Schmollers Jahrbuch 124 (2004), 257 – 282
Duncker & Humblot, Berlin

The Use of New Technology and Occupational Mobility: An Event History Analysis of the Swiss Labor Market

By Axel Franzen and Ben Jann

Abstract

The investigation of the consequences of new technologies has a long standing tradition within economics. Particularly, labor economists are wondering how the introduction of new technologies, e.g. personal computers, have shaped labor markets. Former research has concentrated on the question of whether on-the-job use of PCs creates a wage bonus for employees. In this paper, we investigate whether the use of PCs increases employees' probability of an upward shift in their employment status and whether it reduces the risk of involuntary labor market exits. We do so by applying event history analysis to the Swiss Labor Market Survey, a random sample of 3028 respondents, and by analyzing a panel sub-sample of 650 respondents conducted recently in Switzerland. Our results show that on-the-job use of PCs was beneficial for employees in the past by increasing their probability of an upward shift by approximately 50%. The analysis also suggests that PC use reduces the risk and duration of unemployment. However, these latter results fail to reach statistical significance.

Zusammenfassung

Untersuchungen über die Konsequenzen neuer Technologien haben eine lange Tradition in den Wirtschaftswissenschaften. Insbesondere wird in der Arbeitsmarktökonomik die Frage diskutiert, wie sich die Einführung neuer Technologien, z.B. von Personalcomputern, auf den Arbeitsmarkt auswirkt. In Bezug auf Personalcomputer hat sich die bisherige Forschung vor allem auf die Frage konzentriert, ob die Nutzung von Computern mit einem Lohnvorteil für die Arbeitnehmer verbunden ist. In diesem Beitrag analysieren wir, ob die PC-Nutzung am Arbeitsplatz die Wahrscheinlichkeit einer Beförderung erhöht und das Risiko, arbeitslos zu werden, reduziert. Diese Chancen bzw. Risiken untersuchen wir mit Hilfe von statistischen Methoden der Ereignisdatenanalyse. Als Datenbasis verwenden wir den Schweizer Arbeitsmarktsurvey, der Angaben von 3028 Befragten enthält, sowie eine Panelbefragung eines Teils der ersten Stichprobe mit 650 Befragten. Unsere Ergebnisse zeigen, dass die PC-Nutzung am Arbeitsplatz zumindest in der Vergangenheit von Vorteil war und die Beförderungschancen der Arbeitnehmer um etwa 50 % erhöhte. Ausserdem legen die Analysen nahe, dass die PC-Nutzung das Risiko des Eintritts in die Arbeitslosigkeit senkt bzw. die Dauer der

Arbeitslosigkeit reduziert. Diese beiden letzten Befunde sind statistisch allerdings nicht signifikant.

JEL-Classification: J62, J64, O33, C24

1. Introduction

New technologies, over and above personal computers and the Internet, did shape modern economies during the last few decades and are expected to have a continuing influence. It is argued and supported by recent studies (Colecchia & Schreyer 2002, Jorgenson 2003) that investments in new technologies increase productivity and growth. New technologies are often skill-biased which has various effects on labor markets such as an increase in the demand for qualified labor, higher returns on investments in education and on-the-job training as well as a higher earnings inequality. These arguments have inspired empirical research on the consequences of the diffusion of new technologies on the labor market. Particularly, it is expected that if the use of PCs at the workplace increase work productivity, they should also create a wage bonus. However, most empirical findings did not confirm this expectation. Although some studies (Krueger 1993, Bell 1996) did find a positive effect for on-the-job PC use on earnings, most others were not able do detect a sizeable wage differential (DiNardo & Pischke 1997, Entorf & Kramarz 1997, Entorf, Gollac & Kramarz 1999, Franzen 2001, Haisken-DeNew & Schmidt 1999).

The discrepancy of the macroeconomic findings on the one hand and the microeconomic studies on the other hand is puzzling. One reason for the differential results could be that employees that use PCs have to conduct general on-the-job training which results in lower wages during the training period and higher promotion rates und consequently higher wages after training. Thus, the positive wage bonus might only show up in the long run and is not detectable by cross-sectional or panel data that observe respondents only for a short time period. Another explanation could be that the ability to use technologies is not passed on to employees in the form of higher wages but rather by other non-monetary benefits such as longer and more secured working contracts. In this paper we therefore search for the advantage of on-the-job use of PCs by analyzing whether it promotes occupational upward mobility, protects employees from unemployment or shortens periods of unemployment.

The remainder of the paper is organized into 4 sections. In section 2 we will briefly summarize theories of career mobility and empirical findings of recent mobility research to justify our hypothesis. Section 3 describes the data. We use the Swiss Labor Market Survey (SLMS), which is a random population survey of 3028 Swiss inhabitants that was conducted in 1998 and a panel subsample of it from 2000. The data is analyzed by event history analysis. Thus, we ask whether the hazard rate of being promoted is higher after employees started to use a PC at the work place and whether their risk of unemployment and the duration of it are reduced due to PC skills. Section 4 presents and interprets the estimation results which are finally summarized and discussed in the conclusion.

2. Theory and Empirical Evidence in Recent Mobility Research

According to Human Capital theory (Becker 1964, Mincer 1974) employees' earnings are determined by work productivity which is dependent on the amount of human capital. Individuals acquire human capital through general education and on-the-job training. The latter can be differentiated into general training and specific training. Employers that provide *general* on-the-job training will pay lower wages during the training period (the costs have to be paid by the employees) and raise wages later to meet the marginal productivity level. Employers that provide *specific* training will have to pay the costs of the training and pay higher wages during the training period but lower than marginal productivity wages afterwards. The theory of career mobility is closely linked to these considerations. Industries which require generally trained employees will offer low occupational entrance positions and higher promotion rates. Employers that require specifically trained personnel will offer higher entrance positions and lower promotion rates. Employees with a given level of education might prefer occupations that offer lower entrance wages and higher promotion rates (which subsequently lead to higher wages) over occupations that offer high entrance wages and lower promotion chances if promotion depends on education and job experience. Thus, wages and occupational position are linked and should both depend on education and job experience. However, in some occupations education and experience are rewarded by higher entrance wages and in others by higher promotion chances that subsequently lead to higher wages (Sicherman & Galor 1990, Hachen 1992). The relation between education and job experience on the one side and wages on the other side can be underestimated if the promotion structure of the industry is not taken into account.

The hypothesis that promotion depends on education has largely been confirmed by empirical research on occupational mobility. Thus, Hall & Kasten (1976) presented evidence from US data (National Longitudinal Survey conducted between 1966 to 1969) that men with higher IQ and higher schooling also have a higher chance of upward occupational mobility. Sicherman & Galor (1990) report a positive effect of education on upward career mobility once the occupation at origin is taken into account in order to control for the opportunity structure (the number of open positions in an occupation). On-the-job experience has only positive effects for within firm promotion. Similarly, Topel & Ward (1992) find that workers are more likely to change jobs with increasing on-the-job experience if wages did not rise at the same time. Tenure (on-the-job experience within a firm) decreases job mobility. Blossfeld (1986), using German data, found that employees with higher general education had experienced faster occupational upward moves and were less likely to experience demotion. DiPrete & Nonemaker (1997) as well as DiPrete et al. (1997) distinguish five different types of mobility: within employer, within industry, between industry, between occupation and involuntary employment exits. According to their findings, better educated employees have higher rates of within employer mobility but lower rates with respect to between industry and between occupation mobility, as well as lower rates for involuntary employment exits. These effects are somewhat stronger in the USA and Sweden, however, less evident in the Netherlands and Germany. Ishida et al. (1997) report that employees with higher college quality scores experience higher promotion chances in Japanese as well as in American companies at the beginning of their careers. Li et al. (2000) analyzed data from Switzerland and conclude that further education after labor market entrance increases the chances of upward mobility. Thus, the beneficial effects of investment in human capital on the chances of upward occupational mobility have consistently been demonstrated.

One form of investment in human capital is the ability to use new technologies, e.g. computers. Thus, employees that have the skill to use computers should either have higher wages and/or should have better promotion chances. Since studies on computer use and earnings could not detect a wage bonus for computer use it is expected that employers rely on the promotion strategy to attract computer-skilled workers. By the same token, better educated people and particularly employees with computer skills should have a lower risk of becoming unemployed or if unemployment occurred, the search time to find new jobs should be lower.

3. Data and Methods

We test the effects of computer skills on the mobility process by analyzing data of the Swiss Labor Market Survey (SLMS). This survey is a random sample of the population living permanently in Switzerland (age range: 18 through 70 years). It contains data on 3028 respondents who were interviewed via telephone in 1998. Comparison of the SLMS survey with data from the Swiss Labor Force Survey (SLFS)[1] indicates that the distribution of some key socio-demographic variables (sex, age, schooling etc.) is almost identical to the SLMS-study (see Table A in the Appendix). In addition to detailed infor-

[1] The SLFS data is conducted by the Swiss Bureau of Statistics and is recognized as one of the most reliable data sources for Switzerland.

mation on socio-demographic variables, the SLMS data set contains complete information on individuals' career histories. Thus, respondents had to report the entrance date and end date of all employment episodes they ever experienced. Moreover, the survey contains the ISCO-88 classification of employees' occupation as well as the sector in which they are employed. Additionally, information on some type of activities employees perform is available, such as whether respondents supervise others or whether they use a personal computer on the job. Of the 3028 respondents, 40 had never had a job and 159 gave incomplete information about their employment biography or some other key variables. This leaves us with a total of 2829 cases for our analysis.

However, the original SLMS survey lacks information on the exact starting date of on-the-job PC use. Since this information is necessary for the purpose of our study, we conducted a written re-questioning from April through June 2000 of 900 respondents who participated in the SLMS study. The sub-sample of 900 was randomly drawn from those respondents who were either employed, unemployed or still in education in 1998 and who live in the German part of Switzerland. Full-time employees were slightly over-sampled. Furthermore, we restricted the panel to those respondents who were not older than 60 years. Of those, 652 valid written questionnaires were returned.[2] For our analysis we had to exclude 64 cases because of incomplete information regarding the employment history or other key variables. Thus, our net sample has 588 cases. Since the original SLMS study included only respondents that had at least reached the age of 18 in 1998, our sub-sample should be representative for the population between the ages of 20 and 62, that is at least partly active on the labor market and that lives in the German part of Switzerland.

We analyze three types of transitions: First, the transition from low or middle occupational status position to a higher occupational category, second, the transition form employment to unemployment, and third, the transition from unemployment back to employment. The measurement of the transition from employment into unemployment and vice versa is straightforward. However the measurement of upward mobility requires some comments. Respondents had to report the status of their employment for every job episode. The questionnaire lists three categories starting with lower status employee, middle status and high status employee with managing responsibilities. Upward mobility is defined in our study if a respondent reported switching during any of

[2] The SAMS study in 1998 had a response rate of 63 % (see Diekmann et al. 1999, Jann 2003). The panel-sample was drawn out of people that also participated in a written follow-up questionnaire additionally to the main telephone interview of the survey. The response rate for the written follow-up questionnaire was 83.7 %. Of the 900 respondents in the panel-sample, 23 died or left Switzerland which leaves 867 valid addresses. Thus, the 652 returned questionnaires constitute a response rate of 75.2 %. The overall response rate of the panel sample is obtained by multiplying all three response rates which results to 39.7 % (see Diekmann & Jann 2001).

the working episodes from a low to a middle or high position or from the middle to the high position. Each of the three transitions we analyze might happen several times in a persons' career. Since it has to be assumed, that there are dependencies between earlier and later transitional events we will only take the first event of each type of transition into consideration.

The dependent variable of our analysis will be the duration until a transitional event occurs (see Table B in the Appendix). In order to estimate the effects of independent variables on the duration we use the proportional hazards model by Cox (1972). The Cox-regression-model can be written as

$$r(t) = h(t)\exp\big(\alpha H(t) + \beta S(t) + \gamma E(t)\big)$$

in which the hazard rate $r(t)$, i.e., the risk of an event at time t (conditional on the fact that it did not occur yet), is the product of an unspecified baseline rate $h(t)$ and the exponent of some covariate vectors that possibly influence the hazard rate (see Blossfeld & Rohwer 1995, Hosmer & Lemeshow 1999). We separate the covariate vectors into three components. $H(t)$ denotes a vector of variables that measure human capital, the vector $S(t)$ includes socio-demographic variables and $E(t)$ contains variables that measure the macro economic development. The parameter vectors α, β and γ model time independent proportional effects of the covariates on the hazard rate $r(t)$ and can be estimated by the partial likelihood method. The baseline hazard rate $h(t)$, however, remains unspecified, i.e. no specific shape is assumed for $r(t)$.[3] For the sake of readability we will report the exponents of the parameters α, β and γ in the following analysis. Unlike the parameters themselves, the exponents can be interpreted straight forwardly as multiplication effects. A coefficient of, say, 1.15 tells us that an increase of the covariate by one unit yields an increase of the hazard rate by 15 %. On the other hand, a coefficient of 0.85 goes along with a reduction of the hazard rate by 15 % for each one-unit increase of the covariate.

From a technical point of view, the covariates in our analysis can be classified into five different categories. A first group of variables captures covariates which do not change their values within an episode (variables like sex or birth cohort). We will call them constant. All other variables are time-dependent, i.e., they might change their values within an episode. First, there are time-dependent covariates with absorbing final state. Basically, these variables measure if a certain event happened within the episode (e.g. if someone received further education or had an employment interruption). They change their values by the time such an event happens and keep it until the end of the episode. A second

[3] It has to be pointed out that the baseline rate $h(t)$ is independent from covariates. This means, the hazard rates are assumed to be proportional for different subgroups like, e.g. men and women. If proportionality between subgroups cannot be assumed, separate or stratified models should be estimated.

kind of time-dependent covariates are sub-episode specific. They reflect a current situation during an episode and therefore might change values back and forth several times (e.g. if someone is currently self-employed or not).[4] Another group of time-dependent variables might be called cumulative. They measure a cumulative process over time and are updated periodically (e.g. work experience, number of jobs). The last class of time-dependent covariates captures period specific aggregate variables. They reflect general characteristics of a certain time period (e.g. yearly unemployment rate). Note that some covariates cannot be assigned to one of the groups in general. The classification only reflects how we treat the variables in our models. Thus, when reporting results, we will always indicate the nature of the covariates (for details on the operationalization of the covariates see Table C in the Appendix). Time-dependent covariates are introduced into the Cox-regression by the method of episode splitting (see Blossfeld & Rohwer 1995).

As mentioned above, our focus lies on the first event for each transition type. Furthermore, our observation window is somewhat restricted. It starts in January 1981, the date when PCs first became commercially available and ends with the date of the interview (in 1998 for the SLMS sample, in 2000 for the panel sub-sample).[5] This gives rise to some methodological problems. Figure 1 shows a few examples of possible event-history observations in our sample. Episodes ending before January 1981 (type A) are excluded from the analysis since they are fully left censored. This might create a sample selection bias. The earlier an episode starts and the shorter its duration, the less likely it will reach the observation window and thus will be excluded from the analysis. If, on the other hand, episodes starting before 1981 are completely removed even if they end after 1981 (type B) a sample selection bias is created too (besides the fact, that the number of cases might be reduced significantly). Guo (1993, see also Klein & Moeschberger 1997) proposed to solving the problem by applying the conditional partial likelihood approach whereby all episodes ending after 1981 are taken into account (all episodes of type B, C, D, and E). However, episodes starting before 1981 (type B) are treated as left truncated, i.e. only the part of the duration which lies inside the observation window is evaluated.[6] Thus, the analysis is conditional on the fact that the

---

4 Note that some sub-episode specific covariates cannot be evaluated if someone becomes temporarily non-employed (e.g. covariates which indicate part-time employment or self-employment). In such cases the covariates will keep their last evaluated values until a new evaluation becomes possible (as proposed by Buchmann et al. 1999: 138).

5 Although information about episodes before 1981 is available in our data, it would be meaningless to estimate an effect for PC use for the 60's or 70's, since there were no PCs available.

6 The approach is closely related to the method of episode splitting for time-dependent covariates. In fact, episodes of type B are simply split at the beginning of the observation window. The difference is that the first part of the episode is then removed

transitional event did not occur up to 1981. For the sake of comparability we restricted the observation window for both samples in the same manner even though we do not estimate any PC-effect for the original SLMS sample.

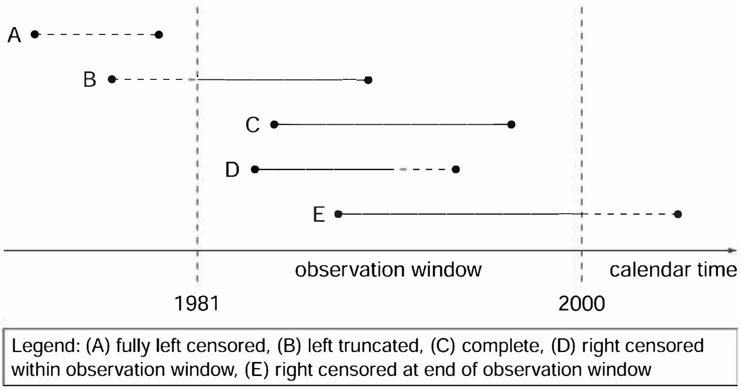

Figure 1: Observation window and types of episodes

Although our focus lies on the last two decades of the twentieth century our analysis is not truly representative for the situation in the labor market throughout that time period. We retrospectively questioned people at the end of the century about their employment history. This creates a sample selection bias since some people may already have died by that time or were too old to be included in our sample. Thus, we increasingly underestimate the mean age of the working population the farther back we travel on the time axis. Figure 2 shows the cross-sectional development of the distribution of the different states our respondents were in throughout the observation window for the main SLMS sample and the panel sub-sample (see Rohwer & Trappe 1997 for a description of the estimation method). In 1981, a large number of the respondents had not yet even entered the labor market. As the proportion of people who had not entered the labor market decreases over time, there is a linear increase in the number of people employed. In the main sample, the proportion of employed respondents stabilizes somewhere around 1991, i.e. the number of new entrants matches the number of exits because of retirement and the sample selection bias mentioned is more or less absent. In the panel sample the selection bias is effective throughout the whole period since the upper age

from analysis. An alternative approach to the problem of left truncation is proposed by Rohwer & Voges (1996). They estimated a pooled logit-model where the dependent variable describes the survival status of individual *i* at calendar time *t*. Additionally, they altered the likelihood function to take right censored cases into account. In the following analysis, we will apply the conditional likelihood approach though.

limit of the respondents is lower than in the main sample.[7] As pointed out, the mean age in both our samples is too young in earlier periods of the observation window. However, the sample selection bias is significantly reduced because we only take the first employment episode of each respondent into consideration.

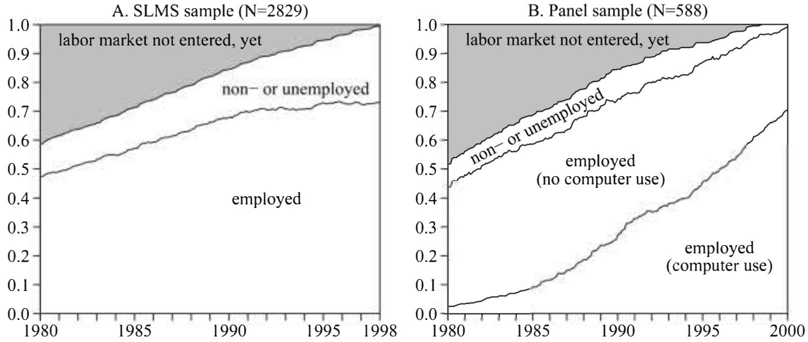

Figure 2: Cross-sectional state distribution in the two samples

Additionally, part B of Figure 2 gives some hints about the vast diffusion of PCs during the eighties and nineties. While in 1981 almost none of the employees used a computer at work, the proportion of computer users in Switzerland climbs up to 70 % in the year 2000.

4. Findings

In what follows we will analyze both surveys, the original SLMS survey as well as the panel sub-sample. Thus, all estimates (besides the PC effect) of the panel sub-sample can be compared to those obtained from the whole sample. Respondents in the SLMS study (and also the second wave of the sub-sample) had to report their employment status for every job episode entered. Categories included workers, low status employee, middle status employee, high status employee, self-employed, and farmer. Since meaningful upward or downward mobility can only be established for shifts between the low, middle and high employee status categories, shifts among the other categories were not taken into consideration. Thus, the analysis of upward mobility is restricted to all respondents who at some point entered the position of low or middle status employee in their work biography and we analyze the first transition into a higher status category. Such an analysis has the advantage that

7 In the panel sample, an additional sample selection bias is created because we only surveyed people being at least partly active in the labor market in 1998.

status shifts are analyzed even if they did not take place within the same industry or occupation.

Table 1 contains the descriptive information of the variables used for the analysis of both samples. The variables refer to respondents' characteristics at the end of the episode first entered, that is, just before the first upward move to a higher occupational position (or at the time when the episode became censored). Thus, 44 % of the selected sample were men (see Table 1, column 1).[8] Respondents took, on average, 11.6 years to reach their highest educational degree and 17 % had participated in some form of further education after school. Average work experience amounts to 14 years and the average number of jobs (including the last one) equaled 2.5. 59 % of our sample were married at the end of the episodes and 12 % were Non-Swiss citizens. 40 % had experienced an employment interruption of more than 12 months. 77 % started in the low employment position and 23 % in the middle.

The means of the panel sub-sample are displayed in column 3 of Table 1. The main difference between the two samples is that the panel sub-sample is restricted to the German part of Switzerland and to the birth cohorts from 1938 onward. Accordingly, respondents of the panel study are younger, have a lower amount of work experience, a lower proportion of married participants and a higher level of school education. However, most of the differences observed between the two samples are small. The higher proportion of male respondents in the panel sample is due to the restriction to people who had been employed at the time of the main survey and the over-sampling of full-time employees.

The results of the analysis of the whole sample via Cox-regression are displayed in Model 1 of Table 2. As expected an occupational upward transition is more likely for individuals with higher human capital. Thus, respondents with higher education have a better chance of being promoted. The chances increase by 9.5 % for every additional year of schooling. Also, participation in some form of further education is on average rewarded by a consecutive upward shift of 52 %. Thus, these results replicate former findings for Switzerland (Li et al. 2000). However, work experience is negatively related to upward moves.[9]

---

8 The proportion of men is relatively low compared to cross-sectional analysis of the labor force. First, this is due to the fact that we take all subjects who had ever been employed into consideration and not only currently employed people. Second, our analysis is restricted to episodes beginning with a job as low or middle position employee. Men more often than women are blue-collar workers or self-employed exclusively over their whole employment biography and thus have a greater probability of not being included in our analysis.

9 We also tested nonlinear specifications of work experience by including a quadratic term of work experience. Since the term was not significant we do not present this model here.

Table 1

Descriptive Information on Time-Constant and Time-Varying Covariates at the End of the Episode (Occupational Upward Mobility)

	SLMS sample		Panel sub-sample	
	Mean	Std. dev.	Mean	Std. dev.
PC use (yes = 1)[a]			0.530	
Occupation specific PC rate	0.514	0.181	0.541	0.175
Education (years)	11.601	2.220	12.030	2.493
Further education (yes = 1)[a]	0.167		0.221	
Work experience (years)[a]	13.775	11.932	12.920	10.173
Number of jobs[a]	2.525	1.835	2.672	1.808
Occupational position (middle =1)	0.233		0.187	
Labor-force interruption > 1 year (yes = 1)[a]	0.396		0.302	
Sex (male = 1)	0.439		0.577	
Non-Swiss citizen (yes = 1)	0.122		0.083	
Married (yes = 1)[a]	0.587		0.521	
Cohort 1951–1965 (yes = 1)	0.437		0.489	
Cohort 1966–1980 (yes = 1)	0.271		0.297	
Part-time employed (yes = 1)[a]	0.224		0.192	
Blue-collar worker (yes = 1)[a]	0.037		0.083	
Self employed (yes = 1)[a]	0.099		0.097	
Employed (yes = 1)[a]	0.731		0.878	
Number of Episodes	1873		411	

[a] Time-dependent covariates, measured at end of episodes. Measurement information about the dependent and independent variables is given in Tables A and B of the Appendix.

Next, it can be observed that an upward shift is less likely the further respondents have climbed the career ladder. The probability of moving from the middle position into the highest status group is reduced by 52 % as compared to the chance of moving from the low into a higher category. Furthermore, upward moves are less likely for individuals who only work part-time or who have experienced an employment interruption of more than 12 months. The effect of marriage depends on the respondents' sex. The chances of married women moving upward are reduced by 49 % compared to unmarried women (effect of marriage) while the chances of men are not affected by marriage (effect of marriage times interaction effect of sex and marriage). This sex specific effect does not come as a surprise and corresponds to findings on earnings regressions (Franzen 2001, Daniel 1995). Next, the model also includes a number of sub-episode effects. Respondents with episodes of self-employment have lower chances of an upward shift. Lower chances can also be observed for individuals who were employed before promotion. This effect can certainly not be interpreted causally. The effect most likely indicates that respondents take short periods of non-employment or unpaid vacations before entering a higher position. This might indicate that upward shifts often go hand in hand with employer changes. However, the number of previously held jobs does not seem to influence promotion chances as such.

Table 2

Occupational Upward Mobility and On-the-Job Use of PCs in Switzerland (Cox-regression; absolute z-values in parentheses)

	SLMS	Panel sub-sample				
	Model 1	Model 2	Model 3	Model 4	Model 5	
PC use (yes = 1)[a)]		1.658** (3.27)	1.430* (2.25)	1.586* (2.53)	1.582* (2.48)	
Occupation specific PC rate	3.116** (4.19)		5.443** (3.64)	2.426+ (1.66)	0.002* (2.28)	4.805** (2.65)
Education (years)	1.095** (4.46)			1.085* (2.31)	2.554** (5.49)	0.824** (5.05)
Further education (yes = 1)[a)]	1.515** (3.64)			1.236 (1.04)	1.212 (0.93)	
Work experience (years)[b)]	0.973* (2.26)			0.935* (2.50)	0.942* (2.17)	
Previous number of jobs[b)]	1.030 (0.91)			1.060 (0.94)	1.017 (0.27)	
Occupational position (middle = 1)	0.484** (5.93)			0.395** (3.50)	0.377** (3.66)	
Employment interruption (yes = 1)[a)]	0.426** (5.41)			0.428** (3.04)	0.369** (3.57)	
Sex (male = 1)	1.246* (2.02)			1.336 (1.37)	1.232 (0.98)	
Non-Swiss citizen (yes = 1)	0.799 (1.64)			1.052 (0.18)	1.158 (0.52)	
Married (yes = 1)[a)]	0.511** (4.28)			0.634 (1.43)	0.482* (2.14)	
Married*Sex	2.102** (3.72)			1.531 (1.11)	2.101+ (1.84)	
Cohort 1951–1965 (yes = 1)[1]	1.429+ (1.91)			0.961 (0.13)	0.900 (0.33)	
Cohort 1966–1980 (yes = 1)[1]	2.038** (2.97)			1.269 (0.57)	1.351 (0.69)	

Part-time employed (yes = 1)[c)]	0.681* (2.51)			0.891 (0.40)	0.005* (0.40)	3.031** (2.66)
Blue-collar worker (yes = 1)[c),2]	0.683 (1.29)			0.488 (1.38)	0.505 (1.31)	
Self employed (yes = 1)[c),2]	0.467** (3.31)			0.595 (1.44)	0.658 (1.15)	
Employed (yes = 1)[c)]	0.367** (7.01)			0.234** (5.58)	0.189** (6.35)	
Unemployment Rate (yearly)[d)]	0.987 (0.41)			1.020 (0.33)	1.008 (0.12)	
Economic growth (yearly)[d)]	1.058* (2.01)			1.091 (1.61)	1.089 (1.58)	
Likelihood-Ratio	285.93**	10.37**	24.00**	109.41**	145.17**	

Notes: Displayed are hazard ratios (exponents of the raw coefficients of the Cox-regression). Subtracting 1 from the coefficient denotes the percentage change on the transition rate. The second column of Model 5 displays interaction effects with the logarithm of process time.

Time-dependent covariates: [a)] absorbing, [b)] cumulative, [c)] sub-episode specific, [d)] period specific
Reference groups: [1] respondents born before 1951, [2] white-collar workers.
** if significance level < 0.01, * if significance level < 0.05, + if significance level < 0.10.
Model 1: *N* of episodes (subjects) = 1873, *N* of events = 564, *N* of left truncated = 928.
Models 2–5: *N* of episodes (subjects) = 411, *N* of events = 172, *N* of left truncated = 171.

Moreover, Model 1 includes the yearly unemployment rate and the gross national product (GNP) to indicate the general shape of the economy. Low unemployment rates as well as high GNP increases indicate that the economy is expanding (see Table D in appendix for the yearly rates). High unemployment rates should reduce occupational mobility and high GNP increases should promote it. The results indeed indicate that upward shifts did occur more often in years of economic expansion (see also DiPrete et al. 1997). However, no significant results emerge for the unemployment rate (see Model 1 in Table 2).

Next we turn to the analysis of on-the-job PC use by using the panel subsample of the SLMS. Figure 3 depicts the proportion of individuals who remain in their starting positions (low or middle).[10] The descriptive comparison of individuals who do not use a PC with those who do suggests that the latter have a higher chance of upward mobility. This bivariate difference shown in Figure 3 is statistically significant (see Model 2 in Table 2). However, there exists an alternative interpretation of the findings. It could be the case that firms or occupations with higher PC adoption expanded faster than others. Thus, the higher upward mobility for PC users could be due to the higher

10 Displayed are the conditional product-limit survivor functions (conditional on the fact of having 'survived' until 1981). Membership in one of the two groups is time-dependent (subjects switch groups when starting to use a computer).

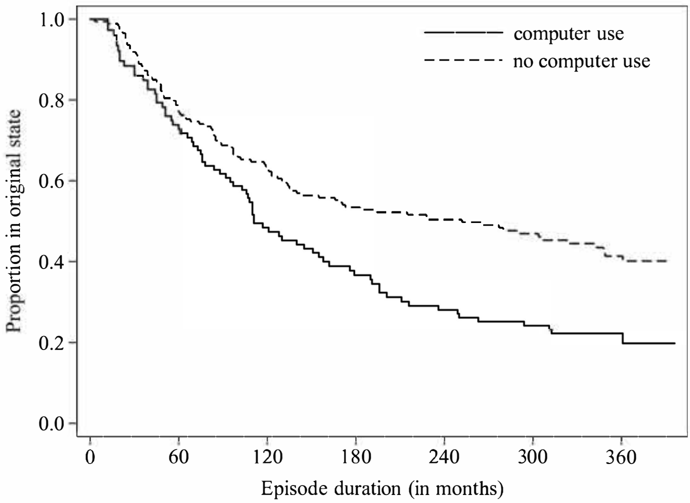

Figure 3: Percentage of respondents that experienced occupational upward mobility for PC users and non-users

growth rates in those firms or occupations. We tested both alternative explanations by controlling for the proportion of PC users in sectors and occupations at the end of the observation window in 1998. No significant effect was found for the rate of PC use in different sectors.[11] However, Model 3 in Table 2 shows that upward mobility is strongly increased in occupations (classified according to the main groups of the ISCO-88 categories) that have a high PC rate. The effect of PC use is reduced to 43 % (see Model 3, Table 2) but increases again to 58 % if we control for further variables (see Models 4 and 5 of Table 2). The finding suggests that the chances for PC users to move upward on the occupational ladder are increased by approximately 50 %. Note also that the effects of most of the covariates (Model 4 and 5) are similar to the already familiar findings of an analysis of the SLMS sample. They are, however, not always significant due to the smaller sample size. The second column of Model 5 in Table 2 tests for interaction effects with the logarithm of the process time. The results reveal that only three interactions are significant. Thus, the assumption of proportionality is fulfilled for most effects and particular for the effect of PC use.[12]

11 We also controlled for sector characteristics by using 14 different industrial branch dummy variables. The estimated PC effect remains robust.

12 In addition, we tested for period effects (effect of calendar time respondents first started to use PCs on upward mobility). No significant period effects were discovered. We also tested for cohort specific PC effects (interaction between birth cohorts and PC

Next, we analyze the transition from employment to unemployment. Theory (Thurow 1975) as well as former empirical findings (e.g. Wolbers 2000) suggests that individuals with higher human capital are less likely to experience episodes of unemployment. The argument is that in times of economic recession employers will first reduce the less qualified (and presumably less productive) work force. Thus, school education as well as work experience should reduce the risk of unemployment. Furthermore, we expect that employees with computer skills are more productive and therefore have a lower risk of becoming unemployed.

We first analyze the risk of all employed individuals contained in the SLMS experiencing an episode of unemployment. The results of such a Cox-regression are displayed in Model 1 of Table 3 (see Table E in the Appendix for descriptive statistics of the covariats). As can be seen education as well as work experience have negative effects on the risk of unemployment. However, both effects are not significant which is most likely due to the traditionally low unemployment rates in Switzerland. Unemployment was below 1 % for most of the eighties in Switzerland. It rose during the first half of the nineties and peaked at 5.2 % in 1997. Since then, unemployment dropped again to 2.3 % (see Table D in Appendix). This low aggregate unemployment rate is of course also reflected in our data set. Thus, of the 2768 analyzed individuals only 210 have ever experienced an episode of unemployment. The positive effect of further education on unemployment is counter intuitive. However, this effect might indicate that employees participate in further education after school if they perceive encountering difficulties on the job market. Thus, the group of employees that engages in further education is most likely to be a selection of individuals that is threatened by unemployment. Hence, the effect of further education on unemployment cannot be interpreted causally.

Increased risks of unemployment can also be observed for Non-Swiss citizens[13], for younger birth cohorts and for individuals who have held a larger number of jobs and who therefore have switched employers more often. As expected the risk of unemployment does decrease if gross national product (GNP) increases. A single percentage point increase in GNP reduces the individual transition to unemployment by 19 % (see also Wolbers 2000 for similar results for the Netherlands).

use). PC use had its biggest impact on upward mobility for the middle birth cohort (1951 – 1965). However, also this effect is statistically not significant. Furthermore, no significant age effects (age of respondents when first PC use occurred) were discovered. Moreover, it could be assumed that the beneficial effect of PC decreases as the number of users increases over time. However, we found no evidence (interaction effect) that the PC effect depends on calendar time.

13 See also Buhmann (1993) who reports higher unemployment rates for Non-Swiss citizens than for Swiss citizens.

Next, we turn to an analysis of PC use and unemployment. As argued with respect to human capital, on-the-job use of PCs should increase individual work productivity and should therefore protect individuals from unemployment. Figure 4 depicts the transition from employment to unemployment for PC users and non-users for the panel sub-sample. No difference is observable for the two groups. This observation is confirmed by Cox-regressions of the transition from employment to unemployment. The effect of PC use points to the expected direction of reducing the risk of unemployment, but the findings are not significant (see Model 2 and 3 of Table 3). Again, as with respect to schooling or work experience, the failure to find a difference is probably due to the low number of cases that report episodes of unemployment. Thus, 40 individuals of the 562 cases included in the panel sub-sample reported periods of unemployment.

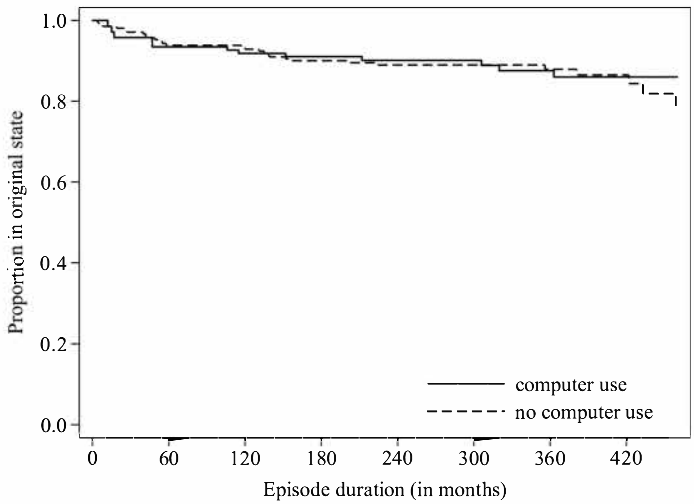

Figure 4: The risk of unemployment for employees with and without PC use

From Model 3 (Table 3) only two statistically significant results emerge. A higher risk of unemployment is observable for Non-Swiss citizens. Thus, foreigners encounter roughly a 1.5 times higher risk of unemployment. Also, episodes of unemployment are more often preceded by episodes of employment instead of non-employment.

Finally, we take a descriptive look at the duration of unemployment of those 40 respondents of our panel sub-sample who lost their jobs. From Figure 5, it can be observed that those with computer skills enter the job market somewhat sooner than those without computer skills. However, a multivariate analysis of the transition from unemployment to employment is not meaningful due to the small number of cases.

Table 3

The Risk of Unemployment and On-the-Job Use of PCs (Cox-regression)

	Model 1 (SMLS)		Model 2 (Panel)		Model 3 (Panel)	
	Coeff.	$\lvert z\rvert$-value	Coeff.	$\lvert z\rvert$-value	Coeff.	$\lvert z\rvert$-value
PC use (yes = 1)[a)]			0.833	0.52	0.758	0.71
Occupation specific PC rate	1.395	0.76			2.820	0.98
Education (y ears)	0.985	0.38			0.991	0.11
Further education (yes = 1)[a)]	1.629*	2.54			1.531	1.00
Work experience (years)[b)]	0.994	0.30			0.977	0.40
Previous number of jobs[b)]	1.226**	4.98			1.060	0.51
Labor-force interruption (yes = 1)[a)]	0.572*	2.40			0.520	1.24
Sex (male=1)	1.166	0.97			1.280	0.66
Non-Swiss citizen (yes = 1)	1.760**	3.24			2.546*	2.01
Married (yes = 1)[a)]	0.737^{+}	1.65			0.565	1.33
Cohort 1951 – 1965 (yes = 1)[1]	2.911**	3.20			1.352	0.40
Cohort 1966 – 1980 (yes = 1)[1]	7.034**	5.04			3.105	1.30
Part-time employed (yes = 1)[c)]	1.215	0.91			1.428	0.64
Low status employee (yes = 1)[c),2]	0.825	1.05			0.844	0.36
Middle status employee (yes = 1)[c),2]	0.538**	2.64			0.759	0.49
High status employee (yes = 1)[c),2]	0.753	1.09			0.661	0.59
Self employed (yes = 1)[c),2]	0.309**	2.81			1.398	0.49
Employed (yes = 1)[c)]	0.605*	2.15			0.356*	1.97
Economic growth (yearly)[d)]	0.814**	4.34			0.957	0.43
Likelihood-Ratio	128.56**		0.28		18.37	

Note: Displayed are hazard ratios (exponents of the raw coefficients of the Cox-regression). Subtracting 1 from the coefficient denotes the percentage change of the transition rate.

Time-dependent covariates: [a)] absorbing, [b)] cumulative, [c)] sub-episode specific, [d)] period specific. Reference groups: [1] respondents born before 1951, [2] blue-collar workers.
** if significance level < 0.01, * if significance level < 0.05, $^{+}$ if significance level < 0.10.
Model 1: N of episodes (subjects) = 2768, N of events = 210, N of left truncated = 1694.
Models 2 – 3: N of episodes (subjects) = 562, N of events = 40, N of left truncated = 297.

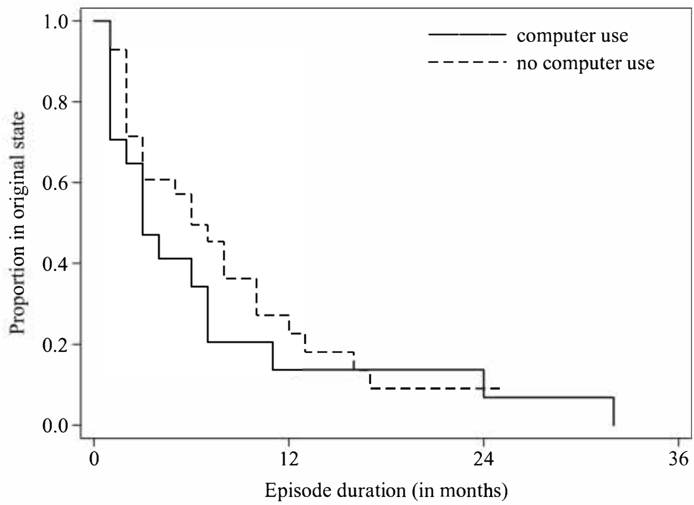

Figure 5: The transition from unemployment to employment for PC users and non-users

5. Conclusions

In this paper we analyzed the consequences of on-the-job PC use for employees in Switzerland. We hypothesize along with Human Capital theory that the ability to use PCs increases work productivity and should thus increase occupational upward mobility. Using event history analysis we first analyzed a random sample of 1873 part-time and full-time employees. This analysis replicates former findings on occupational mobility. Thus, employees with higher levels of education and participation in some form of further education have a higher probability of experiencing an upward shift during their work career. Furthermore, upward shifts are more likely during times of macro-economic expansion, e.g. increases in gross national product. However, longer periods of employment interruption, as well as part time work, decrease the chances of upward shifts. The analysis also shows that marriage only has a negative effect on chances of moving upward for women. This finding corresponds to results from former earnings studies, which show a marriage premium for men, but a wage penalty for women (Daniel 1995).

Next we analyzed the effect of on-the-job use of PCs by using a panel subsample of 411 employees of our original sample. This analysis consistently shows that employees moved upward after starting to use a PC on the job. We estimate that PC use increases the chances of an upward move by approximately 50 %. The PC effect is therefore strong. Our interpretation of this finding supports the hypothesis that investment in computer specific human capital is rewarded by the labor market.

In a further step, we took a look at the risk of unemployment. According to labor market theory, employers should first lay off the less qualified workforce in times of economic recession. Our analyses confirm this hypothesis. Schooling as well as work experience decreases the risk of unemployment. However, both findings are not significant which might be due to the low rate of unemployment in Switzerland. Of 2768 part-time and full-time employees of our sample, only 210 experienced an episode of unemployment. The positive effect of further education on the unemployment rate can most likely not be interpreted causally. On the contrary, it seems reasonable to assume that employees participate in further education when they perceive a risk of losing their jobs. Thus, employees that participate in further education are most likely to be a selection of those who face a higher risk of unemployment before participating in further education. Unfortunately, our data contains no information on the particular type of further education. We expect that those educational programs reduce the risk of unemployment in which participants develop the skills to use new technologies, e.g. computers. Clearly, and as expected, the individual risk of unemployment is strongly influenced by macro-economic indicators of economic recession. Thus, a higher GNP-rate decreases the individual risk of unemployment.

Finally, we analyze the risk of unemployment with respect to on-the-job use of computers. Again the expectation is that those using PCs should have a lower risk. Our results point to this direction, but are not statistically significant. However, our sub sample has only 40 employees who experienced episodes of unemployment and the sample is therefore too small to expect significant results. We also took a descriptive look at the duration of unemployment for those 40 respondents. Employees with PC skills seem to be able to return to the job market sooner than others. But this finding is also not statistically significant. However, taking the results from all models together, our findings do suggest that PC users have advantages on the job market over compared to non-users.

References

Becker, G. S. (1964): Human Capital. A Theoretical and Empirical Analysis with Special Reference to Education. Columbia University Press: New York.

Bell, B. D. (1996): Skill-Biased Technical Change and Wages: Evidence from a longitudinal Data Set. Nuffield College Oxford: Mimeo.

Blossfeld, H.-P. (1986): Career Opportunities in the Federal Republic of Germany: A Dynamic Approach to the Study of Life-Course, Cohort and Period Effects. European Sociological Review, 2, 208 – 225.

Blossfeld, H.-P. / *Rohwer,* G. (1995): Techniques of Event History Analysis Modeling. New Jersey: Lawrence Erlbaum Associates, Mahwah.

Buchmann, M. / *König,* M. / *Li,* J. H. / *Sacchi,* S. (1999): Weiterbildung und Beschäftigungschancen. Chur / Zürich: Rüegger.

Buhmann, B. (1993): Wer sind die eingebürgerten Schweizer? Eine Analyse auf Grund der Schweizerischen Arbeitskräfteerhebung. Swiss Journal of Economics and Statistics, 129, 491 – 503.

Colecchia, A. / *Schreyer,* P. (2002): The Contribution of Information and Communication Technologies to Economic Growth in Nine OECD Countries. OECD Economic Studies, 34, 153 – 171.

Cox, D. R. (1972): Regression Models and Life-tables. Journal of the Royal Statistical Society, 34 (Series B), 187 – 220.

Daniel, K. (1995): The Marriage Premium. In M. Tomasi & K. Ierulli (eds.), The New Economics of Human Behavior, pp. 113 – 125. Cambridge: Cambridge University Press.

Diekmann, A. / *Engelhardt,* H. / *Jann,* B. / *Armingeon,* K. / *Geissbühler,* S. (1999): Der Schweizer Arbeitsmarktsurvey 1998: Codebuch. University of Bern: Bern.

Diekmann, A. / *Jann,* B. (2001): Der Schweizer Arbeitsmarktsurvey, Panel 2000. Ergebnisbericht und Codebuch. University of Bern: Bern.

DiNardo, J. E. / *Pischke,* J. S. (1997): The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too? Quarterly Journal of Economics, 112, 291 – 303.

DiPrete, Th. A. / *de Graf,* P. M. / *Luijkx,* R. / *Tahlin,* M. / *Blossfeld,* H.-P. (1997): Collectivist versus Individual Mobility Regimes? Structural Change and Job Mobility in Four Countries. American Journal of Sociology, 103, 318 – 58.

DiPrete, Th. A. / *Nonnemaker,* K. L. (1997): Structural Change, Labor Market Turbulence, and Labor Market Outcomes. American Sociological Review, 62, 386 – 404.

Entorf, H. / *Gollac,* M. / *Kramarz,* F. (1999): New Technologies, Wages, and Worker Selection. Journal of Labor Economics, 17, 464 – 491.

Entorf, H. / *Kramarz,* F. (1997): Does Unmeasured Ability Explain the Higher Wages of New Technology Workers? European Economic Review, 41, 1489 – 1509.

Franzen, A. (2001): Wages and the Use of New Technologies: An Empirical Analysis of the Swiss Labor Market. Swiss Journal of Economics and Statistics, 137, 505 – 523.

Guo, G. (1993): Event-History Analysis for Left Truncated Data. Sociological Methodology, 23, 217 – 243.

Hachen, D. S. (1992): Industrial Characteristics and Job Mobility Rates. American Sociological Review, 57, 39 – 55.

Haisken-DeNew, J. P. / *Schmidt,* Ch. M. (1999): Money for Nothing and Your Chips for Free? The Anatomy of the PC Wage Differential. German Institute for Economic Research, Berlin: Mimeo.

Hall, R. E. / *Kasten*, R. A. (1976): Occupational Mobility and the Distribution of Occupational Success Among Young Men. The American Economic Review, 66: 309–315.

Hosmer, D.W. / *Lemeshow*, S. (1999): Applied Survival Analysis. New York: Wiley.

Ishida, H. / *Spilerman*, S. / *Su*, K.-H. (1997): Educational Credentials and Promotion Chances in Japanese and American Organizations. American Sociological Review, 62, 866–882.

Jann, B. (2003): The Swiss Labor Market Survey 1998 (SLMS 98). Schmollers Jahrbuch, 123, 329–335.

Jorgenson, D. (2003): Information Technology and the G7 Economies. World Economics, 4, 139–169.

Klein, J. P. / *Moeschberger*, M. L. (1997): Survival Analysis. Techniques for Censored and Truncated Data. New York: Springer.

Krueger, A. B. (1993): How Computers Have Changed the Wage Structure?: Evidence from Microdata, 1984–1989. Quarterly Journal of Economics, 108, 33–60.

Li, J. H. / *König*, M. / *Buchmann*, M / *Sacchi*, S. (2000): Influence of Further Education on Occupational Mobility in Switzerland. European Sociological Review, 16, 43–65.

Mincer, J. (1974): Schooling, Experience, and Earnings. New York: National Bureau of Economic Research.

Rohwer, G. / *Trappe*, H. (1997): Describing Life Courses. An Illustration Based on NLSY Data. Max Planck Institute for Human Development, Berlin: mimeo.

Rohwer, G. / *Voges*, W. (1996): Soziale Bedingungen der Mortalität. Methodenbezogene Überlegungen anhand des SOEP. University of Bremen: Mimeo.

Sicherman, N. / *Galor*, O. (1990): A Theory of Career Mobility. Journal of Political Economy, 98, 169–192.

Thurow, L. (1975): Generating Inequality. New York: Basic Books.

Topel, R. H. / *Ward*, M. P. (1992): Job Mobility and the Careers of Young Men. The Quarterly Journal of Economics, 107, 439–479.

Wolbers, M. H. J. (2000): The Effects of Level of Education on Mobility between Employment and Unemployment in the Netherlands. European Sociological Review, 16, 185–200.

Appendix

Table A

Comparison of the Swiss Labor Market Survey (SLMS) with the Swiss Labor Force Survey (SLFS)

	SLMS (1998) $N = 3028$	SLFS (1998) $N = 13636$
Sex		
Male	46.9%	47.0%
Female	53.1%	53.0%
Age		
18 – 30 years	20.7%	21.2%
31 – 40 years	27.0%	27.4%
41 – 50 years	20.2%	19.4%
51 – 60 years	17.8%	17.2%
61 – 70 years	14.3%	14.8%
Marital status		
single	30.0%	29.7%
married	57.0%	56.6%
divorced	8.8%	9.2%
widowed	4.2%	4.5%
Household size		
1 person	25.5%	24.9%
2 person	32.3%	33.3%
3 person	14.5%	15.3%
4 person	18.5%	18.4%
5 and more persons	9.2%	8.2%
Schooling		
Primary school	17.5%	18.1%
Secondary I	61.0%	61.7%
Secondary II	12.9%	11.9%
University	8.6%	8.3%
Employment status		
Full time	51.3%	52.6%
Part time	21.5%	22.1%
Not working	27.2%	25.3%

Note: Unweighted data. The Swiss Labor Force Survey (SLFS) is conducted by the Swiss Bureau of Statistics and recognized as one of the country's most reliable data sources.

Table B

Dependent Variables, Definition of Episodes

Variable	Definition
Occupational upward mobility	The episodes in question capture the duration from the first entrance into a job of low or middle occupational status to the first transition into a higher status category. An episode is right-censored if no such transition could be observed until the date of the interview. It is *not* censored if the subject leaves the initial occupational status and becomes unemployed, non-employed, self-employed or employed as a blue-collar worker. Such changes are controlled for by sub-episode specific covariates. An episode is treated left-truncated if it started before January 1981.
Risk of unemployment	The episodes in question capture the duration from the first job in a subjects' employment biography to the first transition to unemployment. An episode is right-censored if no instance of unemployment could be observed until the date of the interview. It is *not* censored if the subject changes jobs or becomes non-employed. Such changes are controlled for by sub-episode specific covariates. An episode is treated left-truncated if it started before January 1981.

Table C

Independent Variables

Variable	Type	Definition
Covariates for both models:		
PC use	A	Turns 1 by the time someone starts to use a computer for work, else 0
Occupation specific PC rate	K	Occupation specific (one digit ISCO-88 groups) PC rate in 1998
Education	K	Highest educational degree expressed in years of schooling
Further education	A	Turns 1 by the time someone receives further education, else 0
Work experience	C	Sum of work experience in years, updated every 12 months
Previous no. of jobs	C	Sum of previously held jobs, updated at every job change
Interruption of employment	A	Turns 1 by the time an employment interruption greater 12 months occurs within an episode, else 0
Sex	K	0 = female, 1 = male

Continuation of Table C

Variable	Type	Definition
Non-Swiss citizen	K	0 = Swiss citizen, 1 = non-Swiss citizen
Married	A	Turns 1 by the time someone gets married, else 0
Cohort 1951 – 1965	K	Equals 1 if born between 1951 and 1965, else 0
Cohort 1966 – 1980	K	Equals 1 if born between 1966 and 1980, else 0
Part-time employed	S	Equals 1 if the respondent currently is part-time employed, else 0; updated at every occupational change
Self-employed	S	Equals 1 if the respondent currently is self-employed, else 0; updated at every occupational change
Employed	S	Equals 1 if the respondent currently is employed at all, else 0; updated at every occupational change
Unemployment rate	P	Reflects the current unemployment rate; updated every year
Economic growth	P	Reflects the current rate of growth of the gross national product; updated every year
Additional covariates for occupational upward mobility:		
Occupational position (middle)	K	0 if episode starts on low occupational status position, 1 if on middle status position
Worker	S	Equals 1 if the respondent currently is a blue-collar employee, else 0; updated at every occupational change
Additional covariates for risk of unemployment:		
Low status employee	S	Equals 1 if the respondent currently is employed in low occupational status, else 0; updated at every occupational change
Middle status employee	S	Equals 1 if the respondent currently is employed in middle occupational status, else 0; updated at every occupational change
High status employee	S	Equals 1 if the respondent currently is employed in high occupational status, else 0; updated at every occupational change

Note: K: constant variable, A: absorbing time-dependent variable, C: cumulative time-dependent variable, S: sub-episode specific time-dependent variable, P: period-specific aggregate variable (time-dependent).

Table D

Unemployment Rates and Economic Growth in Switzerland 1981 – 2000

	Unemployment Rate	GNP
1981	0.2	1.6
1982	0.4	–1.4
1983	0.9	0.5
1984	1.1	3.0
1985	1.0	3.4
1986	0.8	1.6
1987	0.8	0.7
1988	0.7	3.1
1989	0.6	4.3
1990	0.5	3.7
1991	1.1	–0.8
1992	2.5	–0.1
1993	4.5	–0.5
1994	4.7	0.5
1995	4.2	0.5
1996	4.7	0.3
1997	5.2	1.7
1998	3.9	2.3
1999	2.7	1.5
2000	2.3[a]	3.3[b]

[a] 1. quarter, [b] estimate.

Source: Statistical Bureau of Switzerland, State Secretariat for Economic Affairs.

Table E

Descriptive Information on Time-Constant and Time-Varying Covariates at the End of the Episode (Risk of Unemployment)

	SLMS sample		Panel sub-sample	
	Mean	Std. dev.	Mean	Std. dev.
PC use (yes = 1)[a)]			0.676	
Occupation specific PC rate	0.504	0.183	0.525	0.176
Education (years)	11.567	2.256	11.902	2.361
Further education (yes = 1)[a)]	0.152		0.210	
Work experience (years)[a)]	18.267	12.878	18.085	10.538
Number of jobs[a)]	3.029	1.958	3.472	1.917
Labor-force interruption > 1 year (yes = 1)[a)]	0.460		0.343	
Sex (male = 1)	0.477		0.603	
Non-Swiss citizen (yes = 1)	0.127		0.073	
Married (yes = 1)[a)]	0.693		0.662	
Cohort 1951–1965 (yes = 1)	0.380		0.470	
Cohort 1966–1980 (yes = 1)	0.232		0.262	
Part-time employed (yes = 1)[a)]	0.221		0.189	
Low status employee (yes = 1)[a)]	0.315		0.270	
Middle status employee (yes = 1)[a)]	0.253		0.260	
High status employee (yes = 1)[a)]	0.170		0.217	
Self employed (yes = 1)[a)]	0.111		0.130	
Employed (yes = 1)[a)]	0.753		0.982	
Number of Episodes	2768		562	

[a)] Time-dependent covariates, measured at end of episodes.