms. Thus, a negative earnings effect of NOF*SIZE follows if firms use the number of previous job moves as an indicator of expected tenure.

The expected earnings effect of the interaction between NOF and SB is negative. Workers can improve matching between individual abilities and job characteristics via quitting. This implies increasing returns. But we expect that the marginal effects are greater for those form less favourable family background. Factors such as nepotism and information asymmetries suggest that the initial job match will usually be better for workers from prosperous families, from the upper classes. They will learn less through jobshopping.

Compared with earnings functions, mobility costs functions are less developed. *Robinson / Tomes* and *Holmlund*[22] use personal and job characteristics such as family size, language, family background, tenure, (tenure)^2,

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19 *Borjas* (1981), 367.

20 *Hashimoto / Raisian* (1985) demonstrate this for Japan and the United States.

21 See *Hashimoto* (1981).

22 *Robinson / Tomes* (1982); *Holmlund* (1984).

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age, marital status and whether a person has recently moved to explain the differences in mobility costs. Instead of marital status we use family size (NOPH) and the employment status of the spouse (SWO). Insofar as job mobility involves migration, we expect that the mobility costs are higher for older workers, larger families and if the spouse is working. Older workers have accumulated consumer durables such as houses. Short term sales entail losses in many cases. If the spouse or other family members also work they have to look for a new job or two households are necessary. The presence of school age children inhibits moving, on the ground that costs will be incurred when changing schools. Nonmonetary mobility costs induced by loss of friends and other local ties have also to be considered.

A worker's ties with the employees will increase with his length of tenure. This is due to firm-specific ties arising from established social relations with co-workers. But after a longer time, if a new generation of workers enters the firm, the ties diminish. Schooling is also hypothesized to affect the costs of moving in the form of reduced costs of information. Additionally, we introduce the degree of on-the-job-training (DOJT) and the position in firm's hierarchy (HIER). On the one hand, DOJT indicates the loss of investment costs in specific human capital by job moves. On the other hand, we suppose that the loss of specific human capital due to turnover is reduced with an improvement in hierarchical position. In other words, the relevant abilities in the top positions of the firms are more general than specific. Finally, the sum of mobility costs increase with the number of job moves (NOF). But persons who have often changed the job possess negligible ties. Through turnover, employees learn to manage further job moves and get information on how to reduce mobility costs. So we expect that the effect of interactions with NOF on mobility costs is usually negative.

It is assumed that marginal mobility costs of the following determinants – TEN, TENSQ, DOJT, S, and SWO – depend on NOF. Since the theory of mobility costs is not well developed, we include an interaction of NOF with itself which summarized all unspecific mobility cost determinants interacting with NOF. From these considerations we obtain the following mobility cost function/expected signs of the coefficients

$$
\begin{aligned}
(14) \qquad C = f\,(&\underset{+}{\text{TEN}}, \underset{-}{\text{TENSQ}}, \underset{+}{\text{DOJT}}, \underset{-}{\text{HIER}}, \underset{-}{\text{S}}, \underset{+}{\text{AGE}}, \underset{+}{\text{NOPH}}, \underset{+}{\text{SWO}}, \underset{+}{\text{NOF}}, \underset{-}{\text{NOF*TEN}},\\
&\underset{+}{\text{NOF*TENSQ}}, \underset{-}{\text{NOF*DOJT}}, \underset{-}{\text{NOF*S}}, \underset{-}{\text{NOF*SWO}}, \underset{-}{\text{NOF*NOF}})\,.
\end{aligned}
$$

From (13) and (14), it is now possible to estimate the optimal mobility function (8a). In this special case, equation (8a) only contains variables which interact with NOF in (13) or (14). We may expect the coefficients on

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the interaction terms with F to have the same sign as the pure effects on optimal NOF. From the coefficients of the interaction terms with NOF in (13) and (14) we are able to determine the signs of the optimal mobility function. They are the same as in (14) and contrary to that of (13), if we maximize the present value of net earnings. The coefficient on F is indeterminate in the optimal mobility function because it is not obvious whether earnings increase or decrease with NOF or NOF*F. Therefore, the implicit form of the complete linear optimal mobility function (8a) is

$$\text{NOF} = f(\underset{?}{\text{F}}, \underset{+}{\text{F*PEX}}, \underset{-}{\text{F*PEXSQ}}, \underset{+}{\text{F*SIZE}}, \underset{+}{\text{F*SB}}, \underset{-}{\text{TEN}}, \underset{+}{\text{TENSQ}}, \underset{-}{\text{DOJT}}, \underset{-}{\text{S}}, \underset{-}{\text{SWO}}) =: f(\tilde{X}). \tag{15}$$

3.3 Estimation and results

NOF as proxy for working history z is a positive integer variable. If we transform this variable by NOF-1 (number of moves, NOM), we may expect that this new variable is poisson-distributed[23]

$$\text{Prob } (\text{NOM} = r) = \exp(-\lambda_i)\,((\lambda_i)^r / r!)\,, \tag{16}$$

where $r = 0, 1, 2, \ldots$ and $\lambda_i = E\,(\text{NOM}_i)$ is the expected number of job-moves of the i-th person. A chi-square test does not reject the hypothesis of (16). Model (15) and (16) can be estimated by the maximum likelihood method. But the ML estimator for a Poisson process is equivalent to an iterated weighted least squares estimator (IWLS), if the process attains a fixed point.[24] The IWLS estimator can be calculated with conventional software packages

$$\hat{\alpha}^{(t)} = (\tilde{X}' \hat{V}^{(t)-1} \tilde{X})^{-1} \tilde{X}' \hat{V}^{(t)-1}\, \text{NOM} \tag{17}$$

where t denotes the iteration step. For $t = 1$, we use OLS estimates. This result is presented in column (1) of Table 1 (p. 87), where the variable F is constructed by assuming constant rates of earnings growth with $g = 0{,}05$. The estimated covariance matrix of disturbances $v\,(\hat{V})$ is a diagonal matrix

$$\hat{V}^{(t)} = \text{diag}\,(\tilde{x}^1\, \hat{\alpha}^{(t)}, \ldots, \tilde{x}_n'\, \hat{\alpha}^{(t)})\,. \tag{18}$$

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[23] See *Maddala* (1983), pp. 51.
[24] See *Jorgenson* (1961); *Chirenko* (1982).

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We have also to consider that the disturbance v of (8a) is F-dependent

$$E(v_i^2) = (2 b_{1z} \gamma_z)^{-2} (\beta_z^2 \sigma_\varepsilon^2 F_i^2 + b_{1z}^2 \sigma_{\tilde{u}}^2 + \gamma_z^2 \sigma_{\tilde{\varepsilon}}^2) \tag{19}$$

$$=: \delta_0 + \delta_1 F_i^2 ,$$

where we assume that all covariances of the error terms u, ε, $\tilde{u}$ and $\tilde{\varepsilon}$ are zero. Using the residuals, the *Breusch-Pagan* test[25] supports the hypothesis of F-dependent heteroskedasticity. Therefore, after the first step, the OLS estimation, but before the next steps with the weighted least squares estimation of the described iterative procedure we apply an estimated GLS approach (EGLS), composed of three steps.[26] Then seven iterative steps follow. Column (2) of Table 1 provides the results of this procedure.

Columns (3) and (4) of Table 1 present estimates with variable rates of earnings growth. The first-order Taylor expansion yields column (3) after OLS estimation and seven subsequent iteration steps of WLS are performed. For the estimation of the two-equation approach with variable rates of growth (8a) and (11) we start with the OLS estimation of (11), where we use NOF as proxy for z and assume as initial value $g = 0{,}05$. The next step is the OLS estimation of (8a), where only those X and W components are used which interact with NOF. F is substituted by the OLS estimate of (11). Then the 3-step-EGLS[27] of (8a) follows. The procedure is continued by a renewed OLS estimation of (11) using estimates of F from (8a) as instrument variable and a repetition of the (8a)-3-step-EGLS approach, where F is substituted by the newest estimates of (11). Seven further iteration steps of WLS from (8a) are added. The procedure converges and the results of the last step are presented in column (4) of Table 1.

The four estimates of optimal mobility functions are each based on the same specification of the earnings and mobility cost function. They differ only in the assumption of the rate of growth and in the estimator used. The results given in column (4) based on the nonlinear two-equation system with NOF-dependent rates of earnings growth have all the expected signs (see (15)). The only insignificant coefficient is that of the dummy variable SWO (SWO = 1, if the spouse is working; SWO = 0, otherwise). Possibly, the crude form of measurement is responsible for this result.

In comparison with the other methods applied in column (1) through (3), the estimation procedure in column (4) produces the best fit and the least number of insignificant coefficients and, as noted earlier, no wrong signs. The estimates in column (4) are preferred on theoretical grounds. Note also

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25 *Breusch / Pagan* (1979).

26 *Judge / Griffiths / Hill / Lütkepohl / Lee* (1985), 434.

27 *Judge / Griffiths / Hill / Lütkepohl / Lee* (1985), 434.

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Table 1: **Estimates of optimal mobility functions ($|t|$ -ratios in parentheses)**

variable	mean	OLS with $g = 0.05$ (1)	IWLS with $g = 0.05$ (2)	OLS with g as function of NOF (3)	IWLS with g as function of NOF (4)
PEX*F	657.84	$0.9663 \cdot 10^{-4}$ (10.14)	$0.3759 \cdot 10^{-4}$ (4.01)		$0.1680 \cdot 10^{-3}$ (20.51)
PEXSQ*F	21707.91	$0.1833 \cdot 10^{-6}$ (1.30)	$0.9806 \cdot 10^{-6}$ (7.26)		$-0.8433 \cdot 10^{-6}$ (6.05)
SIZE*F	211.28	$0.1565 \cdot 10^{-3}$ (1.59)	$-0.6172 \cdot 10^{-4}$ (0.57)		$0.6695 \cdot 10^{-3}$ (14.16)
SB*F	201.28	$0.9853 \cdot 10^{-4}$ (2.13)	$0.1451 \cdot 10^{-5}$ (0.03)		$0.2324 \cdot 10^{-3}$ (10.16)
F	66.65	$-0.7540 \cdot 10^{-2}$ (17.81)	$-0.9835 \cdot 10^{-2}$ (21.32)		$-0.4168 \cdot 10^{-3}$ (15.83)
TEN	11.03	$-0.4085 \cdot 10^{-1}$ (15.29)	$-0.5462 \cdot 10^{-1}$ (20.27)	$-0.6041 \cdot 10^{-1}$ (20.41)	$-0.1756 \cdot 10^{-1}$ (6.32)
TENSQ	268.71	$0.5104 \cdot 10^{-3}$ (12.16)	$0.5979 \cdot 10^{-3}$ (13.91)	$0.1203 \cdot 10^{-2}$ (21.66)	$0.3617 \cdot 10^{-3}$ (7.61)
DOJT	2.47	$-0.8250 \cdot 10^{-1}$ (4.97)	$-0.5310 \cdot 10^{-1}$ (3.26)	$-0.7553 \cdot 10^{-1}$ (4.66)	$-0.7016 \cdot 10^{-1}$ (4.06)
S	10.00	$-0.2162 \cdot 10^{-1}$ (3.19)	$-0.2345 \cdot 10^{-1}$ (3.66)	$-0.1168 \cdot 10^{-1}$ (1.84)	$-0.2641 \cdot 10^{-1}$ (3.71)
SWO	0.51	$-0.1815 \cdot 10^{-1}$ (0.66)	$0.7280 \cdot 10^{-2}$ (0.27)	$0.7018 \cdot 10^{-1}$ (2.73)	$-0.4642 \cdot 10^{-1}$ (1.55)
PEX	9.87			$0.4435 \cdot 10^{-1}$ (23.43)	
PEXSQ	325.70			$-0.4417 \cdot 10^{-3}$ (15.10)	
HIER	1.73			$0.3508 \cdot 10^{-1}$ (2.60)	
SIZE	3.17			$-0.1604 \cdot 10^{-2}$ (0.18)	
TIME	1.19			$0.2939 \cdot 10^{-2}$ (1.28)	
SB	3.02			$0.1116 \cdot 10^{-1}$ (2.57)	
MEN	0.66			$0.4692 \cdot 10^{-1}$ (1.52)	
AGE	38.83			$0.2803 \cdot 10^{-1}$ (18.36)	
const.	1	3.7615 (49.22)	4.0456 (54.22)	1.5861 (13.99)	3.1505 (38.24)
$\bar{R}^2$ (SER)		0.1786 (0.925)	0.8941 (0.659)	0.9013 (0.626)	0.9500 (0.578)
steps of iteration		1	11	8	17

Description of variables: g-rate of earnings growth, F-factor of earnings growth (see eq. (6) and (10)), PEX-previous experience, PEXSQ-PEX^2, SIZE-firm size (ordinal scale 1 - 5, 1-small firm, 5-large firm), SB-social background, measured by father's occupation status (ordinal scale, 1-lowest value, 7-highest value), TEN-tenure, measured by the number of years in the current firm, TENSQ = TEN^2, DOJT-degree of on-the-job training, measured by an ordinal scale (1-lowest value, 4-highest value), S-schooling, measured by the number of years, SWO-dummy variable (SWO-1, spouse is working, SWO-0, otherwise), HIER-position in the hierarchy of the firm measured by an ordinal scale (1-lowest stage, 4-highest stage), TIME-working time, measured by scale 1 - 4: 1 (full time), 2 (20 to < 40 hours per week), 3 (15 to < 20 hours per week), 4 (< 15 hours per week), MEN-dummy variable (MEN = 1 man, MEN = 0 otherwise), AGE-age of the person, NOF-number of firms, SER-standard error of regression.

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that the first-order Taylor expansion in column (3) is not as specific as the approach employed in column (4).

There are not directly comparable results from other studies. But *Mincer / Jovanovic* and *Leighton / Mincer*[28] have estimated mobility functions with the number of job moves in the last two or three years as the dependent variable. Their independent variables are TEN, TENSQ, S – as in column (4) – supplemented by other variables. All signs on the common variables agree with those reported here.

The relative importance of the determinants in our optimal mobility function is given by BETA coefficients (not reported in Table 1). These show that F, SIZE, PEX, SB and S (in descending order) have the largest effects on NOF. Interpreting the estimates in column (4) conventionally and not as the optimal mobility function, we might conclude, that persons with inferior social background, higher schooling level, limited previous experience, and working in small firms have (too) low a propensity to change job. In particular, the SIZE result is at odds with the standard empirical findings.

Returning to the optimal mobility function, we have to compare the estimated optimal number of job moves (ONOM) with the actual number (NOM). In Table 2 the frequency distribution of DIFF = ONOM − NOM is given. It seems sensible to characterize the turnover behavior of persons from classes 1 and 2 as overoptimal and that of persons from classes 4 and 5 as underoptimal. We can conclude that the behavior of more than 60 percent of the sample is rational. Overoptimal turnover is observed less than underoptimal turnover.

Table 2: **Frequency distribution of differences between the optimal and actual number of job moves (DIFF)**

class h	DIFF	n_h/n	$\sum_{h=1}^{H}(n_h/n)$
1	≤ -2	0.003	0.003
2	> -2 to ≤ -0.5	0.180	0.183
3	> -0.5 to $< +0.5$	0.602	0.785
4	$\geq +0.5$ to $< +2.$	0.209	0.994
5	$\geq +2$	0.006	1.000

It is of interest to question whether the frequency distribution in Table 2 is random or systematic. For this purpose we define two dummy variables

[28] *Mincer / Jovanovic* (1981); *Leighton / Mincer* (1982).

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$$D_1 = \begin{cases} 1 \text{ if DIFF} \leq 0 \\ 0 \text{ otherwise} \end{cases}$$

$$D_2 = \begin{cases} 0 \text{ if } -0{,}5 < \text{DIFF} < +0{,}5 \\ 1 \text{ otherwise} \end{cases}$$

and apply some maximum-likelihood estimates of probit models.

The results are presented in Table 3. From columns (1) and (2) we may conclude that persons with limited previous experience, high degree of on-the-job-training, inferior social background, and whose spouse is not working have too low a propensity to move, or that employees with opposite characteristics change too frequently. To decide which interpretation is correct, we must examine the estimates given in column (3) and (4). It emerges that young men with completed high school, a high degree of on-the-job training, limited previous experience, with an inferior family background do not behave rationally under the net earnings maximization assumption. Some of these characteristics describe employees who have recently begun their working career.

Table 3: **Maximum-likelihood estimates of probit models to determine systematic factors of underoptimal mobility behavior (asymptotic $|t|$-ratios in parentheses)**

exogenous variables*	endogenous variables D_1 (1)	(2)	D_2 (3)	(4)
NOF		3.9816 (23.66)		−0.0445 (1.57)
AGE		−0.0085 (1.35)		−0.0168 (6.41)
MEN		−0.1006 (0.63)		0.1609 (2.54)
S	−0.0061 (0.42)	0.0297 (0.92)	0.0235 (1.64)	0.0288 (2.32)
TEN	0.0010 (0.37)		−0.0022 (0.83)	
PEX	0.0232 (10.72)		−0.0074 (3.60)	
SIZE	−0.0292 (1.40)		0.0095 (0.46)	
DOJT	−0.1156 (3.18)		0.0735 (2.08)	
SWO	0.1746 (2.93)		−0.2193 (3.76)	
SB	0.0283 (2.89)		−0.0243 (2.53)	
const.	0.3107 (1.90)	−9.8641 (16.82)	−0.4538 (2.83)	0.0767 (0.45)
(−2) log likelihood ratio	184.44	2313.55	47.06	66.40

* See Table 1.

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From the results of Table 3 we would emphasize two major points. First, labor turnover is important in the beginning of the working history to inquire into potential job opportunities and one's abilities in order to improve job matching. And, as we previously mentioned, employees with a low degree of knowledge and with less favourable family background can improve their economic chances by turnover. But our results show that in both cases the "solution" will not sufficiently be used. In short, the mobility of these persons is underoptimal. Second, persons with a high degree of on-the-job training have a tendency to indulge in underoptimal mobility behavior. It is rational that they do not change their jobs as frequently as persons with a low degree of on-the-job training. Specific human capital which cannot be used in other firms results from on-the-job training. But we suppose that the general human capitel effects of on-the-job training which induce greater potential job opportunities are underrated, because the information on the current firm is better than on other firms.

Summary

Under maximizing behavior, an optimal mobility function is derived from an earnings function and a mobility cost function, where the coefficients are variable depending on working history. Two approaches are distinguished: one with uniform and one with variable rates of growth. The most important determinants of optimal number of jobs are the earnings growth factor, previous experience, firm size, social background, and schooling. A comparison between optimal and actual number of job changes and the ML estimator of a probit model reveals that high skilled workers with limited experience and poor family background have a propensity to quit that is too low.

Zusammenfassung

Ausgehend von einkommensmaximierendem Verhalten wird aus einer Einkommens- und einer Mobilitätskostenfunktion eine Funktion des langfristig optimalen Arbeitsplatzwechsels abgeleitet. Unterschieden werden zwei Ansätze mit variablen Koeffizienten, wobei einmal von einer konstanten und zum anderen von einer individuell variierenden Einkommenswachstumsrate ausgegangen wird. Die wichtigsten Bestimmungsfaktoren des optimalen Arbeitsplatzwechsels sind: Einkommenswachstumsfaktor, bisherige Berufserfahrung, Firmengröße, Schichtzugehörigkeit und Schulausbildung. Ein Vergleich zwischen der optimalen und der tatsächlichen Anzahl an Arbeitsplatzwechseln sowie die ML-Schätzung eines Probitansatzes zeigen, daß gut ausgebildete Arbeitskräfte mit geringer Berufserfahrung und solche, die aus unteren sozialen Schichten kommen, eine zu geringe Mobilitätsneigung besitzen.

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