Pay, promotions, and performance

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6 LEARNING ON JOBS

Identifying the Beneficial Effects of Job Mobility Using Matched Employer-Employee Data[100]

"The strongest principle of growth lies in human choice"- George Eliot (1876)

An important cause for the existence of internal labor markets (ILMs) is firm-specific human capital. When employees often change companies, this will inheritably lead to the loss of firm-specific human capital, and hence to a wage reduction. However, the upside of a job switch, from the employee's perspective, is a potentially better-matched job that compensates for the loss of firm-specific human capital. In this study, a novel rationale for job switching is introduced. It is proposed that workers are likely to learn new skills after a switch, which they can combine with skills gathered in previous jobs. The coalescent human capital that is created can increase their value for the new employer and lead to a higher wage level after a job switch. An analysis of matched employer-employee data from Denmark underpins this positive effect of job mobility on the wage level of employees.

6.1 Introduction

Most professional services firms have an up-or-out promotion system, i.e. if an employee is not promoted within a fixed time period, he or she is forced to leave the company. The risk of being fired for employees in such firms increases when fewer promotion slots become available. This risk increases further if employees from outside are newly hired at higher levels of the organization rather than using the internal labor market. These 'industry-hires' deviate from the normal career path and do not use the general port of entry at the bottom of the pyramid. But why do professional service companies sometimes choose to hire outsiders, and, in so doing undermine their promotion-based incentive system? Moreover, some employees leave a professional service firm and enter a new organization at a relatively high level and climb the organizational ladder at a fast pace. Would they have reached the same level if they had started to work for this other firm at the start of their career?

These questions are a specific example of something much broader and lead to a novel view on job mobility[101] and human capital. Conventionally, the existence of ILMs (i.e. the labor market *within* a single firm) is explained by theories that exemplify the difficulty to find a better-matched employer and the loss of human capital in the process of a job switch. This study combines the economic literature on job mobility and ILMs with the psychological literature on learning and organizational change, thereby increasing the understanding of the behavior by employees and employers described in the paragraph

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[101] Throughout this chapter I will use job mobility as mobility between firms and not vertical or horizontal moves within an organization.

above. Empirical tests of the effect of historical job mobility on wages are performed using a Danish employer-employee matched data set. Since workers will only switch firms if the wage offer is higher than the wage at the incumbent firm, it is necessary to control for endogeneity. Following the study by Light and McGarry (1998), I take account of the correlation between unobserved heterogeneity and job mobility. In contrast to their study, I find that historical job mobility increases the wage level of employees.

The chapter is organized as follows. In the next section the hypothesis that job mobility may generate higher wages is developed. Section 6.3 discusses the data and the methodology, in Section 6.4 the results are presented and the last section concludes.

6.2 Theoretical Background

6.2.1 Job-mobility models

Chapter 2 discussed different theories dealing with job-mobility (Section 2.3). The mover-stayer model (e.g. Blumen et al., 1955), matching models (e.g. Stigler, 1961; Burdett, 1978; Jovanovic, 1979a; Jovanovic, 1979b) and human capital theory (e.g. Becker, 1962) all generate predictions about the relationship between job separation and wages. In Section 2.3 these predictions have been enumerated.

The mover-stayer model assumes heterogeneity between workers; movers are believed to be less productive by nature and earn lower wages. The search model and human capital theory assume that workers will only voluntarily switch companies if this is accompanied by a wage increase. These models predict that a switch will be accompanied by a one-off wage increase, but do not predict long-term effects of the number of job separations on the wage level, since only the last match and the accumulated general skills are expected to influence wages.

The experience model is the only model that predicts a relationship between the number of job separations and the wage level over time *within* a job. The model assumes that unsuccessful matches will lead to many turnovers and thus a negative relationship between job mobility and wages. However, no model predicts that job separations enhance the value of employees over time.

6.2.2 A new perspective on learning

Within cognitive psychology, learning is a much-studied concept. At the beginning of the previous century, psychologists such as Thorndike and Pavlov formalized ideas about learning by means of trial-and-error. A common way to depict learning is by means of learning curves, which plot the amount of trials and the skills learned.[102]

An attribute that most learning curves have in common is a period of rapid learning (even stepped learning can occur) followed by a plateau of slow learning or no learning at all (Yelle, 1979). Hence, individuals in a specific job have learned all the skills required at some stage that will be hard to improve any further. A new job will include novel tasks,

[102] Through experiments, starting in 1936 (Wright, 1936), various shapes of learning curves have been established, such as S-shaped curves and log curves with diminishing learning over time.

providing the possibility to start a new learning curve with a potentially steep period of learning still ahead.

Additionally, the speed of learning in the current job can be affected by the knowledge gained in previous tasks. Already at the beginning of the previous century (Thorndike and Woodworth, 1901), the transfer of learning was substantially embedded within psychology (Cohen, 1991). Examples of empirical tests supporting this thesis include Bassok and Holyoak (1989), who study the transfer of knowledge between algebra and physics, and Schilling et al. (2003), who show in "Learning by doing *something else*" how related variation in work does indeed increase the learning rate. The results show that under specific circumstances, people are able to apply relevant previous knowledge to new problems. Although evidence of spontaneous transfer is rare, the role of prior experiences seems unarguable (Carraher and Schliemann, 2002).

Linking this psychological literature of learning to human capital theory provides interesting insights. Acquiring new knowledge (new human capital) can be enhanced by previous knowledge: for example, from a previous job. Transferring experience (e.g. problem-solving skills, communication and people skills) that new employees have gathered in their previous occupation can make their learning curve for the new job steeper.

These arguments show how switching jobs can be a method to optimize the human capital of employees; it indicates a theoretical background for the case example mentioned in the introduction. Naturally, a promotion within a firm can also offer new challenges and lead to a new learning curve. However, not all firms are able to offer sufficient promotion opportunities (see also the results in the previous two chapters). The desire of employees to find new learning opportunities will make them search outside the incumbent organization. In particular, the specific job opportunities offered by other organizations are often not available in the present organization, simply because the specific type of job does not exist.[103]

On the basis of this learning argument, mobility under the right circumstances can be beneficial for employees, leading to the following hypothesis:

> *Hypothesis: Ceteris paribus, gathering work experience and thus building human capital at a limited number of different employers can have a positive effect on the wage level.*

This hypothesis does not imply that it is optimal for an employee to continuously switch workplace, in the extreme case switching workplace every day. The mover-stayer model, search models, experience models, and human capital theory all provide arguments indicating the negative effects of this type of behavior. The beneficial effect of job mobility resulting from the learning argument should be traded off with the previously acknowledged negative effects, leading to an inverted U-shaped relationship between job mobility and wages.

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[103] For example, the introduction to this chapter discussed the case of workers leaving professional service firms and entering other organizations at a high level (and vice versa). It reflects an example of workers seeking new challenges (a new learning curve) and combining the development of the skills the new job requires with existing knowledge.

6.2.3 Related research: organizational change

Up to this point, theories that take the individual employee as a starting point have been discussed. This section will conceptually review the perspective of the organization. In particular, two situations will be described in which changing requirements will enhance the likelihood of hiring from the outside.

The first situation refers to changes in the type of human capital required. Some types of human capital have to be acquired in the labor market by hiring people with specific experience, since these abilities are not available internally. For example, entrance into new product markets or industries may require specific knowledge and experience. A well-known technique to deal with the lack of certain capabilities is by means of mergers or acquisitions (M&A) (e.g. Coff, 1999). The M&A literature has long acknowledged the possibility of acquiring outside knowledge rather than pursuing in-house development, but as yet this idea has not been captured within the field of personnel economics. Hiring from the outside, or, in other words the 'acquisition' of employees, is a way to quickly obtain knowledge the firm is currently lacking. In a way, this can be viewed as M&A of certain skills and experience, which can be more efficient than training incumbents. Analogous to taking over a firm and paying a takeover premium to acquire specific capabilities, it could be expected that firms would also be willing to pay a premium for employees with specific capabilities.

The second situation refers to the way organizations deal with changing environments. Tushman and Romanelli (1985) describe 'punctuated equilibrium theory' within the organizational change literature. A period of disappointing performance can trigger a reorientation that requires rapid organizational change (Romanelli and Tushman, 1994). Organizational change can be necessary to escape 'mental prisons'. An upshot of rapid organizational change upon poor financial performance can be CEO-replacement (e.g. Parrino, 1997). The chance of hiring an outsider to replace the incumbent CEO increases when financial performance drops (e.g. Huson et al., 2004, and the results in Chapter 5). Executive succession and an increase in top-management heterogeneity in its turn will increase the chance of strategic reorientation (Tushman and Rosenkopf, 1996). Outsiders can possess a type of human capital that incumbents do not have and are free of the mental prison persisting among the incumbents. For example, a new top-manager can be hired with specific restructuring or industry experience and who is less committed to previous decisions. Nonetheless, teams can also have a tendency to "close ranks" and opt for less diversity. Boonen, Van Olffen, van Witteloostuijn, and De Brabander (2000) investigate forces that can pull top management team homogeneity as well as those that pull top management team heterogeneity. They show that top management team homogeneity, after turnover of dissimilar top managers, is positively related to (short-term) firm performance. Still, organization change theory (cf. Hannan and Freeman, 1984) provides an argument why within an organization the decision to hire from within usually prevails, but that under certain circumstances hiring from the outside can be more effective.

These two arguments – the lack of certain capabilities within an organization and the necessity to escape mental prisons – shed a different light on job mobility. Whereas job mobility is often seen as driven by supply, the demand side (the hiring firm) is usually neglected. A firm can be willing to pay a premium to acquire missing capabilities or a fresh look at the organization, which will be combined with firm-specific human capital, yet to be acquired. An illustration of the perceived benefits of hiring from the outside can be found within academia. After postgraduates finish their Ph.D, mobility between universities is

standard practice to avoid preferential treatment, to optimally allocate talent, and to promote the interchange of ideas.[104]

6.3 Data and Methodology

6.3.1 Data

The data are taken from Danish companies. Before discussing the particulars of the data, two features of the Danish labor market should be discussed. First, the Danish labor market is a mix between the Scandinavian and Anglo-Saxon labor market models. On the one hand, Denmark offers unemployment benefits up to 90 percent of the previously earned wage. These benefits explain the image of Denmark as being a typical Scandinavian welfare state. On the other hand, employees can be fired at short notice or even on the spot (for blue-collar workers). As a result, the average tenure of Danish workers is comparable to the tenure in countries such as the USA and the UK, contrary to the typical tenure of Sweden that is at the high-end of the distribution. Figure 6.1 depicts the average tenure per country, taken from OECD Employment Outlook (1997).

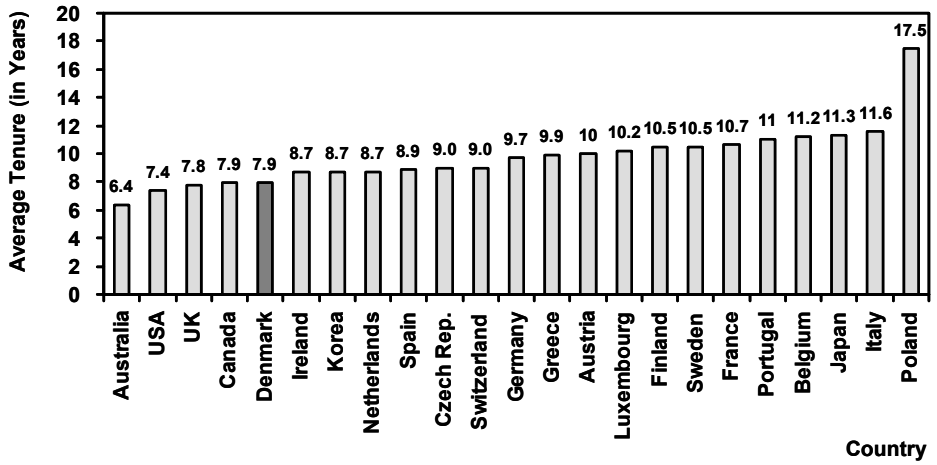

Figure 6.1: Average tenure per country

[104] The mobility of the academic job market in the U.S. is well known (e.g. Cawley, 2004), but is also common in other countries. For example, Tilburg University in the Netherlands explicitly states the importance of exchanging workers with other universities and applies this as a policy. Their strategic communication (Tilburg University, 2001) contains the following statement: "In young talent recruitment, there is a strong preference for hiring candidates who completed their Ph.D. outside Tilburg."

A second feature of the Danish labor market concerns the characteristics of companies. Danish companies are quite small, relative to, for instance, U.S. companies (Eriksson and Werwatz, 2003). The lower ability of small companies to organize occupational and hierarchical changes (Gibbs et al., 2003) increases the likelihood of job mobility since promotions or lateral movements within small firms are less likely.

The data source used in the present study is constructed and maintained by the Center for Corporate Performance, CCP, and Statistics Denmark. This subset of the Integrated Database (IDA) for Labor Market Research includes career data on individuals who have worked in the private sector in at least one year between 1980 and 2000. Both employees and workplaces have been given a unique code so that individuals can be traced over time and job switches become visible. A limitation is that data on the workplace are only available for November of each year, making multiple switches during a year or the exact date of a job switch unobservable.

From this data set, a sample was taken of individuals who all started working in the same year (1981). This way, it is possible to control for cohort effects (differences in wages caused by a different starting year) and have a sample where all employees have roughly the same amount of labor-market experience, and who have thus had the same amount of time to search for better-matching jobs (see search models). 1981 is selected as the starting year of the employees considered in order to investigate job mobility over the longest possible time period.[105] This provides a balanced sample of employees who are traced over a 20-year period. The original set of workers consists of all Danes who have worked in the private sector at some stage in the period 1980-2000 (n= 2,516,848) and are over 15 in 198l. The following selection criteria applied to exclude various groups of employees: (1) they have prior work experience; (2) they were without a workplace in 1981; (3) they are 35 years of age or older.[106] Furthermore, (4) the workplaces of the workers have to be observable in all years; and (5) the wage level has to be observable in the years 1981, 1989 and 2000, since the wage levels in these years are used in this analysis (see Table 6.4). Statistics Denmark also provides information on the reliability of the hourly wage, based on the pension payments, and advises against using wage levels unaligned with the statutory pension contributions: (6) workers with unreliable wage information are excluded. The remaining panel consists of 17,140 Danish workers who began their career in 1981. The strict selection criteria, summarized in Table 6.1, create a final sample that includes a specific cohort. A drawback is that workers who have experienced unemployment are excluded, which is likely to create a sample with a relatively small proportion of involuntary turnover. The different estimation methods that will be used to test the hypothesis are now discussed.

[105] To ensure that individuals with prior work experience are excluded, the starting year is 1981 instead of 1980. The data of 1980 were used to verify that 1981 is indeed the starting year of a career of each individual worker. The sample consists of employees for whom all data were available throughout the 20-year period, thereby excluding workers who have experienced unemployment, worked abroad, etc.

[106] Light and McGarry (1998) use a sample of 2,292 young workers in the U.S.

Table 6.1: Sample creation

Number of Respondents	Reason for Exclusion
2,516,848	People who worked in any of the years 1981-2000
- 2,181,314	(1) Workers with prior work experience
335,534	
- 238,614	(2) Workers without a workplace in 1981
96,920	
- 8,751	(3) Age of 35 or above
88,169	
- 62,890	(4) Workplace is not observed in all years
25,279	
- 2,577	(5) Wages are not observed in 1981, 1989 and 2000
22,702	
- 5,562	(6) Wage information is unreliable
17,140	

6.3.2 Model specification

At the outset, this study uses a technique similar to Light and McGarry (1998). Their study investigates a comparable research question and uses a sophisticated technique to deal with problems of endogeneity. One important difference between the present study and theirs is that the data set used here does not allow observing multiple switches of workplace within a single year or the difference between voluntary and involuntary turnover. On the other hand, the present study has a broader scope, since it includes men and women, while Light and McGarry only study male workers. Furthermore, an important extension of this study is that a longer period is investigated (a 19-year timeframe instead of 8).

The specification of the model used here is based on a basic wage equation[107] (see Light and McGarry, 1998):

$$w_{ijt} = X_{ijt}\beta_1 + M_{ijt}\beta_2 + \Psi_{it}\beta_3 + \varepsilon_{ijt}, \qquad (6.1)$$

in which w_{ijt} denotes the log of real hourly wages for individual *i* on job *j* at time *t*. The vector X_{ijt} consists of *E*, the individual's total labor market experience measured in full-time year equivalents until time *t,*[108] and *T*, the tenure of the individual at the current firm. Both variables are measured in years. The squared terms of tenure and experience are also included.

The vector M_{ijt}, the focus of the study, consists of the historical mobility rate of the individual, Γ, and its square, Γ^2. The mobility rate is defined as the number of workplaces a person has had relative to experience:

[107] I use wages as a proxy for utility.

[108] Experience refers to full-year experience, i.e. calendar years of experience are adjusted by the proportion which the employee worked part-time.

$$\Gamma = \text{mobility rate} = \frac{\#\text{ of job changes}}{\text{Years of experience}}. \qquad (6.2)$$

The third vector, Ψ_{it}, includes control variables such as education level, a gender dummy, marital status, a part-time work dummy, and dummy variables indicating the industry of employment.[109] Some control variables used by Light and McGarry (1998) are not included in my study.[110]

The structure of the fourth component, the error term ε_{ijt}, equals:

$$\varepsilon_{ijt} = \varphi_{ij} + \alpha_i + \nu_{ijt}. \qquad (6.3)$$

The first part of the error term, φ_{ij}, is a time-invariant workplace-specific error term. The second part, α_i, is a fixed individual-specific error component, while ν_{ijt} is a time-varying error component. ν_{ijt} is assumed to be white noise, implying that the job-match-specific error term (φ_{ij}) is independent of time. A violation of this assumption would lead to biased estimates.

Measurement problems are caused by selectivity. Employees receiving job-offers below their current wage level are not likely to leave their firm voluntarily. Therefore, the group of employees who are observed to voluntarily switch firms is a selective group of individuals who have received a better-paid job-offer. Directly estimating the effect of mobility on wages without taking the selectivity issue into account will lead to biased results.

Therefore, the wage equation is estimated using an instrumental variable approach (IV/GLS), comparable to that of Light and McGarry (1998). All variables regarding mobility, tenure, and experience (and the squared and interaction terms) will be instrumented, as well as the education variable and the part-time dummy. All endogenous variables can be time-varying within-person as well as time-varying within-job. The deviations from the means (either within-person or within-job) of both the endogenous and exogenous regressors, as well as the means themselves of the exogenous regressors will be used as instruments in the estimation in order to overcome the problem that arises from the error structure described above. These deviations are valid instruments since they are uncorrelated with the error term by construction. The number of children, and dummies for the region in which a person lives are used as additional instrumental variables, following Light and McGarry (1998), but the number of years worked by the partner was not used, since partners who have a career in the public sector are not observed in the database.

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[109] Appendix A6 contains a Table A6.1 with the descriptive statistics of all variables included in the wage estimations.

[110] No information is available about health status or about union activities. Moreover, indicators of the region in which a Dane lives are unavailable, which might not cause problems since Denmark is a relatively small country. I do use a dummy indicating whether a person lives in a city as an instrument in the estimates, comparable to the instrument “degree of urbanization” used by Light and McGarry (1998). Instead of using the unemployment rate and a wage index, the model is estimated both with and without year dummies, as proposed in the study of Light and McGarry as alternative control variables.

6.4 Results

Since this study takes a similar approach to job separations as the study by Light and McGarry (1998), the analyses will be structured in the same manner. Tables 6.2 to 6.5 can be directly compared with the same tables in the Light and McGarry study. I will compare the results and discuss similarities and discrepancies, after which I will focus specifically on the hypothesis proposed in Section 6.2.

6.4.1 Descriptive statistics

The distribution of job separations is shown in Table 6.2. The table shows that, for the complete 19-year period, the mean number of separations is 4.5 (s.d. 2.7). This value is 2.4 (s.d. 1.6) for the first 8 years, which is lower than the 4.9 (s.d. 4.1) observed by Light and McGarry (1998). In general, I observe a lower mobility rate for all periods, which can partly be caused by the inability to observe multiple job separations within a single year. Similar to Light and McGarry (1998), the sample proves to consist of workers who are heterogeneous in their mobility patterns. A straightforward way to observe this pattern is by investigating the non-switchers. In my sample, 71 percent of the workers have at least one job separation in the first four years. Only 52 percent of the employees who do not switch in the first period of four years change jobs in the second period of four years.[111]

Table 6.2: Distribution of the number of job separations during the first 2, 4, 8 and 19 years of career

	2 Years		4 Years		8 Years		19 Years	
Number of Job Separations	*No of Workers*	*% of Sample*	*No of Workers*	*% of Sample*	*No of Workers*	*% of Sample*	*No of Workers*	*% of Sample*
0	10048	58.6%	5011	29.2%	2408	14.0%	746	4.4%
1	5840	34.1%	6315	36.8%	3643	21.3%	1626	9.5%
2	1252	7.3%	4173	24.3%	4178	24.4%	2418	14.1%
3	0	0.0%	1393	8.1%	3333	19.4%	2652	15.5%
4	0	0.0%	248	1.4%	2083	12.2%	2570	15.0%
5	0	0.0%	0	0.0%	1026	6.0%	2191	12.8%
6	0	0.0%	0	0.0%	361	2.1%	1724	10.1%
7	0	0.0%	0	0.0%	88	0.5%	1240	7.2%
8	0	0.0%	0	0.0%	20	0.1%	815	4.8%
9	0	0.0%	0	0.0%	0	0.0%	505	2.9%
10+	0	0.0%	0	0.0%	0	0.0%	653	3.8%
Total	17140	100.0%	17140	100.0%	17140	100.0%	17140	100.0%
Mean	0.583		1.274		2.397		4.476	
Std. Dev.	(0.665)		(1.010)		(1.589)		(2.663)	

Table 6.3 presents job durations by sub-sample based on the total number of job separations so far. The average worker has three separations in the period 1981-2000. The first two jobs have an average duration of approximately four years (3.7 and 3.6).

[111] An overall slowdown over time in the number of job separations could also lead to a lower percentage of workers changing in the second period of four years (52 percent versus 71 percent). To check this alternative explanation, the group of switchers has also been investigated. The results show that workers who have switched in the first four years continue to be extremely mobile in the second period of four years, again indicating that some workers are inherently more mobile.

Further into their careers, this increases from a duration of 4.9 years in the third job to an average duration of 6.9 years for the fourth job. This indicates that average job duration increases per job, an observation, which is quite consistent throughout the sample and has been noted in previous studies (e.g. Topel and Ward, 1992; Light and McGarry, 1998). It is important to note that in my sample the true duration of the last job for each group is unknown, and therefore the average tenure is censored. This makes the observation that the duration increases per job, including the last observed job, even more noteworthy.

Table 6.3: Duration of jobs held during the first 19 years of career

		Number of Job Separations in Period 1981-2000									
Job Number		*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	Mean	*19*	7.495	4.686	3.712	3.177	2.856	2.602	2.317	2.247	2.171
	Std. Dev.	*(0)*	(5.663)	(3.850)	(2.932)	(2.368)	(2.113)	(1.776)	(1.505)	(1.396)	(1.324)
2	Mean		11.505	5.384	3.576	2.740	2.332	2.153	1.821	1.731	1.498
	Std. Dev.		(5.663)	(4.533)	(3.204)	(2.495)	(1.984)	(1.748)	(1.378)	(1.209)	(0.948)
3	Mean			8.931	4.853	3.515	2.614	2.197	1.936	1.653	1.492
	Std. Dev.			(5.309)	(3.807)	(3.058)	(2.266)	(1.775)	(1.510)	(1.225)	(1.025)
4	Mean				6.859	4.246	3.088	2.486	2.056	1.834	1.682
	Std. Dev.				(4.678)	(3.407)	(2.543)	(2.097)	(1.654)	(1.343)	(1.271)
5	Mean					5.322	3.577	2.892	2.217	1.954	1.759
	Std. Dev.					(3.983)	(2.932)	(2.354)	(1.718)	(1.493)	(1.313)
6	Mean						4.530	3.113	2.737	2.144	1.878
	Std. Dev.						(3.505)	(2.569)	(2.140)	(1.647)	(1.384)
7	Mean							3.557	2.627	2.423	1.950
	Std. Dev.							(2.890)	(2.175)	(1.917)	(1.468)
8	Mean								3.288	2.350	2.088
	Std. Dev.								(2.605)	(2.015)	(1.613)
9	Mean									2.664	2.151
	Std. Dev.									(2.055)	(1.608)
10	Mean										2.330
	Std. Dev.										(1.866)
	Number of observations	746	1626	2418	2652	2570	2191	1724	1240	815	505

Table 6.4 (a and b) describes the beginning and end-wages and the percentage increases in wages for the sample.[112] I split the sample into different sub-groups based on the number of job separations and investigate two time frames: an 8-year period (Table 6.4a) and a 19-year period (Table 6.4b). Table 6.4a can be compared directly with the study by Light and McGarry (1998). One difference is striking: their study finds that the group with no job separations has the highest start- *and* end-wage. I find that this group has the highest initial wage (DKK 74.2), but it does not have the highest end-wage (DKK 145.9). Workers with five separations in the first 8 years have the highest end-wage (DKK 156.6) and also the largest percentage increase (199 percent) (all differences are significant at the 1 percent level).[113]

Table 6.4b presents the results for the period 1981-2000. The results are similar to Table 6.4a: workers with zero switches have the highest wage in 1981, but their end-wage is below the wage level of switchers. The highest end-wage, as well as the largest

[112] Wages are CPI-deflated and converted to 2000 levels.

[113] The large percentage changes in wage is consistent throughout the groups. All groups, including the employees who do not switch within the 8-year period, have an average increase of above 100 percent. The results points towards a steep wage-experience profile.

percentage change in wage, is reported for the group that switches between seven to nine times in the 19-year period.

Table 6.4a: Wage changes in the first 8 years of career

		Number of Job Separations						
Variable		*0*	*1*	*2*	*3*	*4*	*5*	*6+*
Initial Wage	Mean	74.2	67.4	66.8	65.8	65.9	64.4	65.5
	Std. Dev.	(31.6)	(29.7)	(30.8)	(30.3)	(30.2)	(28.8)	(30.8)
Final Wage	Mean	145.9	151.6	151.8	153.4	155.1	156.6	153.3
	Std. Dev.	(37.7)	(39.9)	(39.4)	(43.9)	(43.9)	(45)	(41.7)
(Percent change in wage)/100	Mean	1.27	1.64	1.74	1.81	1.85	1.99	1.8
	Std. Dev.	(1.11)	(1.41)	(1.93)	(1.67)	(1.73)	(2.48)	(1.76)
Number of observations		2408	3643	4178	3333	2083	1026	469

Table 6.4b: Wage changes in first 19 years of career

		Number of Job Separations					
Variable		*0*	*1-2*	*3-4*	*5-6*	*7-9*	*10+*
Initial Wage	Mean	75.8	70.1	67	66.1	64.9	64
	Std. Dev.	(35)	(31)	(30.1)	(30.1)	(29.8)	(27.9)
Final Wage	Mean	168.1	177.6	183	187.8	193.2	182.9
	Std. Dev.	(52.8)	(64.5)	(87.4)	(75.3)	(103.7)	(63.3)
(Percent change in wage)/100	Mean	1.63	1.98	2.31	2.41	2.58	2.39
	Std. Dev.	(1.92)	(1.8)	(3.16)	(2.32)	(2.79)	(2.15)
Number of observations		746	4044	5222	3915	2560	653

6.4.2 Estimates

Table 6.5a contains the estimates of the parameters using three different techniques: OLS, IV/GLS with within-person means and differences as instruments, and IV/GLS with within-job means and differences as instruments. The different assumptions concerning the error structures in the models cause differences in results across the three columns. The estimations in Table 6.5a do not include mobility variables and are used as a benchmark. The coefficients for the experience and tenure variables provide interesting results. I find small negative tenure effects in the first two columns. In comparison, Light and McGarry (1998) find wage increases of 20.8 percent (1), 15.0 percent (2) and 12.0 percent (3) for a marginal increase in tenure (of one year). My results imply that tenure has no effect on income in the Danish labor market, something that has been noted before (see Bagger, 2004, who finds similar results). Furthermore, I find highly significant positive effects for years of experience, in line with the results in Table 6.4 (a and b). Overall, the results show that experience is highly valued by companies, while tenure is not. The relationship between most of the control variables and the wage level is as expected. For example, education has the expected positive effect on wage. Furthermore, the estimates indicate higher wages for men, which in itself is the base of a large stream of literature around gender wage differentials. A surprising result is the significant positive effect of part-time work on wages.

The propositions expressed in Section 6.2 are empirically tested and the results are presented in Table 6.5b. The inclusion of the mobility rate is a direct extension to the work

by Light and McGarry (1998). Columns (4), (6) and (8) show the estimation results of the same three specifications as in Table 6.5a, including the mobility rate.[114] The mobility rate varies both across and within jobs, and therefore the deviations from within-person means (estimations (6) and (7)) and within-job means (estimations (8) and (9)) are included as additional instruments for the IV/GLS models. The estimated coefficients for the instrumented mobility rate vary between 0.199 (column (4)) and 0.223 (column (6)) and are significant at the 1 percent level. This points to a positive relationship between the mobility rate and the wage level. The mobility rate squared is included in the remaining three columns ((5), (7) and (9)). The estimates show a mediating effect of the mobility rate squared on the wage level, pointing to an inverted U-shaped relationship. In all three estimations, the magnitude of the coefficients shows that the optimal mobility rate is between 0.7 and 0.8 (smaller than 1, the maximum value that the variable can take). This implies that mobility has an optimal level. In contrast to Table 6.5a, tenure in the new estimations has a positive effect on wages, and tenure squared a negative effect, in line with the original estimations by Light and McGarry (1998).

In order to gain a better understanding of the impact of the mobility rate on wages, I calculate the predicted wages for different types of workers. I consider three types: type 1 does not switch jobs in the 19-year period. Type 2 is an average worker in terms of job mobility, separating 3 times: after 4 years of tenure in his/her first job, after 4 years of tenure in the second job, after 5 years in the third job, and having a tenure of 7 years in the last job. Type 3 of workers switch jobs every other year and have a total of 9 separations. All types are unmarried males, working full-time in the wholesale/retail industry in a non-government job. The person is assumed to have finished 12 years of education and is out of school at present, thereby taking the modal values for dummy variables and the mean values for continuous independent variables.

Figures 6.2a and 6.2b show the predicted wages over time, using the estimates of columns (8) and (9) of Table 6.5b. Figure 6.2a shows that the average Type 2 worker will end up with an 10.4 percent higher wage in 2000, relative to a Type 1 worker. A Type 3 worker will have a final wage that is 14.8 percent above the wage level of Type 1. In Figure 6.2b the wage patterns of the three different types are shown again. The wage increase for Type 2 and Type 3 workers are 11.2 percent and 19.0 percent using the estimates including the variable mobility rate squared (column (9)), in line with the results in Table 6.4.

[114] A curious characteristic of the model used by Light and McGarry (1998) is the time-invariant attribute of the main variables of interest, the number of job separations. In a panel data regression this means that, for example, the total number of job separations (in their case, the number of separations in a 2-year (TJ2) and an 8-year (TJ8) period) are expected to already have an effect on the initial wage at the start of a career. Using their technique, I find a significant positive relationship between TJ2 and wage, and a smaller but negative coefficient for TJ8. Overall, this indicates a positive effect of job separations on wages, but these coefficients are not robust in the different models (OLS and IV/GLS). Moreover, the time-invariant characteristic is an unattractive assumption to test my hypothesis and makes the interpretation complicated. Therefore, I choose to incorporate the mobility rate as an additional variable in the estimation models, which is time-varying within jobs.

Table 6.5a: Estimates of alternative wage models, analogous to Light and McGarry (1998)

	OLS (1)		IV/GLS (2)		IV/GLS (3)	
	Coef.	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Experience	0.091***	4.48E-04	0.087***	3.87E-04	0.076***	5.81E-04
Experience squared / 10	-0.030***	2.05E-04	-0.027***	1.73E-04	-0.023***	2.51E-04
Tenure	-0.003***	3.58E-04	-0.002***	3.09E-04	0.001***	3.88E-04
Tenure squared / 10	-3.91E-04	2.58E-04	-1.42E-03***	2.22E-04	-0.002***	2.43E-04
Part-time (dummy)	0.114***	1.73E-03	0.095***	1.51E-03	0.092***	1.93E-03
Education	0.031***	2.66E-04	0.096***	8.37E-04	0.101***	1.37E-03
In school (dummy)	-0.311***	1.83E-03	-0.117***	3.33E-03	-0.085***	5.30E-03
Male (dummy)	0.145***	1.13E-03	0.126***	3.19E-03	0.135***	4.06E-03
Married (dummy)	0.020***	1.17E-03	-0.013***	1.30E-03	0.022***	1.80E-03
Divorced (dummy)	0.035***	3.15E-03	-0.022***	3.20E-03	0.019***	3.62E-03
Agriculture and mining	0.011***	3.22E-03	-0.014***	3.95E-03	-0.031***	4.02E-03
Manufacturing	0.108***	1.40E-03	0.085***	1.76E-03	0.089***	1.80E-03
Energy	0.085***	6.01E-03	0.058***	7.59E-03	0.073***	7.71E-03
Construction	0.044***	1.93E-03	0.030***	2.53E-03	0.031***	2.58E-03
Transport	0.103***	2.10E-03	0.080***	2.61E-03	0.097***	2.73E-03
(Financial) services	0.151***	1.72E-03	0.077***	2.33E-03	0.085***	2.42E-03
Public	0.085***	2.27E-03	0.037***	2.71E-03	0.045***	2.78E-03
Government (dummy)	-0.039***	1.94E-03	-0.042***	2.17E-03	-0.045***	2.22E-03
Intercept	3.882***	3.79E-03	3.119***	1.10E-02	3.081***	1.78E-02
Error structure	v_{ijt}		$\alpha_i + v_{ijt}$		$\varphi_{ij} + \alpha_i + v_{ijt}$	
R^2 (overall)	0.573		0.504		0.487	
N (individuals)	17,140		17,140		17,140	
N (observations)	328,145		328,145		328,145	

**p < .10, two-tailed tests.*
***p < .05, two-tailed tests.*
****p < .01, two-tailed tests.*

Table 6.5b: Estimates of alternative wage models, including mobility rate

	OLS				IV/GLS				IV/GLS			
	(4)		(5)		(6)		(7)		(8)		(9)	
	Coef.	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Mobility rate	0.199***	2.65E-03	0.414***	7.30E-03	0.223***	3.03E-03	0.556***	8.08E-03	0.216***	5.74E-03	0.747***	1.77E-02
Mobility rate squared			-0.280***	8.85E-03			-0.389***	8.77E-03			-0.481***	1.51E-02
Experience	0.083***	4.57E-04	0.078***	4.92E-04	0.082***	3.89E-04	0.073***	4.26E-04	0.076***	5.72E-04	0.070***	6.04E-04
Experience squared / 10	-0.026***	2.08E-04	-0.024***	2.18E-04	-0.025***	1.74E-04	-0.022***	1.84E-04	-0.024***	2.48E-04	-0.022***	2.50E-04
Tenure	0.008***	3.84E-04	0.010***	3.87E-04	0.007***	3.28E-04	0.010***	3.30E-04	0.010***	4.56E-04	0.020***	5.53E-04
Tenure squared / 10	-0.005***	2.62E-04	-0.004***	2.62E-04	-0.005***	2.25E-04	-0.005***	2.21E-04	-0.006***	2.56E-04	-0.008***	2.63E-04
Part-time (dummy)	0.112***	1.71E-03	0.113***	1.71E-03	0.098***	1.49E-03	0.101***	1.47E-03	0.093***	1.90E-03	0.100***	1.90E-03
Education	0.031***	2.64E-04	0.030***	2.64E-04	0.091***	8.33E-04	0.090***	8.35E-04	0.100***	1.37E-03	0.098***	1.39E-03
In school (dummy)	-0.300***	1.82E-03	-0.297***	1.82E-03	-0.113***	3.30E-03	-0.105***	3.28E-03	-0.079***	5.28E-03	-0.069***	5.34E-03
Male (dummy)	0.143***	1.12E-03	0.144***	1.11E-03	0.122***	3.35E-03	0.122***	4.66E-03	0.129***	4.46E-03	0.126***	5.58E-03
Married (dummy)	0.019***	1.16E-03	0.020***	1.16E-03	-0.011***	1.29E-03	-0.011***	1.29E-03	0.016***	1.78E-03	0.011***	1.78E-03
Divorced (dummy)	0.032***	3.12E-03	0.032***	3.12E-03	-0.022***	3.17E-03	-0.023***	3.15E-03	0.013***	3.57E-03	0.009**	3.57E-03
Agriculture and mining	-0.009***	3.20E-03	-0.008**	3.20E-03	-0.024***	3.93E-03	-0.028***	3.95E-03	-0.036***	3.98E-03	-0.034***	4.00E-03
Manufacturing	0.106***	1.39E-03	0.105***	1.39E-03	0.081***	1.75E-03	0.075***	1.77E-03	0.081***	1.79E-03	0.071***	1.82E-03
Energy	0.081***	5.96E-03	0.080***	5.95E-03	0.053***	7.54E-03	0.049***	7.59E-03	0.063***	7.65E-03	0.050***	7.70E-03
Construction	0.041***	1.92E-03	0.042***	1.92E-03	0.029***	2.52E-03	0.027***	2.54E-03	0.029***	2.56E-03	0.026***	2.58E-03
Transport	0.101***	2.09E-03	0.101***	2.08E-03	0.072***	2.60E-03	0.063***	2.61E-03	0.082***	2.73E-03	0.064***	2.79E-03
(Financial) services	0.156***	1.71E-03	0.158***	1.71E-03	0.074***	2.32E-03	0.066***	2.36E-03	0.076***	2.41E-03	0.064***	2.45E-03
Public	0.081***	2.25E-03	0.080***	2.24E-03	0.032***	2.69E-03	0.027***	2.70E-03	0.039***	2.76E-03	0.032***	2.78E-03
Government (dummy)	-0.039***	1.92E-03	-0.039***	1.92E-03	-0.043***	2.15E-03	-0.043***	2.15E-03	-0.049***	2.20E-03	-0.056***	2.21E-03
Intercept	3.848***	3.79E-03	3.857***	3.79E-03	3.132***	1.10E-02	3.143***	1.13E-02	3.043***	1.78E-02	3.008***	1.82E-02
Error structure			v_{ijt}				$\alpha_i + v_{ijt}$				$\varphi_{ij} + \alpha_i + v_{ijt}$	
R^2 (overall)	0.580		0.581		0.518		0.517		0.499		0.498	
N (individuals)	17,140		17,140		17,140		17,140		17,140		17,140	
N (observations)	328,145		328,145		328,145		328,145		328,145		328,145	

**p < .10, two-tailed tests.*
***p < .05, two-tailed tests.*
****p < .01, two-tailed tests.*

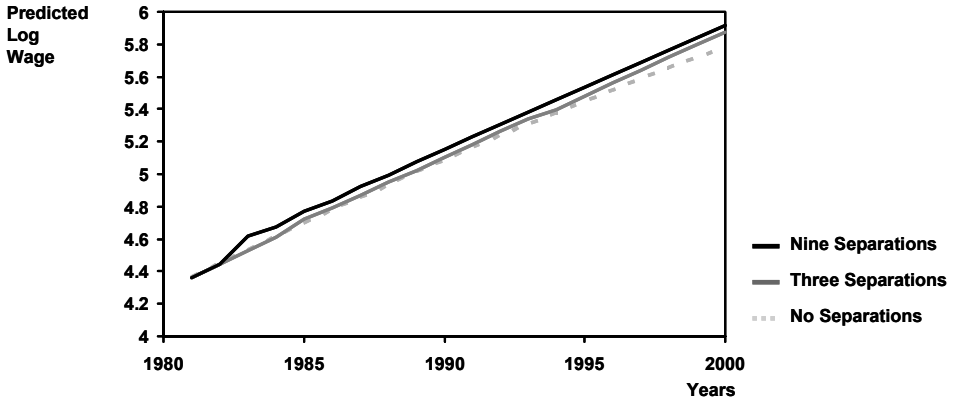

Figure 6.2a: Predicted log wages over time by mobility pattern (Specification (8))

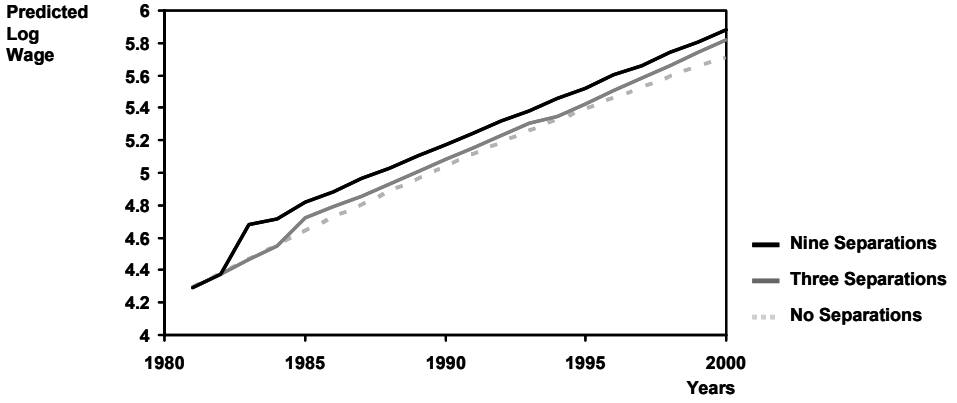

Figure 6.2b: Predicted log wages over time by mobility pattern (Specification (9))

6.4.3 Robustness of the results and limitations

The results in Table 6.5b are in line with the hypothesis, although some unexpected results are found: specifically, the absence of an optimal mobility rate. In order to check if the results are robust, I have performed regression analyses on specific subsets of the entire sample. Splitting the sample based on gender or white-collar versus blue-collar workers did not change the results on the variables of main interest. I included year dummies as proposed by Light and McGarry (1998), and these did not affect the results either. Finally, I estimated the regressions for the group of individuals with a year of data missing (for example, due to unemployment) and again found similar results.

A limitation is caused by the data used: it was not possible to identify within-year job switches. For this reason, the actual number of previous jobs will be higher for those employees who have had multiple job switches within a single year. Therefore, the sample includes only a small number of workers who actually switch often. To be precise, only 3.81 percent of the employees actually switch 10 times or more in a 19-year period, whereas Light and McGarry (1998) previously observed 13.7 percent of their sample

switching 10+ times in an 8-year period. This makes estimations of an optimal switch rate probably inaccurate, simply because only the positive effect is monitored. Furthermore, the tests can be extended in different ways. First, it is possible to test different cohorts and extend the database, in order to control for cohort effects. Second, a more specified model can be developed, testing and controlling for interaction effects.

One of the main difficulties of research on job mobility is caused by the obvious problem of endogeneity. As explained, voluntary job mobility is more likely when the pending job offer is better than the current job. Since it is not possible to distinguish between voluntary and involuntary mobility, this causes a potential bias. Nonetheless, involuntary job separations would have a dampening effect on the wage level and thus a diminishing effect on the relationship between mobility and wages. Thus, the beneficial effect of job mobility by itself appears to be unobservable. Also, numerous reasons for voluntary job separation exist that are not directly related to the wage level of the new job (for example, a moving spouse). These arguments lead to the expectancy that wages will in fact not increase upon such a job switch. The result that job changes were found to increase the wage level (given these other reasons for job changes), strengthens the result found.

6.5 Conclusion

Many different theories discuss job mobility, but most models assume there is no relationship between the number of job separations and the wage level within a job. The experience model is an exception. This model is the only model that assumes that the number of job separations has a (negative) effect on wages. In line with this, previous research has long established a positive relationship between tenure and wages. It has been ascertained that wages increase when better-matched jobs are found.

This study takes a different perspective. Lateral hiring by professional service firms and the strong preference for universities to hire PhD students from other universities indicate, in an anecdotal manner, that applying skills and experience to another organization can be quite beneficial for both individual employees and organizations. Using matched employer-employee data from the CCP in Denmark, I find that while taking account of endogeneity, job mobility *by itself* is positively related to wages.

I use the approach of Light and McGarry (1998), and find contradicting results on the relationship between job mobility patterns and wages. Light and McGarry (1998) do find that a modest amount of switching leads to the highest wage *increase*, but the start-wage and end-wage of switchers is lower compared with the wages of non-switchers. In contrast, the present study shows that the number of job separations has a positive effect on wages leading to higher end-wages. A possible explanation for this difference is provided by the characteristics of the country in which the data is gathered. Danish companies are small relative to the companies in the U.S. The chance that a job opening can be filled internally (i.e. that an appropriate match is made with the capabilities of incumbents) is dependent on the size of an organization, making internal career paths less probable in smaller companies. It is likely that in such an environment external job mobility is necessary for wage increases. Also, this study explores the first 20 years of careers, while in fact this is likely to be a period when mobility is most beneficial, as shown by Bingley and Westergård-Nielsen (2006). Future research could further explore the specific circumstances in which the beneficial effects of job mobility exceed the benefits of long tenure. Even more so, the in this study established positive effects of job mobility on wages after controlling for endogeneity shows an additional white space in current economic theory. The development of a theory that models the buildup of coalescent human capital combining experiences from different workplaces is the keynote suggestion for future research.

Appendix A6

Table A6.1: Descriptive statistics

Variable (short)	Variable (description)	Average	Std.Err.
Log wage	Natural Logarithm of hourly wage in DKK	4.903	0.419
Mobility rate	Number of job switches divided by years of experience	0.245	0.216
Mobility rate squared	-	0.107	0.170
Experience	Full-time years of experience	9.255	5.465
Experience squared / 10	-	11.553	10.821
Tenure	Years working at current organization	3.340	3.844
Tenure squared / 10	-	2.593	5.193
Part-time (dummy)	Dummy equals 1 if person works less than 32 hours a week	0.116	0.320
Education	Years of education	12.323	2.040
In school (dummy)	Dummy equals 1 if person is in school	0.144	0.351
Male (dummy)	Dummy equals 1 if person is male	0.630	0.483
Married (dummy)	Dummy equals 1 if person is married	0.347	0.476
Divorced (dummy)	Dummy equals 1 if person is divorced	0.025	0.156
Agriculture and mining (dummy)	Industry of employment (dummy)	0.026	0.160
Manufacturing (dummy)	Industry of employment (dummy)	0.266	0.442
Energy (dummy)	Industry of employment (dummy)	0.006	0.080
Construction (dummy)	Industry of employment (dummy)	0.090	0.286
Wholesale and retail (dummy)	Industry of employment (dummy)	0.212	0.408
Transport (dummy)	Industry of employment (dummy)	0.074	0.262
(Financial) services (dummy)	Industry of employment (dummy)	0.132	0.338
Public services (dummy)	Industry of employment (dummy)	0.193	0.395
Government (dummy)	Dummy equals 1 if organization is related to the public sector	0.216	0.412