On the impact of education on human capital depreciation, wage growth, and Tenure

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Thèse présentée à la Faculté des
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par
Sylvain WEBER

pour l'obtention du grade de
Docteur ès Sciences Économiques et Sociales
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Membres du jury de thèse:

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Thèse n° 750
Genève, mai 2011

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La Faculté des sciences économiques et sociales, sur préavis du jury, a autorisé l'impression de la présente thèse, sans entendre, par là, n'émettre aucune opinion sur les propositions qui s'y trouvent énoncées et qui n'engagent que la responsabilité de leur auteur.

Genève, le 6 mai 2011.
Le doyen
Bernard Morard

Remerciements

Je souhaite exprimer ici mes remerciements aux personnes qui, de près ou de loin, ont contribué à la concrétisation de ce travail de thèse de doctorat.

Je commence logiquement par mon directeur de thèse, Yves Flückiger, qui m'a toujours accordé une confiance aveugle. À ce propos, la façon dont il a géré mon engagement est révélatrice. Un matin d'août 2006, Yves me lance un coup de fil et me dit quelque chose dans le genre: "Passe cet après-midi; il faut que tu signes ton contrat rapidement!". À ma connaissance, il n'avait jusque-là jamais été question d'un quelconque contrat... Tout au long de ma thèse, Yves m'a suivi du coin de l'oeil et bien qu'il n'ait pas souvent été présent physiquement, je savais qu'il comptait sur moi et que je pouvais compter sur lui.

Jean-Marc Falter est sans doute la personne qui a eu la plus grande influence sur cette thèse. Non seulement par ses conseils aux niveaux économique et académique, mais aussi et surtout grâce aux activités extra-professionnelles que nous avons partagées: randonnées à ski (jeudi ou mardi ou quel que soit le jour pour autant qu'il fasse beau et que l'enneigement le permette), sorties à vélo, matchs de hockey ou de foot... Jean-Marc est toujours de bonne humeur et prêt à détendre l'atmosphère en papotant sur le tennis ou tout autre sujet, généralement sportif mais pas uniquement.

Marcelo Olarreaga a rejoint le comité de cette thèse tardivement, mais ses conseils avisés et pointus ont été hautement productifs. Je remercie Marcelo pour ses nombreuses qualités, notamment sa disponibilité, sa bonne humeur, sa générosité et sa décontraction.

José Ramirez a quant à lui suivi cette thèse dès sa conception et en est même l'instigateur. À l'image d'Yves, José n'était pas forcément très présent, et je prends sa supervision distante comme une marque de confiance. Notre longue bataille pour l'obtention de données (pourtant pas particulièrement sensibles) n'a malheureusement pas été couronnée de succès, mais je suis certain que nous referons équipe pour le meilleur tout prochainement.

Je remercie Giovanni Ferro Luzzi du fond du coeur pour tout ce qu'il a fait pour moi ces quelques dernières années. Parmi les faits marquants, Giovanni

m'a notamment fait acheter un bateau, sur lequel nous avons certes passé de bons moments, mais dont l'entretien m'oblige à travailler 80 heures par semaine. Giovanni m'a également initié aux échecs, qui m'ont fait perdre jusqu'à 80 heures par semaines. Plus sérieusement, si Giovanni n'est pas présent dans le jury de cette thèse, c'est tout simplement qu'il m'est trop proche.

Andrea Baranzini a été et restera mon premier mentor. Son zèle extrême et sa façon méticuleuse de travailler ont laissé sur moi des traces indélébiles. Bien que nous n'ayons absolument pas collaboré dans le cadre de ma thèse, Andrea n'en est pas moins mon co-auteur modal, ce qui démontre clairement notre affinité. Notre goût partagé pour la bière et le foot a bien évidemment été un facteur clé dans le développement de notre amitié.

Cyril Pasche et moi avons partagé le désormais mythique bureau 5265 (et bien plus que cela!) durant un peu plus de trois ans. Si Cyril avait été moins pressé de finir sa belle thèse, nous aurions pu prolonger quelque peu cette période hors du commun. Il y aura toujours quelques Guinness au frais, au cas où nous aurions envie de nous remémorer quelques-uns de ces moments extraordinaires, comme les nombreuses fois où nous étions proches de *serrer*.

Sans les nommer individuellement, je remercie tous mes anciens et actuels collègues de feu le département d'économie politique. Au fil du temps, nombre d'entre eux sont également devenus des amis.

Quelques vieux et fidèles amis méritent largement leur place dans ces remerciements: Antonin, Fabien, François, Gilles, Oliver, Simon, ... Ils m'ont souvent aider à me changer les idées, ce qui, par moment, est d'une valeur inestimable.

Finalement, je dois d'immenses mercis à mes proches. Mes parents tout d'abord, sans qui rien n'aurait été possible et qui m'ont toujours offert un cadre idéal à la poursuite de mes études. Mon frère, Florian, par son esprit de compétition inépuisable m'oblige à toujours viser plus haut. Il m'a toujours suivi de très près (pour les études s'entend car pour tout le reste il y a bien longtemps qu'il m'a surpassé) et ne m'a pas autorisé le moindre moment de relâchement.

Dorota, mon épouse, m'a inlassablement remis sur le droit chemin, surtout dans les derniers mois, alors que le navire prenait l'eau de toute part et que j'étais plusieurs fois tenté par le laisser couler. Parallèlement, elle n'a heureusement pour moi jamais cessé de me rappeler qu'il y avait autre chose que la thèse dans la vie. Sans son soutien sans faille, je n'ose songer à quoi ressemblerait aujourd'hui mon travail. Cette thèse est donc également la sienne.

Short content

Contents

List of Figures

List of Tables

General Introduction

1 Motivation

Two of the most important aspects of a job are how much it pays and how long it is likely to last. This thesis is concerned with both. The first and second chapters deal with individual earnings and their evolution, whereas the third one investigates job tenure.

The thesis emphasizes the importance of the qualitative nature of schooling. In the classical approach, it is customary to measure education solely as the number of years spent in school. This purely quantitative approach does not take into account the qualitative aspects of educational systems. Switzerland, with its widely developed dual education system, constitutes an ideal candidate to observe differences across education types. It enables the researcher to compare workers with a similar education length but completely different skills.

A contribution of the thesis to the literature is indeed to take advantage of the Swiss educational system to define education groups on the basis of the type of education, instead of using the usual classification by education length. As a general finding, the results show that education type is more determinant than education length regarding many labor market aspects. Consequently, education type should be considered in studies regarding the labor market whenever parallel tracks coexist in an educational system.

Because any of us goes to school during his youth and spends thereafter most of his life working, the topics covered in this thesis might interest anyone at a personal level. Moreover, given their importance in the budgets and their implications for the society as a whole, education and labor market policies count among the most challenging issues governments have to deal with. Hence, the subjects treated are relevant at the government level too.

2 Overview

The three chapters of this thesis provide empirical analyses based on a single dataset: the Swiss Labor Force Survey (SLFS). The methodologies and the variables used differ widely across the chapters though.

Chapter 1 deals with the measurement of the human capital depreciation rate, which has become a crucial topic in the advanced economies that rely heavily on knowledge. More precisely, this chapter focuses on the relationship between education and human capital depreciation. This question has received little attention in the literature, yet the evidence is mixed. Among the few papers dealing with the measurement of human capital depreciation (Mincer & Polachek, 1974; Groot, 1998; Arrazola, De Hevia, Risueno, & Sanz, 2005), one can find in turn a positive, negative or even a non-existent correlation between the level of education and depreciation.

Instead of considering the usual criterion of education length, we classify workers as possessing either a general human capital (proxied by academic studies, i.e., high schools and universities) or a specific human capital (proxied by vocational studies, i.e., apprenticeships, professional and technical schools, and universities of applied sciences). Our estimates show that human capital depreciation is lower for workers with general education than specific education. The fact that education type is relevant in the determination of human capital depreciation might explain part of the lack of consensus about the link with education length.

Chapter 2 aims at disentangling the effects of several components of experience on individual wage growth. In addition to general labor market experience and job tenure, the standard earnings determinants used in the human capital theory (Becker, 1964), occupational experience and industrial experience are considered in the model. If job tenure is a proxy for firm-specific skills and labor market experience is a proxy for general human capital, there is admittedly still room for intermediate components of human capital between these two extremes. Assuming that some human capital is transferable across occupations and industries leads to the introduction of these additional occupational and industrial components of experience. A question we additionally explore is whether the returns to different components of experience differ by education groups.

This chapter is located at the intersection of two branches of the literature. The first is the methodological literature on estimating the sources of wage growth when tenure and experience are potentially endogenous (following the seminal papers by Altonji & Shakotko, 1987; and Topel, 1991), and when industrial and occupational experience are considered in the wage equation (see Kambourov & Manovskii, 2009; and Sullivan, 2010; for the latest references). The second branch of the literature related to this chapter is the substantive literature on sources of wage growth and how these differ by education level (see among others Connolly & Gottschalk, 2006; Schönberg, 2007; or Dustmann & Pereira, 2008).

Our empirical estimations show that, for all education groups, general labor market experience is the far most important determinant of lifecycle wage growth, occupational experience having a positive but quantitatively weaker impact. If occupational experience is included in the wage equation, the returns to tenure and industrial experience become negligible and unsignificant. Workers with apprenticeship training constitute a special case, with a wage growth that is different than other education groups. Their returns to general experience are in fact lower than for both the less-educated (compulsory school) and the more-educated (university) workers, even though their education length would place them in between. For these workers with apprenticeship training, occupational experience appears to be a non-negligible determinant of wage growth, and mobility costs seem to be larger. The type of education thus matters more than education length in the determination of wage growth.

Chapter 3 takes a less usual look at the labor relationship and investigates the determinants of job tenure. Job stability has been widely studied through tenure, its most straightforward indicator (see for example Burgess & Rees, 1996; Booth, Francesconi, & Garcia-Serrano, 1999; Gottschalk & Moffitt, 1999; Gregg & Wadsworth, 2002; or Mumford & Smith, 2004). However, papers providing a proper econometric analysis of tenure are few, and we here use duration models to provide a careful analysis. Our results do not show any clear decrease in job stability over the last two decades. A more important concept but also more complicated to analyze is job insecurity. It is more important in the sense that what matters for a worker is not to keep his job forever, but to have a job as long as he wants one. Job insecurity is therefore not only related to tenure, but also to the reason why a job terminates and what happens next. If the job ends because the worker has decided so or if he is able to find a new job immediately, there is no job insecurity. To investigate this concept, one therefore needs to take into account the job termination reason and the destination state following a separation.

When considering multiple destination states (new job, unemployment, inactivity) and multiple termination reasons (quit, layoff, other reasons), the determinants are found to be radically different. This proves by itself that such distinctions are crucial. For instance, education increases the probability a worker quits and also increases his chances to move job-to-job. Conversely, education decreases the risk of being laid-off and the hazard rate towards unemployment and inactivity. Job insecurity, defined as the hazard of a job terminating in a layoff or as the hazard of a job being followed by unemployment, does not show any clear evolution through time. The general feeling that the labor market becomes increasingly insecure is disputed by our results.

When studying tenure, wage appears as a crucial but complicated variable. Indeed, it seems clear that wage affects the incentive to keep one's job. But wage also depends on tenure. Hence, there is a clear endogeneity problem. Nevertheless, some authors simply include individual wages in the tenure regressions (Topel & Ward, 1992; Hirsch & Schnabel, 2010). The novel feature we propose in this chapter is to use industry wage differentials (industry premiums) to take account of wage levels while trying to circumvent the endogeneity problem. As expected, we find that the separation rates are lower in industries where wage premiums are large, as this reduces incentives to quit for workers and to dismiss workers for firms.

Chapter 1

Human Capital Depreciation and Education Level*

1 Introduction

Industrialized economies increasingly rely on knowledge. As a consequence, human capital depreciation, roughly defined as the decrease of a worker's market value, has become a crucial subject. Studying human capital depreciation should help answer questions such as: How long should people educate? What kinds of training should be promoted? When and how should workers re-train after schooling? At what age should people retire? Despite its relevance, it has received little empirical consideration.[1]

This chapter investigates the link between human capital depreciation and education level, with an emphasis on potential differences between general and specific education. It seems legitimate to think that general skills depreciate slower than specific ones. Indeed, workers with a general human capital should be able to move to a new technology or to a new job while taking with them most of their human capital. On the contrary, workers with mostly specific human capital will be locked in a particular technology or a particular job. Were they to move, they would lose a substantial share of their human capital.

The relationship between human capital depreciation and education length has received some attention in the literature but no consensus has been reached. On the one hand, depreciation would increase with education level

*This paper was presented at the Annual Conference of the European Association of Labour Economists (EALE), Amsterdam (Netherlands), September 2008; and at the annual conference of the Society of Labor Economists (SOLE), Boston (USA), May 2009.

[1]A thorough review of the economic literature dealing with the causes of skills obsolescence is provided by De Grip & Van Loo (2002).

if elementary skills do not suffer from depreciation, as argued by Neuman & Weiss (1995) and Ramirez (2002). On the other hand, education might reduce depreciation when it allows the worker to adjust more easily to his environment, as Weisbrod (1962) contends. In the same vein, Gould, Moav, & Weinberg (2001) postulate that less educated workers are relatively more invested in technology-specific skills, and will therefore suffer higher rates of human capital depreciation due to technological improvements.

The literature on health economics also provides some insights about the link between education and depreciation (see for example Muurinen, 1982; Grossman, 2000). In models of demand for health, the stock of health is assumed to depreciate over time, and education reduces the health depreciation rate through its impact on life-style selection, diet and exercise decisions, or the more efficient production of health from better medical knowledge, more information about alternative sources of care, etc. Even though we are not directly interested in health in this chapter and we do not even observe it, health is part of the human capital, along with education. The positive impact of education on health might thus be reflected in a lower human capital depreciation rate for the more educated.

The empirical evidence regarding the impact of education on depreciation is mixed and sparse. Mincer & Polachek (1974) find a larger depreciation rate for more educated female workers; yet, Arrazola et al. (2005) do not find any significant difference across education groups, and Groot (1998) obtains contradictory results on two separate datasets.

To the best of our knowledge, studies taking account of both education length and education type (i.e., the qualitative features of the educational system) simultaneously are not available in the literature. Therefore, the present study provides a possible explanation for the lack of consensus on the link between depreciation and education level. If depreciation depends on education type rather than on education length, the literature might have missed the point.

We use Arrazola & De Hevia's (2004) model on data from the Swiss Labor Force Survey (1998-2008) to estimate a human capital depreciation rate for several education groups. The originality of the chapter relies on the way education groups are defined. Instead of using an exclusively quantitative approach and separating workers by years of education, we use qualitative aspects of the educational system and separate them by education type.

Switzerland is an ideal candidate for the analysis of the qualitative aspects of education, because its educational system is constituted by two tracks. At the end of compulsory school (6 years of primary school followed by 3 years of secondary school), youngsters can either attend a higher level of secondary school or begin vocational studies. In the "academic" track of the educational system, students attend a high school during 4 years, which gives them access to (traditional) universities. In the “vocational” track, a large share of time (3 to 4 days a week) is devoted to practical work in a company, and the remainder (1 to 2 days a week) is allocated to theoretical studies at a vocational school. Universities of applied sciences provide a tertiary level of education in the vocational track.

Following Becker’s (1964) terminology, human capital acquired through vocational studies can be considered as relatively specific,[2] and that obtained through academic studies as more general. Hence, using Swiss data allows to test whether workers with similar education length but different education type suffer different rates of human capital depreciation.

The empirical estimates show that human capital depreciation is significantly related to the skills’ type, and not only to education length. Workers with vocational training suffer a faster depreciation than those with an academic background. General skills (provided by academic studies) better protect workers against depreciation than specific skills (provided by vocational studies).

The remainder of the chapter is organized as follows. Section 2 builds an earnings equation where human capital depreciation appears as a parameter. Section 3 describes the SLFS data that are used for the empirical estimations. Section 4 discusses different sets of estimates, and conclusions are offered in section 5.

2 The Model

The model we use is borrowed from Arrazola & De Hevia (2004). In order to clarify the hypotheses and the justifications of the model, we present it in details.

Human capital theory (Becker, 1964; Ben-Porath, 1967) assumes that individuals invest in themselves to increase their future earnings. The earlier they make educational investments, the longer they will be able to collect benefits from those, so that it is more profitable to acquire skills early in one’s life. “Rational allocation requires that most of the investment be undertaken at younger ages. Thus schooling, a largely full-time activity, precedes job-training, a largely part-time activity, and the latter diminishes with age, terminating years before retirement” (Mincer, 1974, p. 13).

During working life, the time devoted to continuing training is subtracted

[2]Obviously not completely firm-specific, but at least occupation-specific in the sense that human capital acquired through the vocational track is transferable across jobs in the same occupation, but with more difficulty to jobs in a different occupation.

from the production of earnings. Actual earnings are therefore always lower than potential earnings. Because the proportion of time devoted to training decreases over time, actual and potential earnings converge, and experience-earnings profiles are increasing and concave. Empirical observations since Mincer (1974) moreover show that earnings peak somewhere before retirement, as in figure 1. To obtain such experience-earnings profiles negatively sloped at the end of career, human capital must necessarily depreciate.

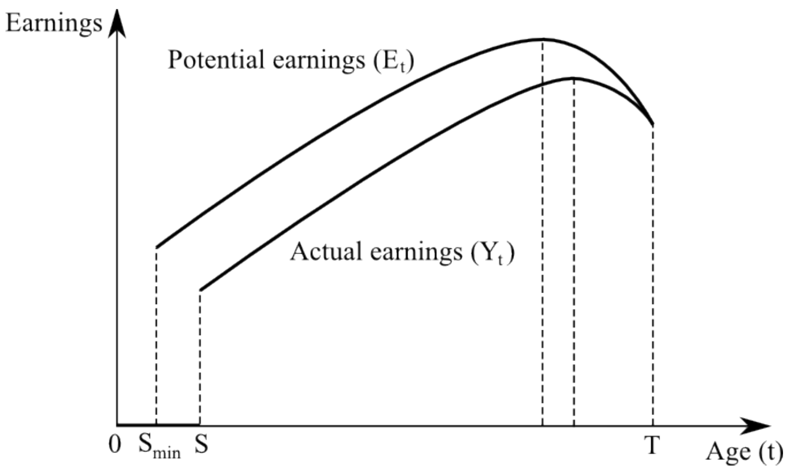
Let s_t be the investment rate, i.e., the proportion of time devoted to the production of new human capital by an individual of age t. The relationship between potential earnings E_t and actual earnings Y_t is then given by:

$$Y_t = (1 - s_t) \cdot E_t \tag{1}$$

Human capital theory implies that s_t must be decreasing over the lifecycle, but does not provide a specific shape for this function. We will assume that s_t declines linearly over one's career until zero at retirement.[3] The investment rate over the lifecycle is therefore given by:[4]

$$s_t = \begin{cases} 1 & \text{if } t \leq S \\ \alpha - \frac{\alpha}{T-S} \cdot (t - S) = \alpha \cdot \left(1 - \frac{X_t}{L}\right) & \text{if } S < t \leq T \end{cases} \tag{2}$$

Figure 1: Experience-earnings profiles with human capital depreciation



Note: S_{min} indicates the minimal age at which youngsters can legally begin work.

[3]As an alternative, a quadratic function has been used for the estimations, and the empirical results do not differ significantly.

[4]Schooling begins at 6 in Switzerland. However, we assume that individuals invest 100% of their time in the production of human capital even before 6. Before that age, human capital is accumulated within the family.

where α is a parameter to be estimated, t is current age, T is (expected) retirement age, S is age at the end of education, X_t is (potential) experience, and L is (potential) total working life duration. These notations are summarized in Figure 2, which helps clarify the relationships between the different variables.

The evolution of the investment rate over the lifecycle is depicted in Figure 3. The α parameter represents the proportion of time invested in training immediately upon leaving school. Due to the assumption that the investment rate declines linearly, α alone determines the complete path of investment during the career.

According to what is usually done in the literature, we assume that potential earnings are exponentially linked to the stock of human capital and

Figure 2: Periods of the lifecycle

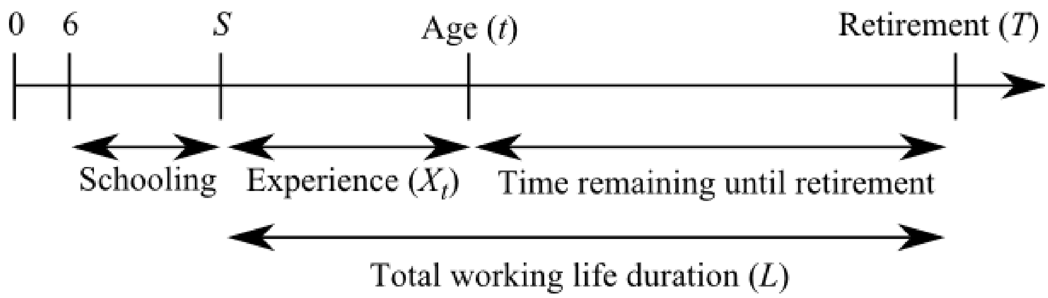
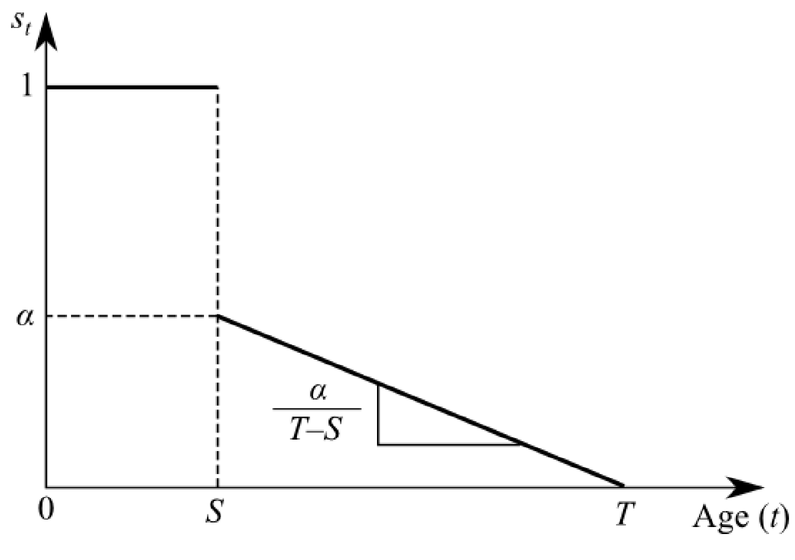


Figure 3: Proportion of time devoted to the production of human capital



other covariates:[5]

$$E_t = W \cdot \exp(\beta_K K_t + \beta_Z Z_t) \tag{3}$$

where W is the return per period on all the human resources that the individual possesses (human capital and ability), K_t is the stock of human capital at time t, β_K is the rental rate of the stock of human capital, Z_t is a set of individual characteristics, and β_Z is a vector of parameters.

The stock of human capital in period t can be expressed as the sum of the stock that was already acquired in the previous period minus the loss incurred because of depreciation, plus the quantity produced during the t^{th} period. Denoting the quantity of new human capital produced during period t by ΔK_t, and the human capital depreciation rate by δ, we have:

$$K_t = K_{t-1} - \delta \cdot K_{t-1} + \Delta K_t = (1-\delta) \cdot K_{t-1} + \Delta K_t \tag{4}$$

By recursion, one finds an expression for K_t as a function of the stock of human capital acquired at the end of education K_S:

$$K_t = (1-\delta)^{t-S} \cdot K_S + \sum_{j=S+1}^{t} (1-\delta)^{t-j} \cdot \Delta K_j \tag{5}$$

Taking the logarithms of (3) and substituting K_t by its expression in (5) gives:

$$\ln E_t = \ln W + \beta_K \cdot \left\{ (1-\delta)^{X_t} \cdot K_S + \sum_{j=0}^{X_{t-1}} (1-\delta)^j \cdot \Delta K_{t-j} \right\} + \beta_Z Z_t \tag{6}$$

Then, taking the logarithms of (1) and introducing (6) leads to an expression for actual earnings, as follows:

$$\ln Y_t = \ln W + \beta_K \cdot \left\{ (1-\delta)^{X_t} \cdot K_S + \sum_{j=0}^{X_{t-1}} (1-\delta)^j \cdot \Delta K_{t-j} \right\} + \beta_Z Z_t + \ln(1-s_t) \tag{7}$$

The final necessary step is to choose values for K_S and ΔK_t, these two variables being unobservable. The stock of human capital at the end of schooling must be related to the level of education, and we assume a direct link with the length of schooling:

$$K_S = S \tag{8}$$

[5]In order to keep the notation as simple as possible, the individual subscript i and the error term are omitted until the final equation (A.1).

We also postulate that the production of new human capital ΔK_t depends directly on the time devoted to this activity:[6]

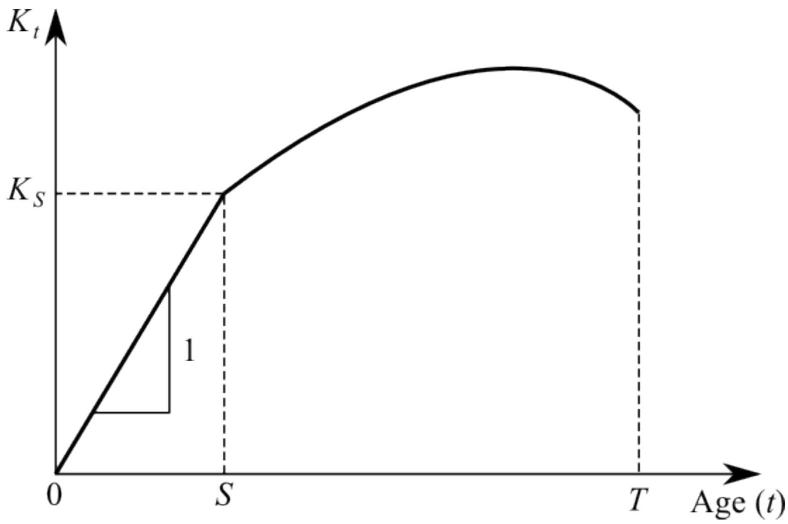
$$\Delta K_t = s_t = \begin{cases} 1 & \text{if } t \leq S \\ \alpha \cdot \left(1 - \frac{X_t}{L}\right) & \text{if } S < t \leq T \end{cases} \tag{9}$$

The complete path of the human capital stock over the lifecycle is shown in Figure 4. Given the assumptions, the stock of human capital grows by 1 unit per year during the schooling period. While the individual is working, his stock of human capital continues to grow, but at a slower rate because investments are reduced. Eventually, investments become too small to offset the effects of depreciation, and the stock of human capital decreases.

Substituting (8) and (9) into (7), simplifying, and adding an individual subscript i and an error term finally yields the equation to be estimated:

$$\ln Y_{it} = \ln W + \beta_K \cdot \left\{ (1-\delta)^{X_{it}} \cdot S_i + \alpha \cdot \frac{1-(1-\delta)^{X_{it}}}{\delta} \cdot \left(1 + \frac{1-\delta}{\delta \cdot L_i}\right) - \frac{\alpha \cdot X_{it}}{\delta \cdot L_i} \right\} + \beta_Z \cdot Z_{it} + \ln\left\{1 - \left(\alpha - \frac{\alpha}{L_i} \cdot X_{it}\right)\right\} + u_{it} \tag{10}$$

Figure 4: Evolution of human capital stock



[6]This simple functional form permits the mathematical tractability of the model. A more realistic function would include a measure of the stock of human capital already acquired (such as (2) in Ben-Porath, 1967), but retrieving a closed form for the earnings equation is then impossible because K_t reenters the sum of the right-hand side of (7).

This equation is nonlinear in the parameters, and there is no apparent transformation to linearize it. Hence, the model must be estimated by nonlinear least squares.

In order to investigate the link between depreciation and education, we let the δ parameter be heterogeneous across education groups. To focus on the differences between general and specific skills, we separate workers on the basis of their education type. Vocational studies are assimilated to specific skills whereas academic studies are understood as general skills. To allow for possible differences in the investment rates between education groups, we also let the α parameter vary.

3 Data

We employ data from the Swiss Labor Force Survey (SLFS), which has been carried out every year since 1991 by the Swiss Federal Statistical Office. The SLFS is designed as a rotating panel, individuals being contacted for (up to) five consecutive years. Among others, the SLFS contains detailed information about the labor status, earnings, education, and the socioeconomic characteristics of the respondents. Major revisions of the survey took place between 1996 and 1998,[7] and we therefore discard all data until 1997 included. This leaves an observation period of eleven years, from 1998 to 2008 included.

About 16,000 individuals were interviewed each year until 2001. The SLFS was enlarged in 2002 to roughly 40,000 individuals, in order to provide accurate statistics at the canton level.[8] Since 2003, an additional sampling of 15,000 foreign households are selected from the Central Aliens Register.

3.1 Sample Selection

Table A.1 in Appendix A details the sample selection, starting from the total numbers of individuals interviewed in the frame of the SLFS (column I). Every person pertaining to the permanent resident population aged 15 and older is eligible for inclusion in the survey, disregarding his labor status. The

[7]In particular, the variables recording education and earnings were reshaped. The encoding of the education variable does not allow the placement of all individuals interviewed before 1996 in a specific category of the recoded variable with certainty. As education is a fundamental variable in the present analysis, we avoid introducing any approximation in its construction. In addition, no distinction was made between the earnings of the main job and potential additional jobs until 1997. Since 1998, the survey differentiates between the earnings from the main job and those from secondary jobs. For the empirical estimations, we only consider main jobs and discard the secondary jobs.

[8]Switzerland is composed of 26 cantons (administrative regions).

original dataset thus contains active workers, apprentices, unemployed, as well as non-active persons. A first filter is applied to retain active workers only (column II).

Self-employed and workers in public administration are then discarded. The sample is restricted to salaried workers, who are employed full-time, and aged between 16 and 65 years.[9] Individuals with recorded gross annual earnings below CHF 30,000 are excluded because many of those observations are probably coding and response errors (column III).[10]

Our contention is that vocational training produces specific human capital whereas academic education produces general human capital. We therefore retain only workers who have either a clear vocational education or a clear academic one. In the vocational group, we place apprenticeships, professional and technical schools, and universities of applied sciences. In the academic group, we have high schools and universities.

In order to test our hypothesis of different depreciation rates for general and specific human capital as cleanly as possible, we also remove PhD holders from the sample (column IV). The latter constitute a peculiarity in the academic group, as they have spent several years studying a particular topic.[11] Their human capital is proportionally more specific than those of typical university graduates. Including PhD holders would therefore go against our hypothesis that members of the academic group possess a general human capital.

Finally, the observations identified as outliers by the algorithm of Billor, Hadi, & Velleman (2000)[12] and those for whom any necessary information is missing are discarded (column V).

[9] In Switzerland, the official retirement age was constant at 65 for men during the entire observation period. For women, however, it was 62 until 2000, 63 between 2001 and 2004, and has been 64 since 2005 (see the tenth revision of the Old-Age and Survivors Insurance). The upper threshold for the inclusion of women in the sample is adapted accordingly. Information about the actual ages at which individuals retire are not available, so that official retirement ages are used. This does however not constitute a severe restriction, since actual retirement ages are remarkably close to official ones in Switzerland (see OECD, 2003a).

[10] Earnings are deflated by the Consumer Price Index (100 = December 2005). In December 2005, CHF 1 was worth USD 0.8 or EUR 0.65.

[11] For example, the author of this thesis has spent 4 years doing nothing else than study labor economics.

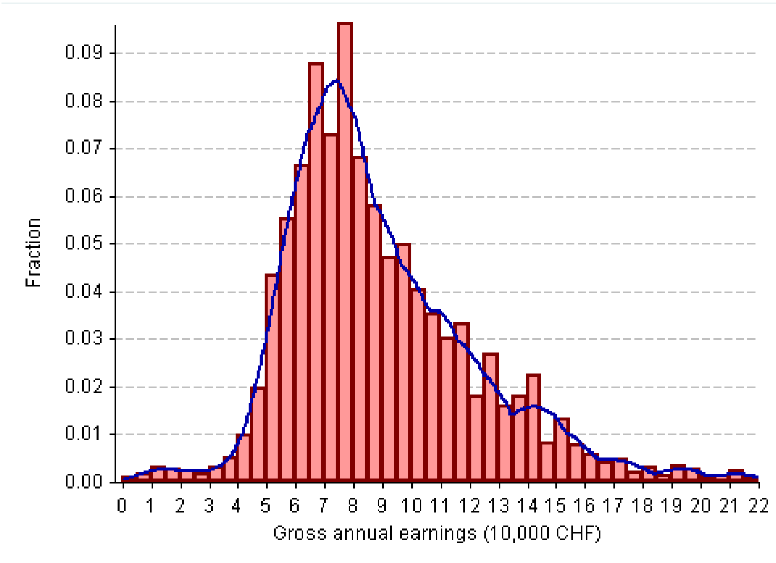
[12] The algorithm is implemented in Stata and described in Appendix D or in Weber (2010).

3.2 Descriptive Statistics[13]

Figure 5 displays the earnings distribution for 2008, without constraining gross earnings to be greater than CHF 30,000. It allows to motivate the choice of the CHF 30,000 threshold for removing individuals: there is a kink in the distribution for this value. The distribution of earnings has the usual right-skewed shape with a mode around CHF 75,000, a median of about CHF 81,000, and an average around CHF 93,000. Table A.2 contains the 2008 descriptive statistics for all the variables used in the estimations.

Table 1 shows the distribution of the final sample by education groups. The most widespread training is apprenticeship, with 48% of the valid observations pertaining to this category. This proportion has however decreased regularly from around 55% in 1998 to 43% in 2008. The second largest group is composed of university graduates, whose proportion has grown from 10%

Figure 5: Earnings distribution in 2008



Notes: The bars are scaled so that the sum of their heights equals 1. The plain line is an appropriately scaled kernel density estimate of the density. The graph is based on the 2008 sample (6,474 ind.) without restricting the gross earnings to be greater than CHF 30,000 (68 ind.), i.e., on 6,542 individuals, and using sampling weights. Earnings over CHF 220,000 (110 ind.) are not displayed to make the graph more readable.

[13]In the main text, we present the analysis for the male sample only. All the corresponding figures and tables for women are reported in Appendix B.

to 23% during the same time window.

The education length, i.e., the minimal time required to obtain a diploma, is constructed from the highest education level achieved. For example, if an individual progresses in a "standard" manner, he will obtain an apprenticeship certificate after 12 years: 9 years of compulsory school, followed by 3 years of apprenticeship. Similarly, to receive a university degree, one needs to spent at least 16 years in school: 9 years of compulsory school, 4 years of post-compulsory school to obtain a high school degree, and at least 3 years in university to earn a bachelor's degree. This approach does not take into account failed years that the student must repeat, and thus measures a "useful" education length, implicitly assuming that failed years do not add anything to the stock of human capital. According to this methodology, the average education length of the sample is almost 13 years and a half.

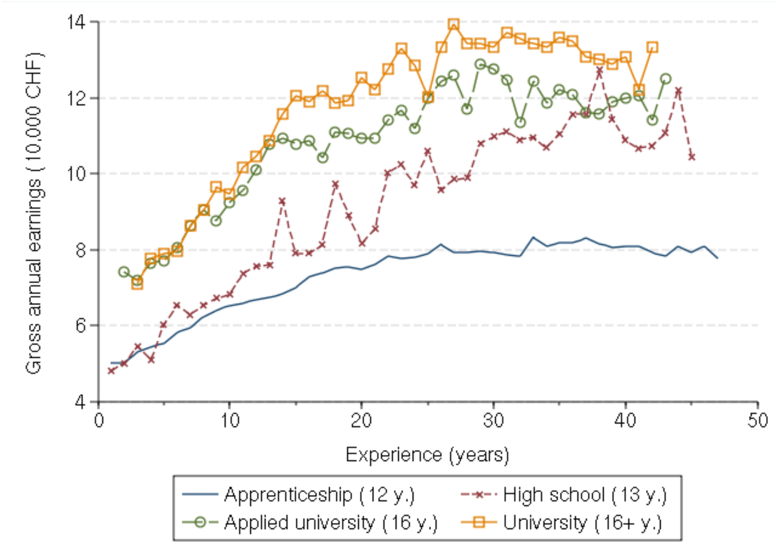
Actual experience cannot be computed from the data. Hence, we rely on potential experience (Mincer, 1974) as a proxy. It is measured as current age minus education length (computed as above) minus 6 (the age at which schooling begins in Switzerland).

Figure 6 displays empirical experience-earnings profiles for some of the education groups we consider. The prominent characteristics are as predicted by the human capital theory: more schooling leads to larger earnings; and earnings increase during one's early career, then level and decrease slightly when retirement approaches, even though the trajectories become quite erratic. Another interesting feature is that earnings profiles are almost flat for poorly skilled workers, whereas they are steep for highly skilled workers. Such an observation would suggest that depreciation is lower for more educated workers, that the labor market experience is more rewarding for the

Table 1: Composition of the final sample

Highest education level	Type	Length (years)	# Obs.	(%)
Apprenticeship	Vocational	12	29,057	(48.3%)
High school degree	Academic	13	4,072	(6.8%)
Professional school	Vocational	14	3,725	(6.2%)
Technical school	Vocational	14	2,921	(4.9%)
Upper professional school	Vocational	15	6,095	(10.1%)
Applied university	Vocational	16	5,123	(8.5%)
University	Academic	16+	9,140	(15.2%)
Total # Obs.		13.54	60,133	(100.0%)
Total # Ind.			27,256	

Figure 6: Empirical experience-earnings profiles



Note: The profiles are based on the final sample (Table 1). Median income is computed for each education group and each year of experience using sampling weights. Information is drawn only when there are at least 15 observations in an education group – year of experience cell.

highly skilled, and/or that workers with higher educational levels invest more in continuing training.

4 Empirical Results

Table 2 displays different sets of estimates obtained by nonlinear least squares on equation (10). Specification I is the exact estimation of (10), the depreciation rate being identical for every worker. To test for possible different depreciation rates across education groups, specification II allows the δ parameter to be heterogeneous. Since the investment rate might also differ, specification III lets the α parameter vary across education groups. Finally, specification IV lets both δ and α vary across education groups simultaneously.

The baseline estimates obtained with specification I indicate an average human capital depreciation rate for male workers in Switzerland of 0.7%. This finding fall in the range of the results presented in the literature. For instance, Johnson & Hebein (1974) find depreciation rates between 1.0% and 3.4%, Heckman (1976) obtains figures between 0.7% and 4.7%, Haley (1976) between 0.5% and 4.3%, and Arrazola & De Hevia (2004) between 1.2% and

1.5%. Some other studies, such as Groot (1998) and Wu (2007), find much larger depreciation rates between 10% and 20% per year.

4.1 Depreciation and Education

Specifications II, III, and IV aim at investigating the link between education and human capital depreciation, which is debated both theoretically and empirically in the literature. At the theoretical level first, Neuman & Weiss (1995) and Ramirez (2002) argue that depreciation must increase with the education level because "elementary school graduate's human capital does not suffer much from obsolescence since the material taught in elementary schools has not changed much over time" (Neuman & Weiss, 1995, p. 946).

Several reasons might nonetheless explain why education reduces human capital depreciation. Weisbrod (1962, p. 113) notes that "persons having more education are likely to be in a position to adjust more easily than those with less education." In other words, education gives greater flexibility and facilitates access to a larger number of job offers. When his environment changes, a better educated worker will rebound more rapidly. Gould et al. (2001, p. 286) develop a model where "higher ability individuals choose to invest in general education and workers with lower ability choose to invest in technology-specific skills. [...] Consequently, less educated workers, who are relatively more invested in technology-specific skills, will suffer higher rates of human capital depreciation due to technological improvements."

Moreover, it is well-established that more educated workers are also those who take more further on-the-job training.[14] Hence, more educated workers acquire more new human capital and re-train more often, which should tend to slow the depreciation of their existing human capital. This could create a negative link between education and human capital depreciation.

Furthermore, health economics models (Muurinen, 1982; Grossman, 2000) assume that education reduces the depreciation rate of the stock of health, through its impact on life-style selection, diet and exercise decisions, the more efficient production of health from better medical knowledge, or more

[14] Mincer (1974, p. 16) develops this argument as follows: "the size of single-period investments [in human capital] is likely to be an index of lifetime investments. Longer schooling is likely to be followed by greater post-school investment, and generally, the serial correlation of installments of investment is likely to be positive." In the same vein, Cipriani (1967, p. 290) states that "diplomas and degrees perform an 'admission-ticket' function; they often provide the means of entry to certain types of on-the-job training." Finally, in an empirical study based on the SLFS data, Gerfin (2004, p. 12) observes that "training participation is more likely for highly educated workers" and that it is "highly correlated over time."

Table 2: Empirical estimates

	I	II	III	IV
$\ln W$	9.490^{***}	9.712^{***}	9.527^{***}	9.683^{***}
	(0.029)	(0.031)	(0.026)	(0.031)
β_k	0.087^{***}	0.079^{***}	0.086^{***}	0.080^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
δ	0.007^{***}	—	0.008^{***}	—
	(0.000)		(0.000)	
$\delta_{\text{vocational}}$	—	0.010^{***}	—	0.010^{***}
		(0.001)		(0.001)
δ_{academic}	—	0.007^{***}	—	0.008^{***}
		(0.001)		(0.001)
α	0.306^{***}	0.348^{***}	—	—
	(0.010)	(0.012)		
$\alpha_{\text{vocational}}$	—	—	0.300^{***}	0.345^{***}
			(0.010)	(0.012)
α_{academic}	—	—	0.415^{***}	0.396^{***}
			(0.012)	(0.013)
# Obs	60,133	60,133	60,133	60,133
# Ind	27,256	27,256	27,256	27,256
Adj. R^2	0.535	0.546	0.545	0.547
LogL	424	1,197	1,120	1,241
AIC	−686	−2,230	−2,076	−2,316
BIC	44	−1,492	−1,338	−1,569

Notes:

Robust standard errors adjusted for individual clusters in parentheses.

Other controls not reported: 2 dummies for marital status, number of dependents, tenure, 1 dummy for language, 1 dummy for cities with over 100,000 inhabitants, 4 dummies for the number of unemployment periods suffered in the last 10 years, 4 dummies for firm size, 5 dummies for the number of subordinates, 2 dummies for the foreigners' permits, 7 dummies for the origin (continents), 10 year dummies (1999-2008), 25 canton dummies, and 15 sector dummies. The complete tables are reported in Appendix C, along with a discussion of the results obtained on the other controls.

information about alternative sources of care, etc. The stock of health certainly is part of the stock of human capital, as healthier workers will be more productive. The positive impact of education on health might thus lead to a negative relationship between education and human capital depreciation.

In brief, there seems to be much more theoretical models supporting the idea that education reduces human capital depreciation than the opposite. However, the empirical evidence is scarce and contradictory. In an empirical study of women's earnings, Mincer & Polachek (1974) find larger depreciation rates for more educated workers. On the other hand, Arrazola et al. (2005) do not find any significant differences across education groups, and Groot (1998) obtains contradictory results when estimating the same model to British and Dutch datasets.

In this chapter, we separate workers on the basis of their education type instead of using the usual length criterion. Our contention is that depreciation does not only depend on education length, but on the specificity/generality of human capital. Workers with vocational education (apprenticeships, professional and technical schools, and universities of applied sciences) are assumed to possess a relatively specific human capital, compared to workers with academic education (high schools and universities). As expected, our results show that the depreciation rate is lower for the academic group than for the vocational group. The former group suffers a depreciation rate of 1.0%, while the rate for the academic group is 0.7-0.8%.[15]

This result might be explained as follows. Workers who possess general skills are able to operate in a wide range of occupations, and to react quickly following changes in their environment. Consequently, the depreciation rate they suffer is low. On the other hand, workers with mostly specific skills are somewhat "locked" in a particular occupation. When changes occur (technological progress for example), they will suffer substantial losses of human capital, either because the skills they possess are not required anymore to operate in their current occupation, or because they have to change jobs and their current skills are not relevant to the new one.

As noted above, better educated workers are more likely to make post-school investments in human capital, and we therefore let the investment rate vary with education. As for depreciation, education type appears to be relevant in the determination of the investment rates, with significant differences across the groups at any conventional level (F-stat = 9.16). We obtain larger α parameters for workers from the academic track. Hence,

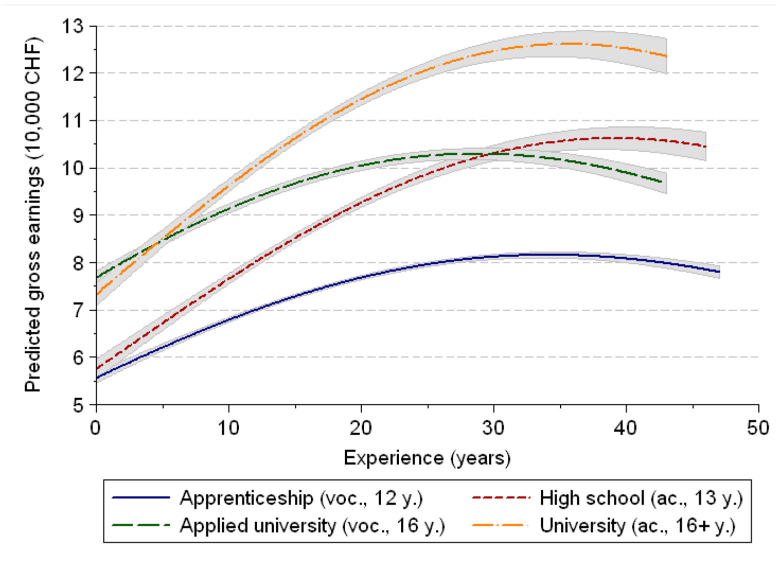
[15] A Wald test for the equality of the two δ parameters leads to an F-statistic of 121.95 with specification II and 118.97 with specification III. The difference between the two groups is thus highly significant and non-negligible.

individuals having acquired more general skills during their youth appear to be those who invest more during their working lives. Individuals from the vocational track, in addition of possessing relatively specific skills, do not invest as much during their career.

Figure 7 shows the experience-earnings profiles predicted by specification IV, which is our preferred one.[16] The profiles globally shift up with education level. However, they are clearly not parallel, and some trajectories even cross under the effect of different depreciation and investment rates. Workers from the academic group, with a lower depreciation rate and a larger investment rate, enjoy steeper experience-earnings profiles. Workers from the vocational group follow a rather flat trajectory. General education therefore seems more beneficial to workers than specific education.

Remarkably, the trajectory for university graduates crosses the one for applied university graduates early in their career. The estimates predict university graduates earn less than workers holding an applied university degree at the beginning of their careers. This finding is noteworthy because it corroborates what is actually observed in the Swiss labor market (SFSO, 2008). The initial earnings difference in favor of applied university students is quickly offset by the larger wage growth enjoyed by traditional university

Figure 7: Predicted experience-earnings profiles (specification IV)



Notes: voc. = vocational, ac. = academic.
Shaded areas are confidence intervals at 99%.

[16]The log-likelihood, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) all indicate that specification IV is to be preferred.

students.

The model also predicts that earnings for high school graduates will exceed those for applied university graduates late in the career. Even if high school workers have spent 3 years less in education, their lower depreciation rate and their larger investment rate suffices to eventually compensate the initial difference. This underlines strikingly the importance of human capital depreciation and of continuing training. In the long run, an initial educational investment could be wasted if these two components are poorly managed.

5 Conclusions

This chapter investigates empirically the relationship between education and human capital depreciation. This topic has received relatively little attention in the literature and yet the few results are contradictory. The present study offers a somewhat unusual approach of the problem. Instead of defining education groups by the standard education length criterion, we rather focus on education type, general or specific. Our view is that general education enables workers to adapt more effectively to new situations they encounter on the job market. Specific education, however, makes workers dependent on a specific workstation or a particular occupation, making them vulnerable to market fluctuations. As a result, human capital depreciation might well be related to education type, and not simply to education length.

We use data from the Swiss Labor Force Survey (SLFS) over 1998-2008, which enables us to take advantage of Switzerland's particular educational system. The vocational track (apprenticeships, professional and technical schools, universities of applied sciences) prepares student for relatively precise occupations, with much of the training being provided directly by a company in the form of internships. The academic track (high schools, universities) provides student with a much broader knowledge that does not directly target an occupation.

Therefore, the vocational track may be thought of as providing more specific skills than the academic track, through which students acquire more general skills, and we assimilate vocational education to specific education and academic education to general education. We find that human capital depreciation is significantly related to the type of skills. As expected, general skills protect workers more effectively against depreciation than specific skills. The depreciation rates we obtain are 0.7-0.8% for general education and 1.0% for specific education. These values fall in the range of the estimates found in the literature.

The experience-earnings profiles resulting from our estimations are steep for workers with general education and relatively flat for those with specific education. These results underscore the need to manage human capital depreciation and not just education. With large depreciation rates, educational investments become useless since they will be quickly eroded. In the long run, workers would in fact be better off with a low initial level of education and a low depreciation rate rather than a high education level and a high depreciation rate.

Appendix A: Descriptive Statistics

Table A.1: Selection of the valid observations

Year	I Total SLFS[a]	II Active workers	III Subsample 1[b]	IV Subsample 2[c]	V Final sample[d]
			Men		
1998	7,379	5,400	3,505	3,119	2,711
1999	7,959	5,835	3,746	3,200	2,815
2000	7,943	5,762	3,626	3,122	2,708
2001	8,432	6,040	3,794	3,335	2,934
2002	18,413	12,820	7,970	6,859	5,872
2003	27,094	18,847	12,503	9,700	8,473
2004	25,053	17,066	11,462	8,859	7,715
2005	23,773	15,936	10,766	8,275	7,018
2006	22,158	14,785	10,001	7,665	6,597
2007	22,304	14,955	10,165	7,855	6,816
2008	21,895	14,547	9,701	7,558	6,474
Total	192,403	131,993	87,239	69,547	60,133
			Women		
1998	8,945	4,756	1,598	1,314	1,120
1999	9,775	5,188	1,697	1,378	1,205
2000	9,800	5,210	1,624	1,340	1,177
2001	10,313	5,520	1,686	1,397	1,232
2002	22,901	12,119	3,595	2,930	2,474
2003	30,608	16,195	5,184	3,843	3,347
2004	29,192	14,948	4,849	3,569	3,043
2005	28,050	14,167	4,637	3,459	2,903
2006	26,136	13,146	4,244	3,106	2,579
2007	26,186	13,309	4,275	3,183	2,696
2008	26,019	13,506	4,355	3,270	2,765
Total	227,925	118,064	37,744	28,789	24,541

[a] 31 individuals were recorded with varying gender across waves. The gender of the 106 observations concerning these individuals was recoded to missing and they do not appear in the count of the original SLFS sample.

[b] Salaried workers (without self-employed and workers in public administration), who are employed full-time, aged between 16 and age retirement age (65 for men, 62-64 for women), and with gross annual earnings of at least 30,000 Swiss francs.

[c] Subsample 1 (column III) less individuals in non-selected education groups and PhD holders.

[d] Observations without missing values in any of the covariates used in estimations and not considered as outliers by the method of Billor et al. (2000).

Source: Swiss Labor Force Survey, 1998-2008.

Table A.2: Descriptive statistics for 2008, by gender

Variable	Whole sample	Men	Women
Gross annual income (December 2005 CHF)	86,584	91,633	72,931
	(34,629)	(36,196)	(25,368)
Education: apprenticeship (12 y.)	0.465	0.470	0.452
Education: high school degree (13 y.)	0.073	0.058	0.114
Education: professional school (14 y.)	0.051	0.043	0.073
Education: technical school (14 y.)	0.042	0.048	0.025
Education: upper professional school (15 y.)	0.109	0.117	0.087
Education: applied university (16 y.)	0.068	0.074	0.052
Education: university (16 y. or more)	0.192	0.190	0.198
Education length (years)	13.626	13.648	13.567
	(1.716)	(1.729)	(1.679)
Experience (years)	20.610	21.874	17.189
	(11.407)	(11.097)	(11.533)
Total potential working life (years)	45.104	45.352	44.433
	(1.763)	(1.729)	(1.679)
Tenure (years)	9.389	10.315	6.885
	(9.650)	(10.072)	(7.875)
Age (years)	40.080	41.365	36.604
	(11.331)	(11.002)	(11.476)
Marital status: single	0.410	0.333	0.618
Marital status: married	0.487	0.580	0.235
Marital status: separated (divorced or widowed)	0.103	0.087	0.147
# dependents	0.732	0.896	0.289
	(1.037)	(1.095)	(0.686)
Dependents (yes/no)	0.393	0.471	0.182
Language: interview = home canton	0.931	0.926	0.943
City $\geq$ 100,000 inhabitants	0.129	0.115	0.167
Foreigners' permit: settlement (C)	0.141	0.147	0.126
Foreigners' permit: residence (B)	0.089	0.082	0.109

(*continued on next page*)

Table A.2 (*continued*)

Variable	Whole sample	Men	Women
Origin: Swiss	0.769	0.771	0.765
Origin: EU15	0.150	0.150	0.152
Origin: EU25 (− EU15)	0.004	0.003	0.009
Origin: Europe (− EU25)	0.048	0.050	0.045
Origin: Africa	0.006	0.006	0.005
Origin: North America	0.004	0.004	0.004
Origin: South America	0.005	0.004	0.009
Origin: Asia	0.011	0.011	0.011
Origin: Australia	0.001	0.001	0.001
Unemployment in the last 10 years: never	0.794	0.808	0.756
Unemployment in the last 10 years: once	0.157	0.146	0.188
Unemployment in the last 10 years: twice	0.036	0.033	0.044
Unemployment in the last 10 years: 3 times	0.009	0.008	0.010
Unemployment in the last 10 years: > 3 times	0.004	0.005	0.002
# subordinates: none	0.526	0.489	0.626
# subordinates: 1-10	0.342	0.359	0.297
# subordinates: 11-19	0.051	0.059	0.028
# subordinates: 20-49	0.049	0.056	0.031
# subordinates: 50-99	0.015	0.017	0.009
# subordinates: 100 or more	0.016	0.020	0.008
Firm size: 1-10	0.167	0.155	0.201
Firm size: 11-19	0.099	0.099	0.100
Firm size: 20-49	0.173	0.176	0.167
Firm size: 50-99	0.127	0.129	0.121
Firm size: 100 or more	0.433	0.442	0.411
# Obs. in sample	9,239	6,474	2,765
# Ind. represented	1,368,951	999,416	369,535

Source: Swiss Labor Force Survey, 2008.

Notes: Standard deviations in parentheses. The descriptive statistics use sampling weights.

Appendix B: Analysis for Women

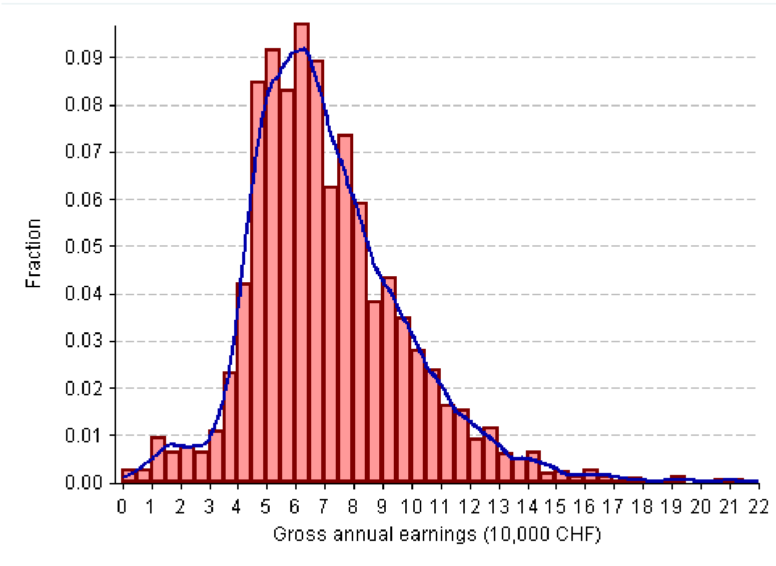
This Appendix shows all descriptive statistics and results for the female sample, allowing for comparisons with the analyses conducted for men in the main text.

Figure B.1 shows the earnings distribution in 2008. As for the male sample, there is a break in the distribution around CHF 30,000, and we remove individuals declaring annual earnings below that threshold.

The number of observations remaining in the final sample (Table B.1) is much lower for women that for men. This is due to our selection criteria (see Table A.1). In particular, a large proportion of the female workers are removed because they are part-time workers (almost 50% of the active women are part-time workers in Switzerland).

The empirical experience-earnings profiles for women are shown in Figure B.2. They are not as well established as those for men, simply because they are based on much fewer observations. However, the main remarks re-

Figure B.1: Earnings distribution in 2008, Women



Notes: The bars are scaled so that the sum of their heights equals 1. The plain line is an appropriately scaled kernel density estimate of the density. The graph is based on the 2008 female sample (2,765 ind.) without restricting the gross earnings to be greater than CHF 30,000 (84 ind.), i.e., on 2,849 individuals, and using sampling weights. Earnings over CHF 220,000 (2 ind.) are not displayed to make the graph more readable.

Table B.1: Composition of the final sample, Women

Highest education level	Type	Length (years)	# Obs.	(%)
Apprenticeship	Vocational	12	11,641	(47.4%)
High school degree	Academic	13	3,147	(12.8%)
Professional school	Vocational	14	2,638	(10.7%)
Technical school	Vocational	14	654	(2.7%)
Upper professional school	Vocational	15	1,644	(6.7%)
Applied university	Vocational	16	1,193	(4.9%)
University	Academic	16+	3,624	(14.8%)
Total # Obs.		13.38	24,541	(100.0%)
Total # Ind.			12,720	

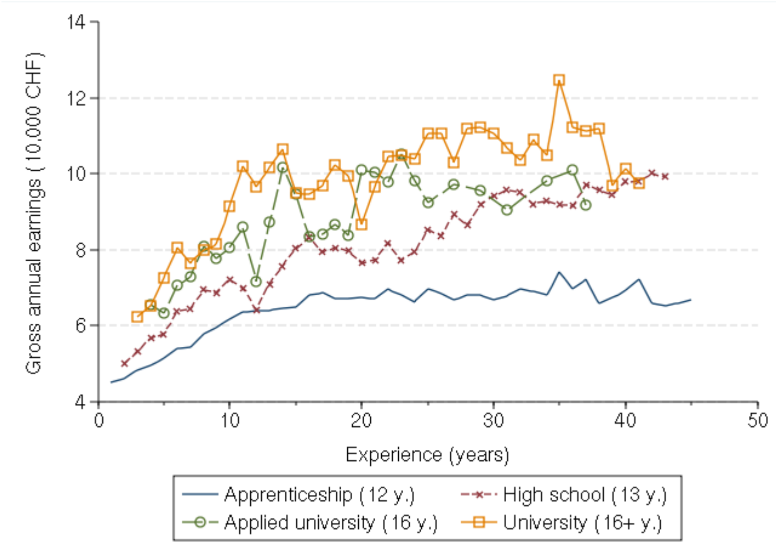
main unchanged: more education leads to higher earnings, and the profiles seem to diverge with experience. One can moreover observe that the spreads between education groups are narrower for women than for men.

Before turning to the results of the estimations for women, we note that very few empirical studies concerned with human capital depreciation provide estimates for women. Their labor market behavior is more difficult to analyze, because of selection issues (non-participation, part-time work, ...). We nevertheless display these results as an illustration. With these potential shortcomings in mind, comparing the estimates for the different genders is still interesting.

Table B.2 displays the results. Our baseline estimate for the human capital depreciation rate of women is 1.4% (specification I), which corresponds to twice that for men. A larger human capital depreciation rate for women seems legitimate, as they are more prone to career interruptions and we cannot control for that. Being out of work could lead to both an interruption in the process of producing new human capital and a more rapid obsolescence of their existing human capital.

Because there are very few results for female workers in the literature, comparing our results is not easy. Mincer & Polachek (1974) obtain depreciation rates between 0.2% and 4.3%, with larger values for more educated women. Arrazola & De Hevia (2004) obtain estimates between 0.3% and 1.2%, but their estimates are non-significant and in fact lower than those for men. Finally, Wu (2007) obtain depreciation rates of 13.2% for white females and of 12.4% for black females. The ranking with their male counterparts is however contradictory: the rate for white females is significantly larger than for white males (11.6%) while the reverse is true for black individuals

Figure B.2: Empirical experience-earnings profiles, Women



Note: The profiles are based on the final sample (Table B.1). Median income is computed for each education group and each year of experience using sampling weights. Information is drawn only when there are at least 15 observations in an education group – year of experience cell.

(depreciation of 18.1% for black males).

When we let the parameters be heterogeneous across education groups, the findings corroborates what we obtain for men: depreciation is larger for the vocational group than for the academic group. In the heterogeneous case also, the depreciation rates correspond to twice that of the corresponding male groups. Finally, Figure B.3 displays the trajectories predicted by specification IV for some groups of education.

Table B.2: Empirical estimates, Women (complete table)

	I	II	III	IV
$\ln W$	9.532^{***}	9.786^{***}	9.412^{***}	9.772^{***}
	(0.052)	(0.058)	(0.046)	(0.058)
β_k	0.087^{***}	0.080^{***}	0.092^{***}	0.081^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
δ	0.014^{***}	—	0.013^{***}	—
	(0.001)		(0.001)	
$\delta_{\text{vocational}}$	—	0.020^{***}	—	0.020^{***}
		(0.001)		(0.001)
δ_{academic}	—	0.016^{***}	—	0.016^{***}
		(0.001)		(0.001)
α	0.441^{***}	0.506^{***}	—	—
	(0.015)	(0.017)		
$\alpha_{\text{vocational}}$	—	—	0.398^{***}	0.506^{***}
			(0.014)	(0.017)
α_{academic}	—	—	0.478^{***}	0.525^{***}
			(0.015)	(0.018)
Married	-0.042^{***}	-0.041^{***}	-0.039^{***}	-0.041^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
Separated	-0.046^{***}	-0.041^{***}	-0.041^{***}	-0.039^{***}
	(0.008)	(0.007)	(0.007)	(0.007)
# dependents	-0.037^{***}	-0.041^{***}	-0.039^{***}	-0.041^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Tenure (years)	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Language	0.036^{***}	0.040^{***}	0.036^{***}	0.039^{***}
	(0.013)	(0.013)	(0.013)	(0.013)
City $\geq$ 100,000 inhabitants	-0.004	-0.007	-0.004	-0.006
	(0.008)	(0.007)	(0.007)	(0.007)
1 unemployment spell	-0.051^{***}	-0.051^{***}	-0.051^{***}	-0.052^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
2 unemployment spells	-0.068^{***}	-0.070^{***}	-0.069^{***}	-0.071^{***}
	(0.009)	(0.009)	(0.009)	(0.009)
3 unemployment spells	-0.078^{***}	-0.078^{***}	-0.079^{***}	-0.079^{***}
	(0.016)	(0.016)	(0.016)	(0.016)
4 or more unemployment spells	-0.143^{***}	-0.151^{***}	-0.152^{***}	-0.153^{***}
	(0.034)	(0.036)	(0.036)	(0.036)
Firm size: 11-19	0.031^{***}	0.032^{***}	0.033^{***}	0.033^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Firm size: 20-49	0.051^{***}	0.051^{***}	0.051^{***}	0.051^{***}
	(0.007)	(0.006)	(0.007)	(0.006)
Firm size: 50-99	0.061^{***}	0.063^{***}	0.062^{***}	0.063^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Firm size: 100 or more	0.098^{***}	0.100^{***}	0.099^{***}	0.100^{***}
	(0.006)	(0.006)	(0.006)	(0.006)

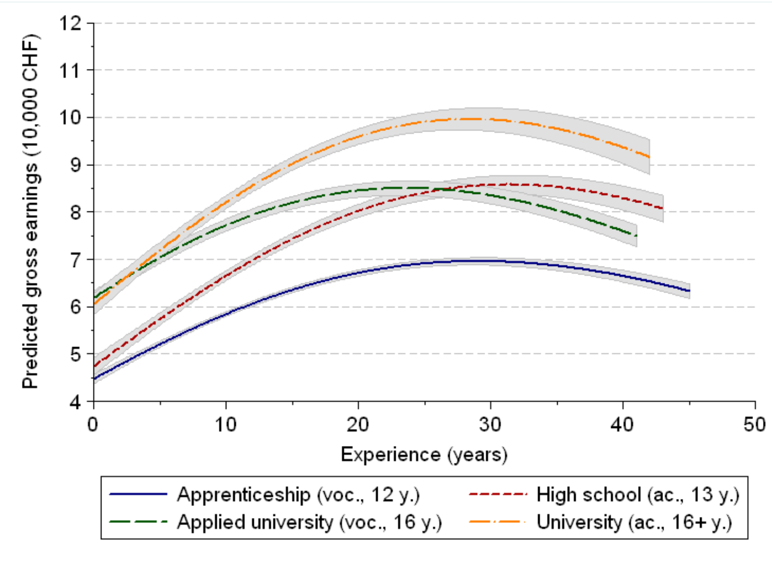
(*continued on next page*)

Table B.2 (*continued*)

	I	II	III	IV
No subordinate	-0.092^{***}	-0.091^{***}	-0.089^{***}	-0.091^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
11-19 subordinates	0.053^{***}	0.056^{***}	0.055^{***}	0.057^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
20-49 subordinates	0.091^{***}	0.088^{***}	0.087^{***}	0.088^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
50-99 subordinates	0.152^{***}	0.149^{***}	0.146^{***}	0.149^{***}
	(0.020)	(0.019)	(0.020)	(0.019)
100 or more subordinates	0.080^{***}	0.078^{***}	0.074^{***}	0.078^{***}
	(0.025)	(0.024)	(0.024)	(0.024)
Foreigners' permit: settlement (C)	-0.036^{***}	-0.041^{***}	-0.041^{***}	-0.042^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
Foreigners' permit: residence (B)	-0.029^{***}	-0.041^{***}	-0.027^{***}	-0.038^{***}
	(0.010)	(0.010)	(0.010)	(0.009)
Origin: EU25 (− EU15)	-0.083^{***}	-0.094^{***}	-0.085^{***}	-0.092^{***}
	(0.028)	(0.028)	(0.028)	(0.028)
Origin: Europe (− EU25)	-0.105^{***}	-0.110^{***}	-0.108^{***}	-0.110^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
Origin: Africa	-0.121^{***}	-0.122^{***}	-0.115^{**}	-0.121^{***}
	(0.047)	(0.045)	(0.045)	(0.045)
Origin: North America	0.109^{***}	0.083^{***}	0.089^{***}	0.083^{***}
	(0.031)	(0.030)	(0.030)	(0.029)
Origin: South America	-0.151^{***}	-0.155^{***}	-0.152^{***}	-0.154^{***}
	(0.025)	(0.025)	(0.026)	(0.025)
Origin: Asia	-0.047	-0.061^{**}	-0.051^{*}	-0.060^{**}
	(0.029)	(0.028)	(0.028)	(0.028)
Origin: Australia	0.272^{***}	0.243^{**}	0.253^{***}	0.244^{**}
	(0.104)	(0.099)	(0.097)	(0.098)
Year dummies	yes	yes	yes	yes
Canton dummies	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
# Obs	24,541	24,541	24,541	24,541
# Ind	12,720	12,720	12,720	12,720
Adj. R^2	0.486	0.499	0.493	0.500
LogL	357	679	526	686
AIC	−552	−1,193	−888	−1,207
BIC	104	−528	−223	−534

Notes:
Robust standard errors adjusted for individual clusters in parentheses.
The log-likelihood values are positive. For continuous outcomes, the log-likelihood is the log of a density, and since density functions can be greater than 1, a positive value for the log-likelihood is possible.

Figure B.3: Predicted experience-earnings profiles (specification IV), Women



Notes: voc. = vocational, ac. = academic.
Shaded areas are confidence intervals at 99%.

Appendix C: Other Covariates

In this Appendix, we display the complete results table and discuss the effects of some interesting controls included in the estimations. It is first remarkable that estimates for the controls are very stable across the different specifications and consistent with the economic literature.

Our results show that being married (compared to single) and having children are associated with larger earnings for male workers but not for women. That can be explained because employers expect married men with children to be more reliable than single ones. On the contrary, being married and having children often goes along with a relative geographical immobility for women. It can also be put forward that many women interrupt their career when they get married or have children so that they may suffer wage losses when returning to the labor market. It is interesting to compare these results with other studies concerned with various aspects of the Swiss labor market. Ferro Luzzi & Flückiger (1998) find that marriage lessens the likelihood to access upper hierarchical positions for women but increases it for men. Flückiger & Ramirez (2001) analyze wages and obtain results completely in line with ours. Finally, Weber (2006) observes that married women need more time to find a new job when unemployed, whereas the reverse is true about married men. It thus appears clearly that marriage and children constitute a plus for male workers but a considerable drawback for women on the Swiss labor market.

Chiswick & Miller (1995) have shown that language fluency is an important determinant of earnings. Even though there is no information about the language skills of the individuals neither about their mother tongue in the SLFS, we use the language used during the interview as a proxy.[17] From this information, we construct a dummy variable indicating if the language chosen by the individual during the survey corresponds to the official language of the canton where he lives. We believe this constitutes a good proxy for integration in the socio-economic environment. In fact, this variable has a positive and significant impact on earnings.

Having been unemployed in the past causes large wage losses. Our results show that the wage penalty increases with the number of unemployment spells. Male workers who were at least four times unemployed in the last ten years incur a wage penalty of 15%. Jacobson, LaLonde, & Sullivan (1993) provide thorough explanations about why unemployed workers

[17] Until 2002, the possible choices to answer the SLFS were the three Swiss national languages: German, French and Italian. But since the introduction in 2003 of a special part exclusively dedicated to foreigners, respondents can additionally choose English, Albanian, Serbo-Croatian, Portuguese, or Turkish.

experience earnings losses in their subsequent jobs and how their earnings recover. While studying the effect of different types of career interruption on wages, Albrecht, Edin, Sundström, & Vroman (1999) show that unemployment spells are the most harmful. They moreover observe that the wage penalty is stronger for men than for women, a result that we obtain as well (compare Tables C.1 and B.2).

Firm size has a clearly positive impact on earnings: employees of firms with at least 100 co-workers earn about 9% more than employees of small firms with up to 10 workers. Even if this firm size wage effect has been widely studied, a definitive explanation has still not been reached (see Oi & Idson, 1999, for a thorough survey and e.g., Lallemand, Plasman, & Rycx, 2007, for a recent analysis). We moreover control for the number of subordinates, which is certainly a good proxy for the level of responsibility borne by a worker. As expected, the results show that the more one has subordinates, the more he earns.

Foreign workers are in general paid less than Swiss. Significant divergences across nationalities can however be observed. First, it should be highlighted that among male workers, UE15 nationals (reference category for the origins) with a residence permit have wages almost identical to Swiss citizens. North Americans as well as Australians seem to earn even more than Swiss workers, but since these coefficients are based on a very small number of observations, they have to be considered with caution. The less paid workers are Africans, with wages 26-27% lower than Swiss.

Table C.1: Empirical estimates, Men (complete table)

	I	II	III	IV
$\ln W$	9.490^{***}	9.712^{***}	9.527^{***}	9.683^{***}
	(0.029)	(0.031)	(0.026)	(0.031)
β_k	0.087^{***}	0.079^{***}	0.086^{***}	0.080^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
δ	0.007^{***}	—	0.008^{***}	—
	(0.000)		(0.000)	
$\delta_{\text{vocational}}$	—	0.010^{***}	—	0.010^{***}
		(0.001)		(0.001)
δ_{academic}	—	0.007^{***}	—	0.008^{***}
		(0.001)		(0.001)
α	0.306^{***}	0.348^{***}	—	—
	(0.010)	(0.012)		
$\alpha_{\text{vocational}}$	—	—	0.300^{***}	0.345^{***}
			(0.010)	(0.012)
α_{academic}	—	—	0.415^{***}	0.396^{***}
			(0.012)	(0.013)
Married	0.048^{***}	0.053^{***}	0.053^{***}	0.054^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Separated	0.031^{***}	0.033^{***}	0.033^{***}	0.033^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
# dependents	0.015^{***}	0.013^{***}	0.013^{***}	0.012^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Tenure (years)	0.000	0.000^{**}	0.000^{**}	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Language	0.017^{**}	0.024^{***}	0.019^{***}	0.023^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
City $\geq$ 100,000 inhabitants	-0.027^{***}	-0.030^{***}	-0.024^{***}	-0.028^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
1 unemployment spell	-0.070^{***}	-0.067^{***}	-0.069^{***}	-0.068^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
2 unemployment spells	-0.103^{***}	-0.100^{***}	-0.104^{***}	-0.101^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
3 unemployment spells	-0.125^{***}	-0.123^{***}	-0.127^{***}	-0.125^{***}
	(0.011)	(0.012)	(0.012)	(0.012)
4 or more unemployment spells	-0.151^{***}	-0.145^{***}	-0.147^{***}	-0.146^{***}
	(0.016)	(0.016)	(0.016)	(0.016)
Firm size: 11-19	0.019^{***}	0.020^{***}	0.020^{***}	0.020^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
Firm size: 20-49	0.034^{***}	0.035^{***}	0.036^{***}	0.036^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Firm size: 50-99	0.057^{***}	0.058^{***}	0.059^{***}	0.058^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
Firm size: 100 or more	0.087^{***}	0.087^{***}	0.089^{***}	0.088^{***}
	(0.004)	(0.004)	(0.004)	(0.004)

(*continued on next page*)

Table C.1 (*continued*)

	I	II	III	IV
No subordinate	-0.105^{***}	-0.106^{***}	-0.104^{***}	-0.105^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
11-19 subordinates	0.088^{***}	0.088^{***}	0.086^{***}	0.087^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
20-49 subordinates	0.116^{***}	0.112^{***}	0.109^{***}	0.111^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
50-99 subordinates	0.179^{***}	0.175^{***}	0.171^{***}	0.174^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
100 or more subordinates	0.237^{***}	0.223^{***}	0.219^{***}	0.221^{***}
	(0.013)	(0.013)	(0.013)	(0.013)
Foreigners' permit: settlement (C)	-0.033^{***}	-0.039^{***}	-0.038^{***}	-0.039^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Foreigners' permit: residence (B)	0.002	-0.014^{**}	0.001	-0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Origin: EU25 (− EU15)	-0.088^{***}	-0.095^{***}	-0.091^{***}	-0.094^{***}
	(0.033)	(0.033)	(0.033)	(0.033)
Origin: Europe (− EU25)	-0.144^{***}	-0.153^{***}	-0.152^{***}	-0.154^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Origin: Africa	-0.261^{***}	-0.269^{***}	-0.270^{***}	-0.270^{***}
	(0.021)	(0.021)	(0.021)	(0.021)
Origin: North America	0.138^{***}	0.107^{***}	0.113^{***}	0.107^{***}
	(0.031)	(0.031)	(0.031)	(0.031)
Origin: South America	-0.166^{***}	-0.179^{***}	-0.172^{***}	-0.177^{***}
	(0.032)	(0.032)	(0.032)	(0.032)
Origin: Asia	-0.177^{***}	-0.196^{***}	-0.190^{***}	-0.196^{***}
	(0.019)	(0.019)	(0.019)	(0.019)
Origin: Australia	0.154^{***}	0.126^{***}	0.130^{***}	0.125^{***}
	(0.043)	(0.040)	(0.041)	(0.040)
Year dummies	yes	yes	yes	yes
Canton dummies	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
# Obs	60,133	60,133	60,133	60,133
# Ind	27,256	27,256	27,256	27,256
Adj. R^2	0.535	0.546	0.545	0.547
LogL	424	1,197	1,120	1,241
AIC	−686	−2,230	−2,076	−2,316
BIC	44	−1,492	−1,338	−1,569

Notes:
Robust standard errors adjusted for individual clusters in parentheses.
The log-likelihood values are positive. For continuous outcomes, the log-likelihood is the log of a density, and since density functions can be greater than 1, a positive value for the log-likelihood is possible.

Appendix D: Outliers' Detection*

D.1 Introduction

The literature on outliers is huge, as proved by Barnett & Lewis's (1994) bibliography of almost 1,000 papers. Despite this considerable research by the statistical community, knowledge apparently fails to spill over and proper methods for detecting and handling outliers are seldom used by practitioners in other fields.

The reason probably lies in that algorithms implemented for the detection of outliers are sparse. Moreover, the few available are so time-consuming that using them may be discouraging. In Stata, `hadimvo` was until now the only command available for identifying outliers. Anyone having tried to use it on large datasets however knows it may take hours or even days to obtain a mere dummy variable indicating which observations should be considered as outliers.

The new command `bacon` presented in this article provides a more efficient way to detect outliers in multivariate data. It is implemented after the Blocked Adaptative Computationally Efficient Outlier Nominators (BACON) algorithm proposed by Billor et al. (2000). BACON is a simple modification of the methodology that was proposed by Hadi (1992, 1994) and implemented in `hadimvo`, but it is much less computationally expensive. As a result, `bacon` runs many times faster than `hadimvo`, even though both commands end up with similar sets of outliers. Identifying multivariate outliers thus becomes fast and easy in Stata, even with very large datasets of tens of thousands observations.

D.2 The BACON Algorithm

The Blocked Adaptative Computationally Efficient Outlier Nominators (BACON) algorithm was proposed by Billor et al. (2000). The reader interested in details is referred to this original article, since only a brief presentation is provided here.

In step 1, an initial subset of m outlier-free observations has to be identified out of a sample of n observations and over p variables. Several distance measures could be used as a criterion, and the Mahalanobis distance seems especially adapted since it possesses the desirable property of being scale-invariant – a great advantage when dealing with variables of different magnitudes or different units. The Mahalanobis distance of a p-

*The article was originally published in the Stata Journal (volume 10: 331-338) and is used with the permission of StataCorp.

dimensional vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})^T$ from a group of values with mean $\overline{x} = (\overline{x}_1, \overline{x}_2, \ldots, \overline{x}_p)^T$ and covariance matrix S is defined as:

$$d_i(\overline{x}, S) = \sqrt{(x_i - \overline{x})^T S^{-1} (x_i - \overline{x})} \qquad i = 1, 2, \ldots, n. \tag{D.1}$$

The initial basic subset is given by the m observations with the smallest Mahalanobis distances from the whole sample. The subset size m is given by the product of the number of variables p and a parameter chosen by the analyst.

Billor et al. (2000) also proposed to use distances from the medians for this first step. This second version of the algorithm is also implemented in `bacon`. We just remind that distances from the medians are not scale-invariant, so that they should be used carefully if the variables analyzed are of different magnitudes.

In step 2, Mahalanobis distances from the basic subset are computed:

$$d_i(\overline{x}_b, S_b) = \sqrt{(x_i - \overline{x}_b)^T S_b^{-1} (x_i - \overline{x}_b)} \qquad i = 1, 2, \ldots, n. \tag{D.2}$$

In step 3, all observations with a distance smaller than some threshold – a corrected percentile of a χ^2 distribution – are added to the basic subset.

Steps 2 and 3 are iterated until the basic subset no longer changes. Observations excluded from the final basic subset are nominated as outliers whereas those inside the final basic subset are non-outliers.

The difference with the algorithm proposed by Hadi (1992, 1994) is that observations are added by blocks in the basic subset instead of observation by observation. Some time is thus spared through a reduction of the number of iterations. Nevertheless, it is important to note that the performance of the algorithm is not altered, as Billor et al. (2000) and section 5 of the present article show.

The reduction in the number of iterations is not the only source of efficiency gain. Another major improvement lies in the way `bacon` is coded. At the time `hadimvo` was implemented, Mata did not exist but it now provides significant speed enhancements to many computationally burdensome tasks, like the calculation of Mahalanobis distances. We therefore coded `bacon` so that it benefits from Mata's power.

D.3 Why Mata Matters for bacon

The command `bacon` uses Mata, the matrix programming language available in Stata since version 9. We explain here how Mata allows `bacon` to run very fast. This section draws heavily on Baum (2008), who offers a general overview of Mata's capabilities.

As we have seen in the previous section, the BACON algorithm requires creating matrices from the data, computing the distances using (D.2), and converting the new matrix containing distances back into the data. Operations that convert Stata variables into matrices or vice versa require at least twice the memory needed for that set of variables, so that using Stata's matrices would consume a lot of memory. On the other hand, Mata's matrices are only views onto, not copies of, the data. Hence, using Mata's virtual matrices instead of Stata's matrices in `bacon` spares memory that can be used to run the computations faster.

Moreover, Stata's matrices are unsuited for holding large amounts of data, their maximal size being 11,000 × 11,000. Using Stata, it would not be possible to create a matrix $X = (x_1, x_2, \ldots, x_i, \ldots, x_n)^T$ containing all observations of the database if the n was larger than 11,000. One would thus have to cut the X matrix into pieces to compute the distances in (D.2), which is obviously inconvenient. Mata circumvents the limitations of Stata's traditional matrix commands, allowing the creation of virtually infinite matrices (over 2 billions rows and columns). Thanks to Mata, we are thus able to create a single matrix X containing all observations whatever n, and then use the powerful element-by-element operations available to compute the distances.

Mata is indeed very efficient for handling element-by-element operations, whereas Stata ado-file code written in the matrix language with explicit subscript references is slow. Since the distances in (D.2) have to be computed for each individual at each iteration of the algorithm, this feature of Mata provides another very important efficiency gain.

D.4 The Syntax of bacon

The syntax of `bacon` is as follows:

`bacon` *varlist* [*if*] [*in*] , `generate(`*newvarname1* [*newvarname2*]`)` [`replace` `percentile(`#`)` `version(`#`)` `c(`#`)`]

`generate` is not optional since it identifies the new variable(s) to be created. Whether you specify two variables or one, however, is optional. *newvarname2*, if specified, will contain the distances from the final basic subset. That is, specifying `gen(out)` creates a dummy variable *out* containing 1 if the observation is an outlier in the BACON sense and 0 otherwise. Specifying `gen(out dist)` additionally creates a variable *dist* containing the distances from the final basic subset.

`replace` specifies that the variable(s) *newvarname1* (and *newvarname2*) be replaced if they already exist in the database. This option makes it easier to run bacon several times on the same data. It should be used cautiously, since it might definitively drop some data.

percentile(#) determines the $1 - \#$percentile of the chi square distribution to be used as a threshold to separate outliers from non-outliers. The default is percentile(.15). Larger numbers identify a larger proportion of the sample as outliers. If # is specified greater than 1, it is interpreted as a percent. Thus, percentile(15) is the same as percentile(.15).

version(#) specifies which version of the BACON algorithm has to be used to identify the initial basic subset in multivariate data. version(1) (the default) identifies the initial subset selected based on Mahalanobis distances. version(2) identifies the initial subset selected based on distances from the medians. Note that in the case of version(2), *varlist* must not contain missing values and you must install the moremata module before running bacon.

c(#) is a parameter that determines the size of the initial basic subset, which is given by the product of c and the number of variables in *varlist*. c must be an integer. By default, c(4) is used.

Finally, let us mention that bacon saves some potentially useful results in r():

Scalars			
r(outlier)	number of outliers	r(iter)	number of iterations
r(corr)	correction factor	r(chi2)	percentile of the χ^2 distribution

D.5 bacon vs hadimvo

Let us now compare bacon and hadimvo considering two criteria: (i) the set of observations identified as outliers, and (ii) the speed. We will see that both commands lead to similar outcomes (providing some tuning of the cutoff parameters), but that hadimvo is terribly slower. bacon thus outperforms hadimvo and should be preferred in any case.

First, let us use the auto.dta dataset to illustrate the similarity of the results obtained through both commands:

```
. webuse auto
(1978 Automobile Data)
. hadimvo weight length, gen(outhadi) p(.05)
  (output omitted)
. bacon weight length, gen(outbacon) p(.15)
  (output omitted)
```

(*Continued on next page*)

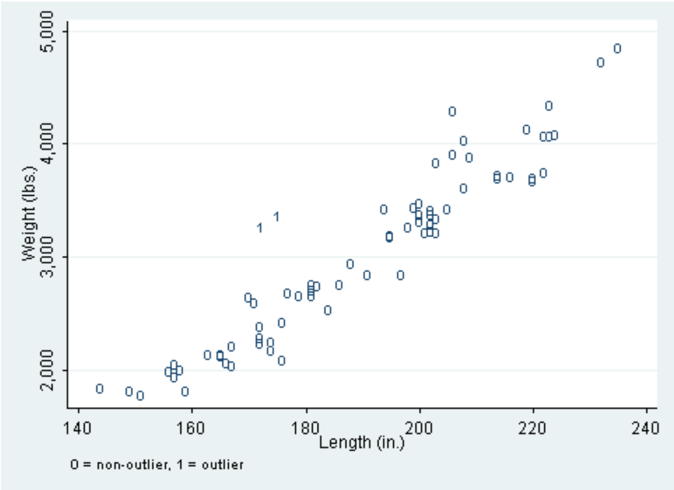
```
. tab outhadi outbacon

     Hadi |
  outlier |  BACON outlier (p=.15)
  (p=.05) |         0          1 |     Total
-----------+----------------------+----------
        0 |        72          0 |        72
        1 |         0          2 |         2
-----------+----------------------+----------
    Total |        72          2 |        74
```

Both commands have identified the same two observations as outliers. Note that the `percentile` parameter was set higher in `bacon` than in `hadimvo`. With a parameter of 5%, `bacon` would not have identified any observation as outlier. It is the role of the researcher to choose the level and it has to be adapted for each dataset, but the default `percentile(.15)` appears to bring sensible outcomes in any case and could always be used as a first benchmark.

With two-dimensional data, it is helpful to draw a scatter plot allowing to see where outliers are located:

```
. scatter weight length, ml(outbacon) ms(i) note("0 = non-outlier, 1 = outlier")
```

Figure D.1: Scatter plot locating the observations identified as outliers



To compare the speed of `bacon` and `hadimvo`, let us now use a larger dataset. Containing about 28,000 observations, `nlswork.dta` is sufficiently large to illustrate our point. Suppose we want to identify outliers with respect to the variables `ln_wage`, `age`, and `tenure`. If we did not have `bacon`, we would type:

```
. webuse nlswork
(National Longitudinal Survey. Young Women 14-26 years of age in 1968)
. hadimvo ln_wage age tenure, gen(outhadi) p(.05)
Beginning number of observations:        28101
              Initially accepted:            4
             Expand to (n+k+1)/2:
```

But at that point, your screen will remain idle. You might become worried and think your computer crashed, but in fact `hadimvo` is simply going to take some long minutes to run its many iterations. And remember: there are "only" 28,000 observations in this dataset. If you are patient enough, Stata will at last show you the outcome:

```
. hadimvo ln_wage age tenure, gen(outhadi) p(.05)
Beginning number of observations:        28101
              Initially accepted:            4
             Expand to (n+k+1)/2:        14052
                Expand,  p = .05:        28081
              Outliers remaining:           20
```

Thanks to `bacon`, you now have an alternative. If you try:

```
. bacon ln_wage age tenure, gen(outbacon) p(.15)
Total number of observations:       28101
   BACON outliers (p = 0.15):          29
      Non-outliers remaining:       28072
```

The solution appears in a few seconds only! Again, we can check that the set of identified outliers is pretty much the same in the two cases:

```
. tab outhadi outbacon

     Hadi |
  outlier |  BACON outlier (p=.15)
  (p=.05) |         0          1 |     Total
----------+----------------------+----------
        0 |    28,072          9 |    28,081
        1 |         0         20 |        20
----------+----------------------+----------
    Total |    28,072         29 |    28,101
```

Given the time `hadimvo` needs and the similarities between the outcomes, it seems clear that `bacon` is preferable.

Since there is no rule for the choice of `percentile`, the practitioner might legitimately be willing to test several values and decide after several trials what set of observations to nominate as outliers. With `hadimvo`, such an iterative process is almost impracticable, unless you are particularly patient and have enough time in front of you. With `bacon` on the other hand, it becomes readily feasible.

Precisely in order to give the possibility of running the algorithm several times without having to add a new variable at each iteration, `bacon` is supplied with a `replace` option. For the user wanting to try several `percentile` values, this option will prove convenient:

```
. bacon ln_wage age tenure, gen(outbacon) p(.1)
outbacon already defined
r(110);

. bacon ln_wage age tenure, gen(outbacon) p(.1) replace
Total number of observations:       28101
   BACON outliers (p = 0.10):           6
      Non-outliers remaining:       28095

. bacon ln_wage age tenure, gen(outbacon) p(.2) replace
Total number of observations:       28101
   BACON outliers (p = 0.20):         160
      Non-outliers remaining:       27941
```

D.6 Conclusion

"The two big questions about outliers are 'how do you find them?' and 'what do you do about them?'" (Ord, 1996). The command `bacon` presented here provides an answer to the first of these questions. The answer to the second is behind the scope of this article and is left to the appreciation of the researcher.

No doubt, `bacon` renders the process of detecting outliers in multivariate data easier. Compared to `hadimvo`, the only other command devoted to this task in Stata, it appears to identify a similar set of observations as outliers. In terms of speed, `bacon` proves to be far faster. Hence, there is no apparent reason to use `hadimvo` instead of `bacon`.

Even if the command `bacon` provides a fast and easy way to identify potential outliers, a certain amount of judgment is always needed when deciding which cases to nominate as outliers and what to do with these observations. Most researchers simply discard outliers, but before you do so, keep in mind that something new and useful can often be learned by looking at the nominated cases.

Chapter 2

Wage Growth: Education Type Matters more than Education Length*

1 The Causes of Wage Growth

The reasons for studying lifecycle wage growth and its causes are numerous. In particular, wage growth is a central concern for active labor market policies, which aim at speeding up the return of unemployed to the labor market. Such policies are based on the view that human capital depreciation is faster when workers remain out of the labor market. The unemployed are often urged to accept a job, even if it does not exactly correspond to what they were previously doing. However, if wages grow essentially with occupational experience, it would be better not to push individuals out of their previous occupation, even at the cost of longer unemployment spells.

The general increase in job mobility observed in Switzerland (Sousa-Poza, 2004) as well as abroad (Kambourov & Manovskii, 2008) is a further reason for studying the sources of wage growth. As job mobility increases, job switches accompanied by occupation and industry changes become more frequent, and such moves might destroy some amount of human capital.

The causes of wage growth have been widely analyzed but no consensus has been reached. The accumulation of different types of human capital obviously plays some role in this process (Topel, 1991), but job shopping

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*This paper was presented at the Interdisciplinary Congress on Research in Vocational Education and Training, Berne (Switzerland), March 2009; at the Young Swiss Economist Meeting (YSEM), Berne (Switzerland), January 2010; and at the Annual Congress of the European Economic Association (EEA), Glasgow (Scotland), August 2010.

also accounts for some part of it (Altonji & Shakotko, 1987).[1] Disentangling the effects of job tenure (seniority), occupational experience, industrial experience, general labor market experience, and job mobility is the task undertaken in this chapter. More precisely, the question we explore is whether the returns to different components of experience differ by education groups. To this end, we define three education categories, namely compulsory school, apprenticeship, and university. Our expectation is that workers with apprenticeship training should benefit a rather low wage growth during their career, because they possess a relatively specific human capital,[2] and because much of the learning is concentrated during the apprenticeship period.

The distinction between general and specific skills is the cornerstone of the human capital theory (Becker, 1964). However, some human capital is probably neither fully firm-specific, nor completely general and transferable across all employers (Stevens, 1994). Skills might indeed be portable across some firms but not all, for example across firms in the same industry or firms employing workers for similar occupations. This suggests possible extensions for the human capital theory, with the introduction of occupational and industrial components of human capital.

Shaw (1984, 1987) was the first to consider the concept of occupational specific human capital. The literature has however failed to build on these early attempts and is now divided between papers considering industrial specific human capital only[3] and those considering both occupational and industrial specific human capital.[4] A usual finding of this literature is that occupational and general experience bring larger returns than industrial experience and tenure. The returns to firm tenure appear to be unsignificant when occupational and/or industrial experience are accounted for.[5] Assess-

[1]Luchsinger, Lalive, & Wild (2003) provide empirical estimations of the returns to tenure and experience in Switzerland, using both models proposed by Altonji & Shakotko (1987) and Topel (1991).

[2]Acemoglu & Pischke (1998, 1999) claim that most of the skills learned during the apprenticeship constitute general training. That does not contradict our assumption though, since we only pretend that workers with apprenticeship training possess a human capital *relatively* more specific than both the less-educated (compulsory school) and the more-educated (university).

[3]See Neal (1995), Parent (2000), Cingano (2003), Dustmann & Meghir (2005), and Connolly & Gottschalk (2006).

[4]See Neal (1999), Goldsmith & Veum (2002), Pavan (2006), Zangelidis (2008), Kambourov & Manovskii (2009), and Sullivan (2010).

[5]All of the papers previously cited, as well as the present chapter, define occupational and industrial experience using information about occupation and industry codes. Experience grows while the worker keeps the same code and is reset to zero if the code changes. This methodology clearly has some drawbacks. For example, some occupations appear very close even when considering broad two-digits classifications, but changing

ing the relative importance of the different experience types is still a matter of discussion.

Professional associations and collective agreements constitute additional arguments in favor of the consideration of occupational and industrial experience. If a professional association acts like a labor union for the members of the occupation, it might influence wages in this occupation. Likewise, collective agreements may play some role in determining wages in an industry.

Occupational specific human capital and industrial specific human capital might be very different one from another. A worker might indeed change industry while keeping the same occupation, or he might switch occupation within the same industry. For example, an economist may move from a bank to a pharmaceutical company, implying a change in industry but not in occupation. Otherwise, the worker may remain in the same bank, but move from a position of economist to a position of financial director, which would imply a change in occupation but not in industry. In both cases, the worker will retain some of his human capital following his move, but that part will be different. Hence, considering both types of experience simultaneously appears fundamental.

In this chapter, we extend Connolly & Gottschalk's (2006) model, adding occupational experience that they do not consider. We are thus able to identify the wage effects of firm tenure, occupational experience, industrial experience, general labor market experience, and improved job match. We provide an empirical estimation using data from the Swiss Labor Force Survey (SLFS). This dataset has several advantages over the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY) used by virtually all the literature on occupational and industrial human capital. First, it is not plagued by the measurement errors in the coding of industry and occupation codes observed in the PSID and the NLSY. Furthermore, the samples available in our data are much larger.

The remainder of the chapter is organized as follows. Section 2 devel-

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codes implies losing all occupational specific human capital. However, the great advantage of occupations and industries classifications is that they are coded in virtually every labor survey, so that approaches based on them only can be broadly replicated.

Poletaev & Robinson (2008), using data from the Dictionary of Occupational Titles, and Gathmann & Schönberg (2010), using data from the German Qualification and Career Survey, bring the analysis one step further. Both of these studies construct, in a different way, measures of the skills needed for each occupation. The interest of such an approach is that jobs can be ranked according to how close they are in terms of their skills portfolio. This surely constitutes an improvement since neither occupation nor industry classifications are especially designed to represent transferability of skills. Unfortunately, the type of data used by Poletaev & Robinson (2008) or Gathmann & Schönberg (2010) are not widely available.

ops the econometric specification. Section 3 describes the SLFS data that are used for the empirical estimations. Section 4 discusses the estimates. Conclusions are provided in section 5.

2 Model Specification

We use an extended version of Connolly & Gottschalk's (2006) model, who do not take occupational experience into account. We start from the following wage equation:

$$Y_{ijt} = \beta_X X_{ijt} + \beta_T T_{ijt} + \beta_O O_{ijt} + \beta_I I_{ijt} + \beta_Z Z_{ijt} + \varepsilon_{ijt} \tag{1}$$

where Y_{ijt} is the logarithm wage of individual i in firm j at period t, X_{ijt} is general experience, T_{ijt} is tenure or firm-specific experience,[6] O_{ijt} is occupational experience, I_{ijt} is industrial experience, and Z_{ijt} is a vector of time-varying characteristics. The β parameters are to be interpreted as returns to the different components of experience. The error term ε_{ijt} is given by:

$$\varepsilon_{ijt} = \mu_i + \nu_{ijt} + \phi_{ij(t)} \tag{2}$$

where μ_i is a fixed individual-specific error component, ν_{ijt} is an idiosyncratic component that accounts for random shocks and measurement errors, and $\phi_{ij(t)}$ is a fixed job match specific component whose expectation is given by:

$$E[\phi_{ij(t)}] = \alpha_0 + \alpha_X X_{ijt} + \alpha_T T_{ijt} + \alpha_O O_{ijt} + \alpha_I I_{ijt} + \eta_{ijt} \tag{3}$$

where η_{ijt} is an error term, and the α parameters are to be interpreted as simple correlations between the expected value of the job match and the different components of experience. The job match component is assumed to be constant within a job, and we stress that (3) only expresses its expectation, not its realization.[7] The idea behind this assumption is that a match possesses a certain underlying value, which is given from the start of a job and does not change over time. The expectation of the match is allowed to change though, because while the worker and the firm "experience" their match, information is revealed, and this alters their *knowledge* of the job match, but not the *intrinsic value* of the match itself. Anyway, the level of the job match component is in fact not important per se, and we focus on its variations between jobs as the model will be estimated in first-differences.

General experience is included in (3) because more experienced workers are assumed to have sampled a larger number of job offers. Job search

[6] In the empirical estimations, we add a squared term for general experience.

[7] For this reason, the subscript t appears in brackets.

models (e.g., Burdett, 1978) predict a positive correlation between general experience and the job match value, so that α_X is expected to be positive: since individuals change job when they receive a better offer, they gradually move toward jobs they are better suited for, i.e., jobs with higher match values.

Tenure is also included in (3), but as neatly explained by Garen (1988, pp. 196-197), the job matching model is inconclusive on the sign of α_T. A legitimate guess would be that since better job matches survive longer, the correlation between the job match component and tenure must be positive. However, this argument ignores the fact that individuals who quit are those who obtain the best alternative offers. This latter effect increases the job match value of quitters and could induce a negative correlation with tenure. The sign of α_T is therefore ambiguous, and which of these two opposite effects dominates has to be determined empirically.[8]

Some factors may reinforce or reduce these effects in practice. With high search costs, only the worst matched workers search for a new job, so that the shortest spells are those with a low ϕ. Job spells with a satisfying value of ϕ last longer. Search costs therefore reinforce the positive correlation between the match component and tenure. On the other side, mobility costs reduce the set of acceptable offers, rendering switches worthwhile only if there is a large increase in the job match component. Mobility costs therefore reinforce the negative correlation between the match component and tenure. These elements will be helpful while interpreting our estimates of α_T.

We include occupational and industrial components of experience in (3) as well. Applying a similar reasoning as for general experience, we expect a positive sign for both α_O and α_I. While spending time within the same occupation or industry, workers are allowed to sample more jobs and to accept potentially better offers. The argument that changers are those who receive the highest alternative wage offers also applies here, but to a smaller extent since occupation and industry changes are much less frequent than simple intra-occupation or intra-industry job changes. The former effect should in this case dominate, and a positive correlation would be observed between the job match component and both occupational and industrial experience. This line of reasoning is consistent with Neal's (1999) model, where workers first

[8]Stevens (2003) constructs an alternative model in which wage offers are endogenous instead of exogenously determined as usually assumed in the literature and in this chapter. Her proposition 2.ii shows that "if the wage-offer function is estimated by ordinary least squares on a sample of accepted wages, there is a negative bias in the coefficient on [firm] specific capital because [firm] specific capital is negatively related to unobserved match quality". According to her model, our α_T coefficient should therefore be unambiguously negative.

search for a good career match (i.e., an occupation and industry for which they are well fitted), and then search for a good firm match inside their career match.

Most previous studies in the literature use an extended version of the instrumental variable methodology originally developed by Altonji & Shakotko (1987).[9] The problem of this approach is that it does not remove the potential biases created by the correlation between tenure and experience variables and the error term in the wage equation.[10] Instead, Connolly & Gottschalk (2006) provide an extension to Topel's (1991) model, which takes explicitly into account the potential correlation between the different components of experience and the error term of the wage equation. The idea of the model is to take advantage of the differences between individuals who stay in their current job, those who move directly from one job to another, and those who change jobs but have an intervening spell of nonemployment between the two.[11][12]

Take an individual i employed in job j on period t. The value of his match amounts to $\phi_{ij(t)}$. The individual searches on the job and accepts a job $j+1$ if the value of this new job $\phi_{i,j+1,(t)}$ exceeds the value of his current job plus the returns to tenure, the returns to occupational experience, and the returns to industrial experience he has to forfeit when switching jobs.[13]

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[9] In the Altonji & Shakotko's (1987) approach, the instrument for tenure is its deviation from job spell means ($Tinst_{ijt} = T_{ijt} - \overline{T_{ij}}$), general experience is instrumented by its deviation from individual means ($Xinst_{ijt} = X_{ijt} - \overline{X_i}$), and occupational (industrial) experience by its deviation from occupation (industry) spell means. These instruments are adequate, since they are by construction uncorrelated with their respective match component.

[10] See Parent (2000, pp. 311-312) or Kambourov & Manovskii (2009, Section 3) for a thorough discussion.

[11] The idea to take advantage of differences between job stayers and job changers can already be found in the early work of Garen (1989).

[12] The model presented here is not flawless either, and some biases in the estimated coefficients might also arise. As we will see, the estimation of some parameters of the model relies on job switchers only. But job switchers are a mixture of workers who are trying to improve their job match and workers who have been laid-off. It is therefore possible that job switchers are different from stayers. It is also possible that workers who change firm and industry are different from workers who change job within the same industry. In order to minimize these potential biases, the model is estimated in first-differences and the types of changes (job-to-job or job-nonemployment-job) are identified as precisely as possible.

[13] This assumes there are neither mobility costs nor search costs, and wage-profiles only differ in intercept but not in slope. See equation (3.3) of Altonji & Williams (1998, p. 239) for a more general formulation.

He will therefore switch job if:

$$\phi_{i,j+1,(t)} > \phi_{ij(t)} + \beta_T T_{ijt} + \beta_O (O_{ijt} - O_{i,j+1,t}) + \beta_I (I_{ijt} - I_{i,j+1,t}) \qquad (4)$$

where $O_{ijt} - O_{i,j+1,t}$ ($I_{ijt} - I_{i,j+1,t}$) is the difference in occupational (industrial) experience between job j and job $j+1$. If both jobs are in the same occupation (industry), this term is equal to zero because no returns to occupational (industrial) experience are lost while switching jobs.

Hence, the variation of the job match between periods t and $t+1$ depends on what the worker does. If he stays in the same job, his job match value remains constant. If he moves directly from job j to job $j+1$ ($JJ = 1$), he forfeits the returns to tenure accumulated in job j, and possibly the returns to occupational and industrial experience. Alternatively, if the worker suffers an intervening spell of nonemployment between two jobs ($JJ = 0$), the incentives for accepting a new job are stronger. The returns to tenure, occupational experience, and industrial experience are already lost when he begins to look for a new job.[14]

Laid-off workers are treated the same way as those who are out of a job, even if they make job-to-job moves, because they will end up nonemployed if they do not accept a new job quickly. Their position is in fact not very different from nonemployment. One could argue that workers facing the end of a fixed term contract should also be included in the same group. However, since they know from the beginning when their contract will end, they are not taken by surprise and have the possibility to plan their transition in advance.

The change in the value of a job match between periods t and $t+1$ can thus be proxied by the following linear approximations:

$$\Delta\phi_{ij} = \begin{cases} 0 & \text{within jobs} \\ \alpha_1 + \alpha_T \widetilde{T}_{ij} + \alpha_O \widetilde{O}_{ij} + \alpha_I \widetilde{I}_{ij} + \Delta\eta_{ij} & \text{if } JJ = 1 \\ \alpha_2 + \Delta\eta_{ij} & \text{if } JJ = 0 \end{cases} \qquad (5)$$

where $\widetilde{T}_{ij}$ is the tenure that is lost when moving from job j to job $j+1$, i.e., tenure at the end of the job j, and $\widetilde{O}_{ij}$ ($\widetilde{I}_{ij}$) is the occupational (industrial) experience that is lost when moving from job j to job $j+1$. If both jobs are in the same occupation (industry), then $\widetilde{O}_{ij} = 0$ ($\widetilde{I}_{ij} = 0$). Parameter α_1 represents the expected increase in the value of the match for a worker

[14] We assume here implicitly that occupational experience and industrial experience disappear completely as soon as the individual becomes unemployed. This surely is an extreme assumption, but it is consistent with the continuous definition of experience spells introduced by Parent (2000) that we use in this chapter. It implies that human capital depreciates instantly when an individual leaves his occupation or industry.

who makes a job-to-job transition, and it should be positive. α_2 represents the expected variation in the value of the match for those who go through a nonemployment spell. It could bear either sign, but is most probably negative since workers who suffer nonemployment spells are often disregarded by employers.

Individual fixed effects can be eliminated by rewriting the earnings equation (1) in first-differences:

$$\Delta Y = \beta_X \Delta X + \beta_T \Delta T + \beta_O \Delta O + \beta_I \Delta I + \beta_Z \Delta Z + \Delta\phi + \Delta\nu \tag{6}$$

Our empirical strategy relies on a two-stage estimator. In a first step, equation (6) is estimated for individuals who stay in the same job, so that $\Delta X = \Delta T = \Delta O = \Delta I = 1$ and $\Delta\phi = 0$. This within-job estimator enables us to estimate the sum of the returns to tenure, general experience, occupational experience, and industrial experience:

$$\begin{aligned} \Delta Y_{within} &= Y_{ij,t+1} - Y_{ijt} \\ &= \beta_X + \beta_T + \beta_O + \beta_I + \beta_Z \Delta Z + \Delta\nu_{ij} \end{aligned} \tag{7}$$

The second stage relies on the estimation of equation (6) using individuals who change job. In the case of a job switch, we have $\Delta T = -\widetilde{T}$, $\Delta X = 1$, $\Delta O = 1 - \widetilde{O}$, $\Delta I = 1 - \widetilde{I}$, and $\Delta\phi$ is given by (5). The between-job estimator is therefore given by:

$$\begin{aligned} &\Delta Y_{between} = Y_{i,j+1,0} - Y_{i,j,\widetilde{T}} \\ &= \begin{cases} (\alpha_1 + \beta_X + \beta_O + \beta_I) + (\alpha_T - \beta_T)\widetilde{T} + \\ \qquad (\alpha_O - \beta_O)\widetilde{O} + (\alpha_I - \beta_I)\widetilde{I} + \beta_Z \Delta Z + (\Delta\eta + \Delta\nu) & \text{if } JJ = 1 \\ (\alpha_2 + \beta_X + \beta_O + \beta_I) - \beta_T \widetilde{T} - \\ \qquad \beta_O \widetilde{O} - \beta_I \widetilde{I} + \beta_Z \Delta Z + (\Delta\eta + \Delta\nu) & \text{if } JJ = 0 \end{cases} \end{aligned} \tag{8}$$

The system formed by equations (7) and (8) allows the identification of all the parameters. First, the estimation of equation (8) for the individuals who make job-nonemployment-job transition ($JJ = 0$) identifies β_T, β_O and β_I, as the coefficients on $\widetilde{T}$, $\widetilde{O}$ and $\widetilde{I}$. The parameters α_T, α_O and α_I are then obtained by summing the coefficients on $\widetilde{T}$, $\widetilde{O}$ and $\widetilde{I}$ for the workers who make job-to-job transitions ($JJ = 1$) with the corresponding β previously identified. Knowing β_T, β_O and β_I, equation (7) identifies β_X. Finally, α_1 and α_2 are obtained through the intercepts of equations (8).

In practical terms, the system of equations (7) and (8) is reduced to a single equation using indicator functions. This single equation, given by (A.1) in Appendix A, can be estimated by ordinary least squares.

3 Data and Statistics

3.1 SFLS Data

We use data from the Swiss Labor Force Survey (SLFS), which is carried out yearly since 1991 by the Swiss Federal Statistical Office (SFSO). Individuals who take part in the survey are contacted for (up to) five consecutive years. The SLFS has gone through substantial revisions between 1996 and 1998. In particular, the variables associated to earnings and schooling were modified. Until 1997, no distinction was made between the earnings of the main job and potentially additional jobs. Since 1998, separate questions are asked about earnings from the main job and from secondary jobs. Moreover, the encoding of the education variable does not allow the placement of all individuals interviewed before 1996 in a specific category of the recoded variable with certainty. Because earnings and schooling are essential variables to our analysis, we discard all data until 1997 included, and we are left with an observation period of nine years, from 1998 to 2006.

A problem that may arise with the use of annual data is that wage observations are likely to be mixtures of wages of the old and new jobs if a job change occurred during the year preceding the interview. Altonji & Williams (2005, p. 388) however contend that “there is no perfect solution to the problem posed by the fact that the average hourly wage over the year may be a mixture from different jobs”. Hopefully, the SLFS contains some monthly information. First, hiring dates are asked instead of employment durations. Tenure information is then coded in a much more precise way than what is done in many longitudinal surveys where tenure is coded in brackets of several years. Second, the SLFS provides information about the activity status for each of the last 12 months if a worker switched jobs. Such an information allows to check if workers moved directly from one job to another or if they had to go through some inactivity or unemployment spell.

3.2 Occupations and Industries

In the literature, industrial experience has been used more widely than occupational experience. However, occupational experience seems at least equally important, since many workers with the same occupation are in different industries. For instance, economists (ISCO 2441) are mainly employed in the financial intermediation sector or in the real estate sector. Besides, many are active in manufacturing, wholesale and retail trade, public administration, or even in the education sector. This example clearly illustrates that using an occupations classification instead of an industries classification will yield completely different partitions. A worker may change industry while keeping the same occupation, or he may change occupation within the same industry.

Regarding wage growth, we believe occupational experience should be more determinant. Occupations relate directly to the workers's job, whereas industry only indicates what the worker's *firm* is doing. Nevertheless, collective agreements are often negotiated at the industry-level, and can therefore influence wages. A priori, it thus seems important to take both occupational and industrial experience into account.

For the measurement of occupational and industrial experience, we follow the continuous spells definition proposed by Parent (2000). Occupational (industrial) experience is given by tenure in current job plus tenure in previous job if both are in the same occupation (industry), and is reset to zero if the individual switches to a job in another occupation (industry). Since we are limited to a rather short panel (the SLFS contains at most 5 consecutive observations), the continuous spells definition is more adapted than the noncontinuous one. Individuals changing jobs more than once in 5 years are very few, so that hardly any noncontinuous spells could be identified.[15]

In our database, occupations are available as four-digit categories (493 unit groups) of the International Standard Classification of Occupations (ISCO 88), and industries as four-digit categories (503 categories in 1995 and 514 in 2002) of the General Classification of Economic Activities. For the empirical analysis, we define both occupations and industries at the three-digit level.

3.3 Reliability of Tenure Data

A serious concern with panel datasets is the reliability of tenure variables. As thoroughly documented by Brown & Light (1992), panel data contain generally many cases where tenure responses are inconsistent with the time elapsed between interviews. Partitioning the data into individual jobs on the basis of tenure responses alone is hazardous. According to Brown & Light (1992), an efficient solution would be to rely on employer codes, because such information should be much more reliable than reported tenure.

The SLFS data usually transmitted to researchers by the SFSO does not contain any employer codes. Even though they actually exist in the SLFS data (codes of the Business and Enterprise Register), they are removed for confidentiality reasons. We could nevertheless obtain a binary variable that simply tells if there was a change in the employer code or not. We thus

[15]The diagram in Appendix B shows how occupational experience is constructed using the continuous or noncontinuous spells definitions.

have two possibilities for partitioning our data into jobs: either by using the information about tenure contained in the original SLFS, or by using the variable indicating changes in the employer codes.

Brown & Light (1992) call these two partitioning methods partition T (based on Tenure information) and partition E (based on Employer codes). The starting point of partition T is to assume that a job is being seen for the first time whenever reported tenure is shorter than elapsed time since previous interview. Internal consistency has then to be imposed, in the sense that tenure must increase in accordance with calendar time. Several methods could be used to impose internal consistency, and we choose to consider the first reported value for each job as the reference point. partition E simply compares employer codes across interviews. Any time the code changes, it is assumed that a new job begins and tenure is reset to zero. Like for partition T, we force tenure to be internally consistent within jobs.

Table 1 illustrates the differences between the two methods, by showing the number of job changes obtained through both of them. Partition E defines roughly twice more job changes than partition T, both for men and women. The explanation probably lies in the definition of the employer codes: a different code is assigned for each workplace. Hence, if a worker moves from one job to another while remaining employed by the same enterprise, it will presumably be counted as a job switch by partition E, but not by partition T. Mergers and acquisitions might also cause some divergences across partitions, but can definitely not explain these substantial differences.

Interestingly, virtually no job changes identified by partition T are not classified as changes by partition E. This tends to indicate that tenure recorded in the SLFS is accurate. We can confidently consider changes identified by partition T as true employer changes. On the other hand, a large number

Table 1: Number of job changes identified by partitions T and E

	Partition E			
Partition T	$NJ = 0$	$NJ = 1$	$NJ = \cdot$	Total
$NJ = 0$	12,722	871	66	13,659
$NJ = 1$	9	952	23	984
Total	12,731	1,823	89	14,643

$NJ = 0$: observation without job change.

$NJ = 1$: observation with a job change.

$NJ = \cdot$: observation with missing information.

of job changes identified by partition E are not identified by partition T. Instead of being true employer changes, these changes are maybe job switches within enterprises.

Finally, note that there is a "missing value" column for partition E. Since the information about employer codes is not contained in the original SLFS data and was added thereafter, some information does not overlap. The empirical estimations will be based on two slightly different samples.

3.4 Sample Selection and Descriptive Statistics[16]

Following the related literature, we restrict our sample to individuals aged 18 to 65, and discard individuals who ever report working in the primary sector (agriculture and forestry) or in the public administration, and those who served as professionals in the military. If an individual declares to be self-employed or to be a homemaker, we eliminate all of his further observations.[17] We also drop the individuals for whom occupation or industry codes are not contained in the respective dictionaries, since they presumably result from coding errors.

The earnings variable is defined as the gross hourly wage rate in 2005 Swiss francs. It is built from the gross annual earnings, the number of paid holidays per year, and the normal weekly working hours.[18] Contrarily to what is done in many datasets, earnings and working hours are not recorded in brackets but as continuous variables, so that calculating an hourly wage rate is less problematic. Nevertheless, the variable recording normal weekly working hours is quite noisy, with some individuals declaring more than 100 hours per week.[19] Fortunately, information about working time comes in two flavors: working hours and working rate.[20] We take advantage of this double information by cross-checking working hours against working rate,

[16]In the main text, we present the analysis for the male sample only. All the corresponding tables for women are reported in Appendix C.

[17]Including individuals who have been homemaker in the past would pose a conceptual problem, since we use potential experience (age − years of education − 6) to define general experience. Indeed, general experience is lower than potential experience for ex-homemakers because they have spent some time out of the labor market. One could argue that the same applies to unemployed. However, general experience increases while workers are unemployed, because they stay on the labor market searching for a job. The fact that unemployed are counted in the workforce confirms this view.

[18]Gross hourly wage rate $= \frac{\text{Gross annual earnings}}{(52-\text{Paid holidays}/5)\cdot\text{Normal weekly working hours}}$

[19]Yet, Fehr & Goette (2005) estimate that "the measurement error [of hourly wages] in the SLFS sample is between 6 and 7 percent. This is low compared to what validation studies of labor force surveys found for the US (see Angrist & Krueger, 1999 for a survey)".

[20]The working rate is defined as the ratio between the number of hours worked and the number of working hours in a full-time job. Full-time jobs, corresponding to a working

and discard individuals for whom the two measures differ too much.[21] The top and bottom 0.25 percent of the hourly wage rate distribution are finally excluded, as well as the top and bottom 5 percents of the wages' variations distribution.

We include part-time workers for sample size reasons and to have a representative sample. However, keeping part-time workers introduces some difficulties in the measurement of wage rates, since a simple unadjusted differential between full-time and part-time wages shows a part-time wage premium, which is contrary to economic theory (see for example Hirsch, 2005). One potential explanation of this problem is that part-time workers are generally not recipients of fringe benefits. To the extent that fringe benefits are not included in the reported earnings of full-time workers, their wage rates will be biased downward. Moreover, since part-time workers are usually not entitled to paid holiday leave, paid sick leave, nor company pension funds[22] they often get a compensation loading on their hourly wage rate, which is therefore upward biased. To control for this potential bias, we use the hour-corrected earnings measure proposed by Blau & Kahn (1996, p. S44).

Individuals are divided into the following three groups: (1) less-educated, i.e., those with compulsory school or less; (2) apprentices; (3) more-educated, i.e., those who hold a university or applied university degree. Apprentices constitute a group for themselves since this is the most popular type of education in Switzerland, and because it is a particular type of education where strong emphasis is placed on on-the-job training.

Table 2 reports the mean annual within-job wage growth for the three different education groups considered and for the pooled samples. Column ΔY gives the average variation in wage rates for individuals who kept their job. Column $\Delta \ln Y$ gives the differences in logarithms, and thus indicates (a linear approximation of) the variations in percentages. The figures show that within-job wage growth increases with education. The wage growth rate of more-educated workers is 1.7-1.9% per year, which amounts to more than twice those for the less-educated (0.6-0.8%). It seems that the wage growth rates measured with partition E are slightly lower than with partition T. This confirms that changes identified by partition T are more substantial.

rate of 100%, imply working 40 to 42 hours per week in Switzerland. Therefore, if an individual works 20 or 21 hours a week, his working rate is 50%.

[21]Concretely, we regress the number of working hours on the working rate. We then predict the number of hours and discard the observations with a number of recorded hours over 125% or below 75% the predicted value.

[22]Company pension funds are the base of the occupational benefit plan; the so-called second pillar of the Swiss pension system. Taxes are generally shared equally between employer and employee.

Table 2: Mean annual within-job wage growth

	Partition T			Partition E		
	ΔY	$\Delta \ln Y$	# Obs	ΔY	$\Delta \ln Y$	# Obs
Less-educated	0.243	0.008	2,313	0.209	0.006	2,173
	(3.030)	(0.099)		(3.001)	(0.098)	
Apprentices	0.504	0.014	6,022	0.482	0.013	5,653
	(2.974)	(0.080)		(2.960)	(0.079)	
More-educated	0.976	0.019	2,154	0.900	0.017	1,976
	(3.503)	(0.068)		(3.470)	(0.068)	
Total	0.573	0.014	13,581	0.538	0.013	12,660
	(3.122)	(0.081)		(3.097)	(0.080)	

Standard deviations in parentheses.

Less educated = compulsory school finished or not.

More educated = university or applied university.

The total number of observations is larger than the sum of the observations for all education groups because some education types are not taken into account for the separate estimations.

Table 3 displays the wage gains made by job switchers, providing separate figures by transition types: job-nonemployment-job ($JJ = 0$) and job-to-job ($JJ = 1$). Large wage increases are observed after job-to-job transitions. For workers who transit through a nonemployment spell, there is no wage growth or even wage losses for apprentices. No clear pattern emerges about the relationship between education and between-job wage growth.

Job-to-job transitions identified with partition T induce a larger wage growth than those identified with partition E. This tends to confirm that partition T implies more substantial changes than partition E. If switches classified as job changes by partition E but not by partition T are only moves inside a firm, it is natural that these changes imply less wage growth.

It is finally interesting to have a look at the reasons why jobs terminate, with the distribution reported in Table 4. The most frequent reasons for job termination are unsatisfying working conditions and a simple desire for change. Layoffs come in third position. Most of the workers who move job-to-job have left their old job because they were unhappy with their working conditions or simply because they wanted to change. We remind that layoffs are all considered as job-nonemployment-job by assumption even if some of them were in fact job-to-job transitions.

Table 3: Mean between-job wage growth (log wages, $\Delta \ln Y$)

	Partition T				Partition E			
	$JJ = 0$	# Obs	$JJ = 1$	# Obs	$JJ = 0$	# Obs	$JJ = 1$	# Obs
Less-educated	−0.008	53	0.060	53	0.003	52	0.034	174
	(0.189)		(0.156)		(0.155)		(0.115)	
Apprentices	−0.014	169	0.041	300	−0.013	163	0.033	639
	(0.160)		(0.119)		(0.161)		(0.106)	
More-educated	0.006	40	0.039	112	0.006	40	0.038	270
	(0.120)		(0.109)		(0.120)		(0.083)	
Total	−0.007	355	0.046	620	−0.007	349	0.035	1,446
	(0.166)		(0.122)		(0.163)		(0.103)	

See notes in Table 2.

Table 4: Job termination reason by type of job transition

	$JJ = 0$		$JJ = 1$		Total	
Layoff	191	61.61%	0	0.00%	191	20.69%
End of limited term contract	18	5.81%	15	2.45%	33	3.58%
Illness/accident	3	0.97%	10	1.63%	13	1.41%
Working conditions not satisfying	44	14.19%	233	38.01%	277	30.01%
Simple change desire	20	6.45%	193	31.48%	213	23.08%
Studies/training	3	0.97%	4	0.65%	7	0.76%
Family/personal reasons	4	1.29%	26	4.24%	30	3.25%
Other reasons	27	8.71%	132	21.53%	159	17.23%
Total	310	100.00%	613	100.00%	923	100.00%

3.5 Comparison of the SLFS with Other Databases

As shown in Table 5, most studies concerned with the returns to different types of experience are based on the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY). Even if we are completely aware that the dataset we use has its own shortcomings,[23] we believe the NLSY and the PSID contain a series of weaknesses that do not

[23] In the SLFS, actual experience is not observed, wages are recorded annually and might therefore sometimes reflect an average of several jobs, and the panel is rather short with individuals interviewed only five consecutive years.

plague the SLFS.[24]

The NLSY is an interesting dataset since it follows workers over their full job history. In our view, the major weakness of this database is that it only contains individuals born between January 1, 1957, and December 31, 1964, so that only relatively young workers are observed. In Parent (2000) for example, the oldest individuals were 38 years old. The sample is thus not representative of the full workforce, whereas mobility clearly depends on the age of the workers. The SLFS is designed to provide information on the structure of the labor force, so that it contains workers of every age group.

Table 5: Databases used in the literature

Articles (in chronological order)	Database	Country	Years
Shaw (1984, 1987)	NLSY	US	1966 – 1975
Abraham & Farber (1987)⋆	PSID	US	1968 – 1981
Altonji & Shakotko (1987)⋆	PSID	US	1968 – 1981
Topel (1991)⋆	PSID	US	1968 – 1983
Neal (1995)	DWS (CPS)	US	1984 – 1990
Margolis (1996)⋆	DAS	France	1976 – 1987
Neal (1999)	NLSY	US	1978 – 1991
Parent (2000)	NLSY	US	1979 – 1996
	+ PSID	US	1981 – 1992
Goldsmith & Veum (2002)	NLSY	US	1979 – 1994
Cingano (2003)	INPS	Italy	1975 – 1997
Dustmann & Meghir (2005)	IAB data	Germany	1975 – 1995
Connolly & Gottschalk (2006)	SIPP	US	1986 – 1996
Schönberg (2007)⋆	Admin. data	Germany	1975 – 2001
	+ NLSY	US	1979 – 1994
Dustmann & Pereira (2008)⋆	BHPS	UK	1991 – 1999
	+ GSOEP	Germany	1984 – 1999
Poletaev & Robinson (2008)	DWS (CPS)	US	1984 – 2000
Sullivan (2010)	NLSY	US	1979 – 2000
Zangelidis (2008)	BHPS	UK	1991 – 2001
Kambourov & Manovskii (2009)	PSID	US	1968 – 1993
Gathmann & Schönberg (2010)	Admin. data	Germany	1975 – 2001
Buchinsky, Fougère, Kramarz, & Tchernis (2010)⋆	PSID	US	1975 – 1992

⋆ does not consider any form of occupational or industrial experience.

[24] A thorough presentation of these databases can be found in Farber (1999).

Our empirical estimations will be based on a very broad range of workers, from their entrance on the labor market around 18, until their retirement around 65.

Further, as reported by Neal (1999, p. 246), the occupation codes of the NLSY data are quite noisy, with many individuals moving back and forth between two occupations while actually staying in the same job. A careful inspection of the SLFS data did not reveal such an undesirable pattern.

Turning to the PSID, we first note that it contains a relatively low number of observations. For example, the sample used by Kambourov & Manovskii (2009) is composed by about 7,000 observations and 900 male individuals. This implies an average number of roughly 550 valid observations per year. Using similar or maybe even stronger sample restrictions, the SLFS leaves a male (female) sample containing more than 1,700 (1,200) observations per year since 1998, for a total of about 16,000 (11,000) observations and 8,000 (6,000) individuals.

Tenure is a crucial variable in our analysis. In the SLFS, tenure information is obtained from the questions: "In which year did you start working in this company?" and "Do you remember in which month?". Tenure is thus coded as a continuous variable on a monthly basis. These questions remained the same since the first wave of the survey. In the PSID however, the formulation of the question about tenure changed,[25] and it is not always clear if the question concerns tenure with the current employer or in the current position. Even more critical, job tenure in the PSID is coded in intervals, so that tenure has to be set arbitrarily somewhere in the interval, usually the midpoint. Brown & Light (1992, pp. 239-245) provide an in-depth discussion of the complications caused by interval coding.

Furthermore, the occupation and industry codes in the PSID come from the 1970 census. As mentioned by Kambourov & Manovskii (2008, p. 68), these classifications are now outdated, and the fraction of workers classified in the "not elsewhere classified" categories is high and increases. In the SLFS, occupations are classified according to the International Standard Classification of Occupations, dating from 1988. Only a negligible proportion of workers are not classified. Industries are classified according to the General Classification of Economic Activities, which has been updated in 2002.

Another unpleasant feature of the PSID is that industry and occupation codes are entered independently each year, as the interviewers do not have access to answers of previous years. The same job description might thus end up being coded differently, depending on the interviewer's interpretation. This leads to many coding errors, and a large proportion of the apparent

[25] These can be found in Appendix A of Kambourov & Manovskii (2009).

occupations and industries switches result in fact from misclassifications. For the period 1968-1980, the PSID released Retrospective Occupation-Industry Supplemental Data Files, which report three-digit Census codes and were coded with information on all the respondent's answers. As Kambourov & Manovskii (2008) show, a much lower number of occupations and industries switches are identified through these additional files, and they are much more reliable. However, studies using observations after 1980 have to rely on the noisy data of the original PSID.

Contrary to what is done in the frame of the PSID, interviewers of the SLFS have access to previous answers and only ask respondents to confirm what they have answered during the last interview (SFSO, 2004, p. 23). The coding is therefore much more consistent and only few coding mistakes arise in the occupation and industry classifications.

Besides, Table 5 highlights some broad characteristics of the literature. First, we notice the general oldness of the data used. Even the most recent studies use data no later than 2001, and the majority uses data up to the mid 1990s. However, it is now established that mobility is increasing over time in developed countries,[26] so that it is important to use data as recent as possible. With data up to 2006, we are using much more recent information than the rest of the literature. Finally, we emphasize that research in this field concerns almost exclusively the US, with only few of the mentioned papers regarding other countries. Using Swiss data, we bring some diversity in this literature and contribute to generalize the empirical observations.

4 Empirical Results

Table 6 reports the empirical results obtained on the pooled sample, i.e., without separating education groups. General labor market experience appears to be the most important factor explaining wage growth. Occupational experience also displays a positive effect on wages, but its quantitative impact is weaker than the effect of general experience. The coefficients on tenure appear to be largely unsignificant. Note however that excluding the occupational and industrial components of experience results in positive and significant estimates of β_T.[27] As soon as either occupational or industrial experience is included in the estimations, the effect of tenure vanishes. This result is quite common in the literature (see for example Kambourov & Manovskii, 2009). Tenure exhibits a positive significant effect only when both

[26]See Sousa-Poza (2004) for an empirical analysis of the evolution of mobility in Switzerland and Kambourov & Manovskii (2008) for an analysis in the US.

[27]The estimations are available on request.

occupational and industrial experience are omitted, which strongly suggests that tenure per se has no impact on wages. Similarly, when occupational experience is included, the effect of industrial experience usually becomes nonsignificant, whereas it is significantly positive when the former is omitted. It is also worth mentioning that the effect of general experience remains similar whatever the variables included.

Even though unsignificant, the estimates for α_T are consistently negative, indicating that tenure is negatively correlated with job match quality. As explained in section 2, job matching models are ambiguous about the sign of this parameter, because two opposite forces are at play: (1) jobs with a long tenure are likely to be good matches and (2) job changers are those who receive the best offers. Empirically, the second effect appears to dominate. Mobility costs reinforce the second effect, rendering changes worthwhile only if they bear a high job match component.

The α_O are positive and significant, indicating that workers have to be compensated for their lost occupational experience when they switch to a new occupation. The α_1 is nonsignificant with partition T but negative and significant at 5% with partition E. Theoretical considerations indicate that α_1 should be positive since it represents the expected change in the match value for an individual who moves job-to-job. If the new job is no better than the old one, then why change? A possible explanation is that the wage rate is only one characteristic of a job: it is the one we observe as researchers, but it is only one among the many considered by the workers (see e.g., Rosen, 1986). Job stability, working conditions, and proximity to home are other characteristics that are likely to be taken into account by workers. Moreover, job-to-job changes are sometimes unintentional, like job changes due to family reasons.

The negative estimates for α_1 could alternatively be explained by the presence of fringe benefits, about which we have no information. A job changer could indeed decide to accept a new job if it provides higher fringe benefits, and even though the offered wage rate is apparently lower than the one he presently gets.

As expected, the estimates for α_2 are negative. This coefficient indicates the change in the job match value for individuals who make job-nonemployment-job transitions. Because they are currently unemployed, such individuals need to find a new job quickly and are ready to accept a lowering of their match.

Additional covariates account for increases or decreases in the number of working hours (dummy variables Hours$^+$ and Hours$^-$), for the variation in the percentage of the cantonal unemployment rate (Δurate), and for continuing training over the previous year (dummy variable Training).

Table 6: Returns to tenure, components of experience, and job match

	Partition T	Partition E
β_X	0.0272***	0.0285***
	(0.0064)	(0.0065)
$\beta_{X^2} \cdot 100$	−0.0472***	−0.0478***
	(0.0032)	(0.0032)
β_T	0.0002	−0.0013
	(0.0012)	(0.0017)
β_O	0.0051***	0.0037**
	(0.0019)	(0.0018)
β_I	0.0005	0.0024
	(0.0017)	(0.0020)
α_T	−0.0022	−0.0021
	(0.0016)	(0.0017)
α_O	0.0053**	0.0034*
	(0.0021)	(0.0019)
α_I	0.0013	0.0031
	(0.0019)	(0.0020)
α_1	−0.0001	−0.0146*
	(0.0092)	(0.0075)
α_2	−0.0317**	−0.0369***
	(0.0124)	(0.0127)
Hours$^+$	0.0141***	0.0147***
	(0.0022)	(0.0022)
Hours$^-$	−0.0168***	−0.0172***
	(0.0022)	(0.0022)
Δurate	−0.0016	−0.0021
	(0.0025)	(0.0024)
Training	0.0013	0.0013
	(0.0014)	(0.0014)
Constant	0.0331***	0.0333***
	(0.0063)	(0.0063)
R^2	0.039	0.040
# Obs	14,556	14,455
# Ind	7,541	7,519

Robust standard errors adjusted for individual clusters in parentheses.

*/ **/ ***: significant at the 1% / 5% / 10% level.

The estimations also contain time fixed effects.

The estimations contain a squared term only for general experience. When squared terms are introduced for the other types of experience, the coefficients are unsignificant, so that they do not add anything to the model and we prefer to simply remove.

The two dummy variables accounting for the variation in working hours indicate that increasing working time is rewarding. Conversely, deciding to work less is penalized by a wage rate cut.[28]

4.1 Results by Education Groups

Table 7 present the results by education groups. The relatively small samples result in large standard errors that sometimes prevent firm conclusions. In particular, the estimations for the less-educated groups do not appear to be extremely robust, with only a few parameters being estimated precisely and quite large differences across partitions T and E. The estimations for the apprentices and the more-educated display more significant estimates and consistency across the two partitions. The results for these latter two education groups therefore seem quite robust.

Our estimates of β_X and β_{X^2} show that the effect of general labor market experience is larger for both the less-educated and the more-educated than for apprentices.[29] These results are corroborates the findings of Dustmann & Pereira (2008) and Schönberg (2007). These two papers analyze wage growth in Germany, which has an educational system similar to the Swiss one, and find that returns to experience for both low- and high-skilled workers are higher than for apprentices. Our results thus confirm that the apprenticeship training produces workers different from all others.

The effects of general experience for the more-educated and the apprentices might be explained by differences in the type of skills acquired. The more-educated workers are university or applied university graduates and they possess more general skills than the apprentices who have received a vocational training especially dedicated to a specific occupation. Hence, the more-educated still have to learn specific tasks when they enter the labor market, and general experience adds to their productivity. Conversely, the learning of apprentices is concentrated during the apprenticeship period, so that these workers already know the tasks they have to perform at the mo-

[28] These results are obtained with the hour-corrected wage measure proposed by Blau & Kahn (1996). Estimations with a non-corrected wage measure reverses the signs of both Hours$^+$ and Hours$^-$, which might indicate a *division bias* (Borjas, 1980). Hence, it appears important to use the hour-corrected wage measure.

[29] Based on the results obtained with partition T, Wald tests for the equality of the β_X and β_{X^2} coefficients lead to F-statistics (p-values) of 1.48 (0.22) and 0.32 (0.57) for compulsory school vs apprenticeship, 0.01 (0.94) and 4.26 (0.04) for compulsory school vs university, and 3.02 (0.08) and 4.56 (0.03) for apprenticeship vs university.

Therefore, the larger wage growth observed for the compulsory school group compared to the apprenticeship group is only weakly significant. Then, the experience-wage profile for university graduates is significantly steeper and more concave than those for apprentices.

Table 7: Returns to tenure, components of experience, and job match, by education group

	Less-educated		Apprentices		More-educated	
	Partition T	Partition E	Partition T	Partition E	Partition T	Partition E
β_X	0.0467**	0.0522***	0.0203**	0.0199**	0.0485***	0.0436***
	(0.0200)	(0.0195)	(0.0083)	(0.0084)	(0.0139)	(0.0139)
$\beta_{X^2} \cdot 100$	−0.0377***	−0.0388***	−0.0436***	−0.0435***	−0.0637***	−0.0648***
	(0.0096)	(0.0096)	(0.0045)	(0.0045)	(0.0083)	(0.0083)
β_T	0.0000	0.0000	−0.0004	−0.0002	0.0022	−0.0017
	(0.0049)	(0.0023)	(0.0018)	(0.0017)	(0.0057)	(0.0060)
β_O	0.0001	−0.0024	0.0070**	0.0064*	0.0060*	0.0067*
	(0.0027)	(0.0020)	(0.0034)	(0.0033)	(0.0036)	(0.0036)
β_I	0.0071*	0.0085***	−0.0012	−0.0014	−0.0011	0.0022
	(0.0041)	(0.0014)	(0.0027)	(0.0026)	(0.0057)	(0.0058)
α_T	−0.0032	−0.0013	−0.0026	−0.0010	0.0041	−0.0012
	(0.0070)	(0.0028)	(0.0022)	(0.0018)	(0.0063)	(0.0061)
α_O	−0.0011	−0.0033	0.0076**	0.0063*	0.0055	0.0072*
	(0.0038)	(0.0023)	(0.0036)	(0.0034)	(0.0044)	(0.0038)
α_I	0.0067	0.0117***	−0.0003	−0.0011	−0.0008	0.0023
	(0.0046)	(0.0019)	(0.0029)	(0.0026)	(0.0062)	(0.0058)
α_1	0.0066	−0.0337	0.0053	−0.0040	−0.0499**	−0.0390**
	(0.0413)	(0.0232)	(0.0122)	(0.0101)	(0.0224)	(0.0160)
α_2	−0.0251	−0.0167	−0.0396**	−0.0389**	−0.0372	−0.0369
	(0.0416)	(0.0349)	(0.0162)	(0.0162)	(0.0284)	(0.0266)
Hours^+	0.0225***	0.0233***	0.0138***	0.0140***	0.0092	0.0106*
	(0.0051)	(0.0052)	(0.0032)	(0.0032)	(0.0060)	(0.0059)
Hours^-	−0.0220***	−0.0248***	−0.0166***	−0.0151***	−0.0103*	−0.0126**
	(0.0060)	(0.0057)	(0.0031)	(0.0031)	(0.0057)	(0.0057)
Δurate	−0.0062	−0.0031	−0.0040	−0.0045	0.0075	0.0052
	(0.0077)	(0.0070)	(0.0036)	(0.0036)	(0.0047)	(0.0047)
Training	−0.0031	−0.0044	0.0018	0.0020	0.0068**	0.0079**
	(0.0051)	(0.0049)	(0.0020)	(0.0020)	(0.0033)	(0.0033)
Constant	0.0539***	0.0583***	0.0258***	0.0247***	0.0557***	0.0508***
	(0.0198)	(0.0193)	(0.0077)	(0.0079)	(0.0133)	(0.0132)
R^2	0.043	0.051	0.042	0.041	0.038	0.046
# Obs	2,419	2,399	6,491	6,455	2,306	2,286
# Ind	1,360	1,350	3,323	3,316	1,285	1,280

See notes in Table 6.

ment of their full-time labor market entry. Their wage rate is relatively high when they enter the labor market and general experience does not bring much to their productivity. Hence, their experience-wage profile is relatively flat.

The point estimates for occupational experience (β_O) are comparable for the apprentices and the more-educated. As a result, occupational experience appears to be relatively important for apprentices, because general experience has a lower effect for them. Occupational experience is a non-negligible determinant of wage growth for apprentices, but it is marginal for the more-educated. The estimates of α_O are positive and significant (especially for apprentices). This suggests workers have to make a gain to accept an offer in a new occupation. It seems natural that apprentices switching occupations require a higher compensation: since their human capital is more occupation-specific, switching occupations must be more difficult for them. Taken together, the estimates of α_O and β_O imply that occupational experience is a much more important determinant of wage growth for apprentices than for any other education group.

The estimates of α_2 reveal that penalties associated with nonemployment spells grow with education. Job changes with an intervening nonemployment spell appear to be highly penalizing for the more-educated. These findings are coherent with the results of Albrecht et al. (1999), who find that the wage loss due to different types of leave is larger for better educated individuals.

The estimates of α_1 are significantly different from zero and negative for the more-educated and for the less-educated with partition E. As we argued before, we expected positive estimates for this parameter, but negative estimates could be explained by the presence of fringe benefits, used to attract workers without apparently raising their wage rate. As shown in the literature on fringe benefits,[30] better educated workers are the more likely to receive fringe benefits. It thus seems plausible that our negative estimates of α_1 for the more-educated is caused by the presence of unobserved fringe benefits.

5 Conclusions

The sources of lifecycle wage growth for different education groups are investigated in this chapter, considering employer tenure, occupational experience, industrial experience, general experience, and job match effects. The methodology draws on Connolly & Gottschalk (2006), which is itself based on Topel (1991). The idea of the model is to take advantage of the differences

[30] See for example Alpert & Ozawa (1986) or Dale-Olsen (2006).

between individuals who stay in their current job, those who move directly from one job to another, and those who change jobs but have an intervening spell of nonemployment. The empirical application we provide is based on Swiss data over the period 1998 to 2006.

General labor market experience appears to be the most important determinant of wage growth, followed by occupational experience, which has a quantitatively weaker impact. When occupational experience is included in the wage equation, returns to tenure and industrial experience become negligible and unsignificant.

Apprenticeship is a particular training in the Swiss educational system that provides trainees with mostly occupation-specific skills. In line with a couple of studies in Germany (Dustmann & Pereira, 2008; Schönberg, 2007), our results highlight that workers with apprenticeship training constitute a special group of workers. Less- and more-educated enjoy a larger wage growth than apprentices, even though their educational attainment would place the latter in-between in terms of education length. This shows education type is a more important characteristic to distinguish than education length alone.

Concerning job transitions, we find that the job match decrease associated to job-nonemployment-job transitions grows with educational attainment. In other words, wage penalties due to nonemployment spells are larger for better educated individuals. Surprisingly, the more-educated men also appear to suffer wage losses when making job-to-job transitions. This may indicate they are compensated in a way we do not observe, plausibly through fringe benefits.

Appendix A: Estimated equation

The complete model rests on a system of equations. However, in practical terms, equations (7) and (8) can be reduced to a single one using indicator functions:

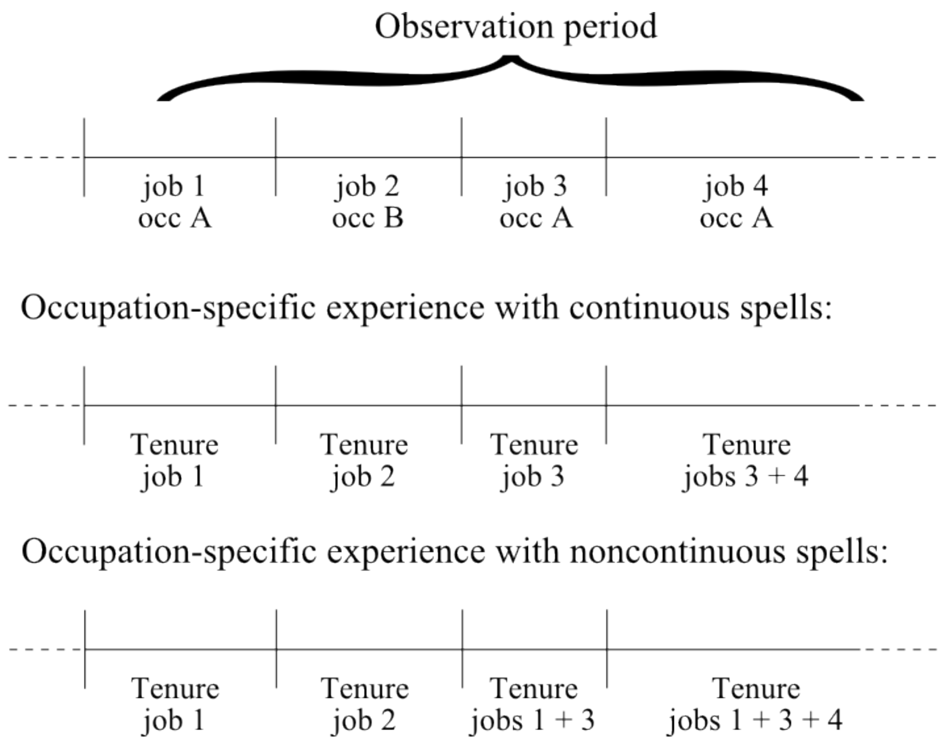
$$\begin{aligned}\Delta Y = {} & a_0 + a_1 \cdot \mathbb{1}_{\{JJ=1\}} + a_2 \cdot \mathbb{1}_{\{JJ=0\}} + \beta_Z \Delta Z \\ & + b_T \widetilde{T} \cdot \mathbb{1}_{\{JJ=1\}} + b_O \widetilde{O} \cdot \mathbb{1}_{\{JJ=1\}} + b_I \widetilde{I} \cdot \mathbb{1}_{\{JJ=1\}} \\ & + c_T \widetilde{T} \cdot \mathbb{1}_{\{JJ=0\}} + c_O \widetilde{O} \cdot \mathbb{1}_{\{JJ=0\}} + c_I \widetilde{I} \cdot \mathbb{1}_{\{JJ=0\}} + \varepsilon\end{aligned} \tag{A.1}$$

where $\mathbb{1}_{\{.\}}$ is an indicator function, i.e., a function taking the value of one if the condition in braces is filled and zero otherwise. Therefore, ordinary least squares can be used to estimate the model, with robust standard errors adjusted for the fact that several observations of the same individual are not independent.

The parameters of interest are then given by the following combinations of the parameters in equation (A.1):

$$\begin{array}{lll} \beta_T = -c_T & \alpha_T = b_T - c_T & \beta_X = a_0 + c_T + c_O + c_I \\ \beta_O = -c_O & \alpha_O = b_O - c_O & \alpha_1 = a_1 - a_0 - c_T \\ \beta_I = -c_I & \alpha_T = b_T - c_I & \alpha_2 = a_2 - a_0 - c_T \end{array}$$

Appendix B: Continuous and noncontinuous spells



Appendix C: Analysis for Women

This Appendix shows all descriptive statistics and results for the female sample, allowing for comparisons with the analyses conducted for men in the main text.

The number of job changes identified with both partitions T and E are displayed in Table C.1. Like for men, partition E defines much more job changes than partition T and virtually no changes are identified by partition T if they are not identified by partition E.

Table C.2 shows that the mean annual within-job wage growth is very close for all education groups (1.5-1.6%). Contrarily to what is obtained for male workers, no significant differences are observed across partitions.

Between-job wage growth rates are shown in Table C.3. For women, unlike for men, all kinds of moves appear to be accompanied by wage growth. Even job-nonemployment-job moves are followed by positive wage changes, which are sometimes larger than within-job wage increases. Note however that the number of observations in each cell is small.

Table C.4 presents the reasons for job termination. The differences with male workers are not really strong, with the most frequent reasons for separation being unsatisfying working conditions and simple desire for change. The largest gap between men and women is observed for the family/personal reason, with women choosing this answer twice more often than men.

Table C.5 reports the empirical results for all female workers pooled together. Like for men, the most important determinant of wage growth is found to be general labor market experience. Interestingly, occupational experience has no significant impact, but instead it is industrial experience that shows a positive and significant coefficient. Women are not active in

Table C.1: Number of job changes identified by partitions T and E, Women

	Partition E			
Partition T	$NJ = 0$	$NJ = 1$	$NJ = \cdot$	Total
$NJ = 0$	8,641	570	98	9,309
$NJ = 1$	5	722	28	755
Total	8,646	1,292	126	10,064

$NJ = 0$: observation without job change.

$NJ = 1$: observation with a job change.

$NJ = \cdot$: observation with missing information.

Table C.2: Mean annual within-job wage growth, Women

	Partition T			Partition E		
	ΔY	$\Delta \ln Y$	# Obs	ΔY	$\Delta \ln Y$	# Obs
Less-educated	0.373	0.015	1,538	0.372	0.015	1,441
	(2.734)	(0.110)		(2.687)	(0.108)	
Apprentices	0.524	0.016	4,110	0.519	0.016	3,831
	(2.935)	(0.093)		(2.920)	(0.092)	
More-educated	0.720	0.016	958	0.708	0.016	887
	(3.174)	(0.076)		(3.197)	(0.077)	
Total	0.569	0.017	9,240	0.566	0.017	8,600
	(2.967)	(0.094)		(2.947)	(0.093)	

Standard deviations in parentheses.

Less educated = compulsory school finished or not.

More educated = university or applied university.

The total number of observations is larger than the sum of the observations for all education groups because some education types are not taken into account for the separate estimations.

the same industries as men, and are known to be concentrated in industries paying relatively low wages. Hence, a possible explanation for the positive effect of industrial experience on women's wages is that collective agreements have a greater impact than on men's wages.

It is interesting that we find largely negative and significant α_T coefficients for women, whereas they are unsignificant for men. This indicates women face larger mobility costs than their male counterparts. Women in Switzerland spend roughly twice more time than men in household work activities (SFSO, 2009b). A woman changing job will therefore have to conciliate household work activities with her new job. She will have less time to adapt to her new environment and will consequently bear higher psychic costs, like stress.

The α_2 coefficient can be interpreted as the wage loss suffered by a worker who moves job-unemployment-job. This loss appears slightly lower for women, which could be expected since they are usually less severely penalized for job interruptions than men (see e.g., Spivey, 2005).

Compared with men, the two dummy variables accounting for the variation in working hours show reversed signs. Working part-time seems to be rewarding for women. Conversely, those who work more apparently earn lower hourly wages.

Table C.3: Mean between-job wage growth (log wages, $\Delta \ln Y$), Women

	Partition T				Partition E			
	$JJ=0$	# Obs	$JJ=1$	# Obs	$JJ=0$	# Obs	$JJ=1$	# Obs
Less-educated	0.026	33	0.068	40	0.030	30	0.032	122
	(0.223)		(0.247)		(0.217)		(0.178)	
Apprentices	0.017	115	0.055	226	0.010	113	0.043	455
	(0.156)		(0.146)		(0.148)		(0.122)	
More-educated	0.021	32	0.066	56	0.010	31	0.042	116
	(0.136)		(0.139)		(0.136)		(0.097)	
Total	0.014	269	0.058	475	0.012	264	0.040	1,004
	(0.160)		(0.157)		(0.158)		(0.127)	

See notes in Table C.2.

Table C.4: Job termination reason by type of job transition, Women

	$JJ=0$		$JJ=1$		Total	
Layoff	106	43.62%	0	0.00%	106	14.89%
End of limited term contract	10	4.12%	14	2.99%	24	3.37%
Illness/accident	2	0.82%	3	0.64%	5	0.70%
Working conditions not satisfying	58	23.87%	207	44.14%	265	37.22%
Simple change desire	29	11.93%	142	30.28%	171	24.02%
Studies/training	7	2.88%	7	1.49%	14	1.97%
Family/personal reasons	17	7.00%	35	7.46%	52	7.30%
Other reasons	14	5.76%	61	13.01%	75	10.53%
Total	243	100.00%	469	100.00%	712	100.00%

Table C.6 displays the results by education group. Because the samples are relatively small, only few coefficients turn out to be significant. An interesting result to point out is the negative and significant estimate of α_T for the apprentices. This result might indicate that female apprentices face higher mobility costs than the other education groups (at least than the more-educated workers).

Table C.5: Returns to tenure, components of experience, and job match, Women

	Partition T	Partition E
β_X	0.0257^{***}	0.0246^{***}
	(0.0090)	(0.0084)
$\beta_{X^2} \cdot 100$	-0.0356^{***}	-0.0363^{***}
	(0.0040)	(0.0040)
β_T	-0.0035	-0.0067
	(0.0031)	(0.0049)
β_O	0.0001	-0.0002
	(0.0037)	(0.0034)
β_I	0.0078^{*}	0.0099^{*}
	(0.0044)	(0.0055)
α_T	-0.0079^{**}	-0.0092^{*}
	(0.0036)	(0.0049)
α_O	0.0040	0.0016
	(0.0047)	(0.0036)
α_I	0.0110^{**}	0.0116^{**}
	(0.0048)	(0.0055)
α_1	0.0082	-0.0076
	(0.0135)	(0.0112)
α_2	-0.0295^{*}	-0.0344^{**}
	(0.0163)	(0.0159)
Hours$^+$	-0.0378^{***}	-0.0369^{***}
	(0.0028)	(0.0028)
Hours$^-$	0.0406^{***}	0.0415^{***}
	(0.0027)	(0.0027)
Δurate	0.0004	0.0003
	(0.0031)	(0.0030)
Training	-0.0001	0.0005
	(0.0018)	(0.0018)
Constant	0.0301^{***}	0.0276^{***}
	(0.0086)	(0.0081)
R^2	0.081	0.083
# Obs	9,984	9,868
# Ind	5,267	5,224

Robust standard errors adjusted for individual clusters in parentheses.

*/ **/ ***: significant at the 1% / 5% / 10% level.

The estimations also contain time fixed effects.

The estimations contain a squared term only for general experience. When squared terms are introduced for the other types of experience, the coefficients are unsignificant, so that they do not add anything to the model and we prefer to simply remove them.

Table C.6: Returns to tenure, components of experience, and job match, by education group, Women

	Less-educated		Apprentices		More-educated	
	Partition T	Partition E	Partition T	Partition E	Partition T	Partition E
β_X	0.0406*	0.0400*	0.0189	0.0229**	0.0859	0.0331
	(0.0238)	(0.0234)	(0.0118)	(0.0115)	(0.0556)	(0.0363)
$\beta_{X^2} \cdot 100$	−0.0426***	−0.0428***	−0.0329***	−0.0311***	−0.0403***	−0.0409***
	(0.0137)	(0.0138)	(0.0055)	(0.0054)	(0.0123)	(0.0127)
β_T	−0.0273	0.0120	−0.0059	−0.0136**	0.0072	0.0323***
	(0.0372)	(0.0089)	(0.0047)	(0.0064)	(0.0056)	(0.0105)
β_O	−0.0035	−0.0055	0.0034	0.0008	−0.0041	−0.0019
	(0.0047)	(0.0040)	(0.0133)	(0.0125)	(0.0130)	(0.0118)
β_I	0.0335	−0.0062	0.0059	0.0144	0.0121	−0.0139
	(0.0369)	(0.0076)	(0.0136)	(0.0135)	(0.0138)	(0.0125)
α_T	−0.0337	0.0072	−0.0077	−0.0157**	0.0075	0.0299***
	(0.0377)	(0.0092)	(0.0053)	(0.0064)	(0.0093)	(0.0106)
α_O	−0.0002	0.0003	0.0114	0.0031	−0.0082	−0.0019
	(0.0077)	(0.0053)	(0.0138)	(0.0127)	(0.0150)	(0.0121)
α_I	0.0602	−0.0035	0.0083	0.0161	0.0084	−0.0138
	(0.0384)	(0.0079)	(0.0139)	(0.0135)	(0.0151)	(0.0127)
α_1	−0.0567	0.0071	−0.0005	−0.0110	−0.0447	0.0122
	(0.0670)	(0.0346)	(0.0185)	(0.0151)	(0.0525)	(0.0408)
α_2	−0.0599	−0.0098	−0.0216	−0.0366*	−0.0381	0.0385
	(0.0765)	(0.0646)	(0.0225)	(0.0212)	(0.0642)	(0.0527)
Hours^+	−0.0276***	−0.0302***	−0.0437***	−0.0428***	−0.0353***	−0.0358***
	(0.0077)	(0.0078)	(0.0041)	(0.0041)	(0.0072)	(0.0071)
Hours^-	0.0491***	0.0501***	0.0413***	0.0416***	0.0225***	0.0220***
	(0.0074)	(0.0073)	(0.0040)	(0.0039)	(0.0080)	(0.0078)
Δurate	0.0020	0.0013	−0.0032	0.0001	0.0058	0.0047
	(0.0099)	(0.0101)	(0.0048)	(0.0046)	(0.0072)	(0.0069)
Training	−0.0132**	−0.0129**	0.0022	0.0033	0.0013	0.0027
	(0.0064)	(0.0064)	(0.0026)	(0.0026)	(0.0049)	(0.0050)
Constant	0.0433*	0.0402*	0.0223**	0.0245**	0.1011*	0.0496
	(0.0231)	(0.0227)	(0.0114)	(0.0112)	(0.0553)	(0.0360)
R^2	0.082	0.077	0.100	0.102	0.107	0.099
# Obs	1,611	1,593	4,451	4,399	1,046	1,034
# Ind	916	903	2,298	2,279	617	615

See notes in Table C.5.

Chapter 3

From Lifetime Jobs to Churning?*[§]

1 Introduction

It is very often taken for granted that lifetime jobs have become much scarcer than in the past. However, popular wisdom is often wrong and some papers have disputed this idea, mainly in the US and UK (Burgess & Rees, 1998), while some others have provided some support (Farber, 2009; Gregg & Wadsworth, 2002). In Switzerland too, in particular during the 1990s the death of the "job for life" paradigm has had important coverage in the media, although the picture was somewhat exaggerated by single but large and visible events like the privatization of the Swiss telecommunications sector. Still, in a report on the labor market status of older workers in Switzerland (OECD, 2003a), the OECD did point to some evidence of structural changes, mainly different attitudes from employers toward the idea that workers stay on the same job throughout their career with an increasing seniority wage profile.

Understanding how tenure evolves and why is important, as it provides relevant information on the nature of the employment relationship. Does more openness in matters of trade and migration flows imply that the latter becomes less stable, as employers can rely on a larger pool of workers (either through the migrant workforce or outsourcing)? It could also be that stronger

*This paper is co-authored with Giovanni Ferro Luzzi.

[§]This paper was presented at the Interdisciplinary Congress on Research in Vocational Education and Training, Berne (Switzerland), March 2011; at the Spring Meeting of Young Economists (SMYE), Groningen (Netherlands), April 2011; at the IZA European Summer School in Labor Economics, Ammersee (Germany), May 2011; and at the European Society for Population Economics (ESPE), Hangzhou (China), June 2011.

competition in the product market make workers and unions less able to extract rent through increasing wage tenure profiles. Another related factor that could jeopardize the lifelong job is the gradual shift from manufacturing to services, where employers demand more versatile skills from workers instead of more rigid specific human capital investment. Demographics may also play a crucial role when the labor supply is affected in its composition by shocks like baby booms or by migration flows. In the literature on specific human capital (Becker, 1964), and in agency models of the employment relationship (Lazear, 1979, 1981), firms are able to reduce turnover (and attendant separation externalities) through increasing wage tenure profiles. However, Valletta (1999) shows that such contracts can be either robust or fragile, depending on how adverse shocks will induce contracting parties to switch to non-cooperative behavior through quits or firing, thus inducing more or less "job security" during the business cycle.

Labor market institutions will clearly also shape the employment relationship. Employment protection (especially provisions making it more difficult to lay off workers with higher seniority) may imply opposing effects on tenure, since employers will find it costly to adjust employment through separations of tenured workers, whereas they will rely mainly on short term contracts on part of their (mainly younger) employees, so as to ensure some flexibility in labor adjustment through cyclical downturns. This "dual" nature of labor markets has been extensively documented, most notably for Spain (see for example Cabrales & Hopenhayn, 1997; Cahuc & Postel-Vinay, 2002) and other South-European countries. In fact, as noted in OECD (2003b), employment protection legislation in Spain (but also France and Italy) seems to dominate the moderating effect of short-term contracts as average tenure is substantially higher than in the UK or the USA. Switzerland clearly belongs to the league of countries with moderate employment protection. The OECD index of overall strictness of employment protection ranked Switzerland as fifth least strict after the US, UK, Canada and Australia. One should therefore expect average (or median) tenure to be quite sensitive to the business cycle. One other important change that has taken place is the introduction of compulsory maternity leave insurance in 2005, which makes it easier for women to keep their jobs in case of a child birth. It is well known that, until recently, Swiss women often interrupted their career in their mid-career for child care reasons. The tendency is now to maintain some attachment to the labor market (e.g. through part time) and it cannot be excluded that the new law has helped in this regard.

In this chapter, we investigate tenure in Switzerland to determine whether or not the duration of employment spells is declining, by trying to account for all factors that may affect the length of the job spell. We rely on the Swiss

Labor Force Survey (SLFS) from 1991 to 2008, which has already been used by Sousa-Poza (2004) to analyze tenure in Switzerland. The latter study is however purely descriptive, and our approach is completely different.

We follow a still rather thin branch of the literature on tenure, by using duration models. We are only aware of very few papers (Topel & Ward, 1992; Booth et al., 1999; Gottschalk & Moffitt, 1999; Bergemann & Mertens, 2004; Hirsch & Schnabel, 2010) using duration models, despite the fact that this methodology is without doubt the most appropriate to analyze tenure spells.

Unlike the bulk of the literature that is concerned with the US and the UK, we study employment stability in Switzerland. This country is an interesting case, thanks to several specific characteristics, like its education system, or the fact that bilateral agreements came into play in the middle of our observation period.

The remainder of the chapter is organized as follows. Section 2 presents our dataset and its main advantages over the datasets used in the literature. Section 3 explains the difficulties encountered when analyzing tenure data and shows why duration models are appropriate for such a task. Section 2.1 displays several statistics based on elapsed tenure. Section 4 presents the results obtained with several duration models. Finally, section 5 summarizes the findings and concludes.

2 Data

We use data from the Swiss Labor Force Survey (SLFS), which is carried out every year since 1991 by the Swiss Federal Statistical Office (SFSO). It contains very detailed information about the labor status, wages, training, socioeconomic characteristics, and the composition of the respondent's household. Individuals who take part in the survey are contacted up to five years in a row, which makes the SLFS an unbalanced panel.

We restrict the sample to individuals aged between 18 and 65 (62 for women), who are not self-employed. Workers from the primary sector and from public administration are discarded, because their employment relationships are particular.[1]

The central variable of our analysis is tenure. It is constructed from the responses to the questions: "In which year did you start working in this company?" and "Do you remember in which month?". Hence, contrarily to what is available in many surveys where tenure is coded in intervals of sev-

[1]Since we now focus on tenure durations instead of earnings, the selection problem is no longer an issue. By definition, an individual is included in our sample (is *at risk*) only if he or she is in employment. For this reason, the analyses for the female sample are included in the chapter instead of in appendix.

eral years, tenure is coded precisely on a monthly basis. Moreover, the SLFS contains information about the activity status of the respondent for each of the last 12 months if he or she changed job during this period. This information enables us to check if the individual passed from one job to another directly or if he or she had to go through some inactivity or unemployment spell between the two.[2]

Since the SLFS gathers information about all individuals living in Switzerland (not only workers), we are able to identify the labor status after an individual leaves his job. We will distinguish between the following destination states: *new job* stands for job-to-job changes, *unemployment* whenever we observe a period of non-employment between two jobs, *training* refers to a job spell which ends for training or educational purposes, and *inactivity* if the labor market is left permanently for retirement or for no defined length to inactivity. In the estimations, we will not show the results for the training destination because too few transitions toward this state occur in our dataset.

Parallel to this classification of destination states, we are also able to identify the reasons why job spells end. We categorize the following termination motives: *layoff* if the separation was initiated by the firm, *quit* if it was initiated by the worker, and *other reasons* if we cannot clearly ascribe the given reason to any of these two categories. Unfortunately, the required information to construct these categories is only available from 1996 onwards.

One could even consider both destination states and termination reasons at the same time. For example, the probability that a worker quits a job for a new one could be different from the probability that a worker quits to inactivity and therefore could be modeled separately. However, to obtain reliable estimates, such an approach would require many more observations than currently at our disposal, and we leave it open to future research.

2.1 Employment Tenure through Time

We first look at some descriptive statistics on *elapsed* tenure, to be able to make some comparisons to what is traditionally used in the literature.

Figure 1 displays the evolution of median elapsed tenure for all men and women between 1991 and 2008, with the expected noticeable gap between genders.[3] With a difference of more than three years in the median tenure of the two groups in 1991 but less than two years in 2008, the spread however seems to be decreasing. In particular, median tenure does not show any clear

[2]This information is only available from 1996 onwards.

[3]All descriptive statistics use sampling weights.

tendency for men, but is on the rise for women during most of the observation period.

In Figure 2, the unemployment rate and the growth rate of real GDP show the evolution of the business cycle in Switzerland over the period 1991-2008. As expected, median tenure is clearly countercyclical. It increased in the early 1990s when unemployment rose and GDP growth was weak. When the economy recovered in the late 1990s, median tenure decreased. Finally, after 2000, median tenure rose again (especially for women), mirroring the rise in unemployment.

The countercyclicality of median tenure is explained by the evolution of hires and separations along the business cycle. Hires are obviously procyclical. Separations are procyclical as well because quits react more strongly than layoffs along the cycle (see Gregg & Wadsworth, (1995) p. 76, or Auer & Cazes, (2000) pp. 387-388). Hence, hiring increases during a boom, inflating the lowest bands of the tenure distribution. Separations also increase, but occur more or less uniformly at all levels of tenure. The overall effect is a fall of median tenure in a tight labor market. During a recession, both hires and separations decline. Moreover, employers usually try to retain workers who have the longest tenure and release the ones they have hired the most recently (on a *last in, first out* basis). The median tenure of the group of workers who keep their job will therefore mechanically rise in the recession.

To best account for both quits and layoffs, we will use unemployment and vacancy rates in our estimations. This latter indicator is rarely included, despite the fact that it "may be a better cyclical guide than the unemployment rate" (Gregg & Wadsworth, 2002, p. 117). One problem with vacancies in Switzerland is that the statistic is solely derived from vacancies which have been announced (on a voluntary basis) by employers to regional employment offices. It therefore only covers a fraction of available jobs at a given time, and it may not even be fully representative of the whole set of vacancies. Still, at the macroeconomic level, the index remains a good indicator of tightness in the labor market.

However, one should keep in mind that separations can originate from either quits or layoffs, which are very different in nature. In line with the literature, we define quits as worker-initiated separations, and layoffs as firm-initiated separations. Hence, workers fear layoffs as they are involuntary but not quits which are voluntary. This might explain the discrepancy between the media's coverage and what is observed in official statistics. Drawing the line between quits and layoffs is thus of primary importance and we will analyze job spells ending with a quit and those terminated by a layoff in two separate duration models, since blending the two causes of separation in the same model could in fact mask the true story. Median tenure might

Figure 1: Median elapsed tenure for men and women, SLFS

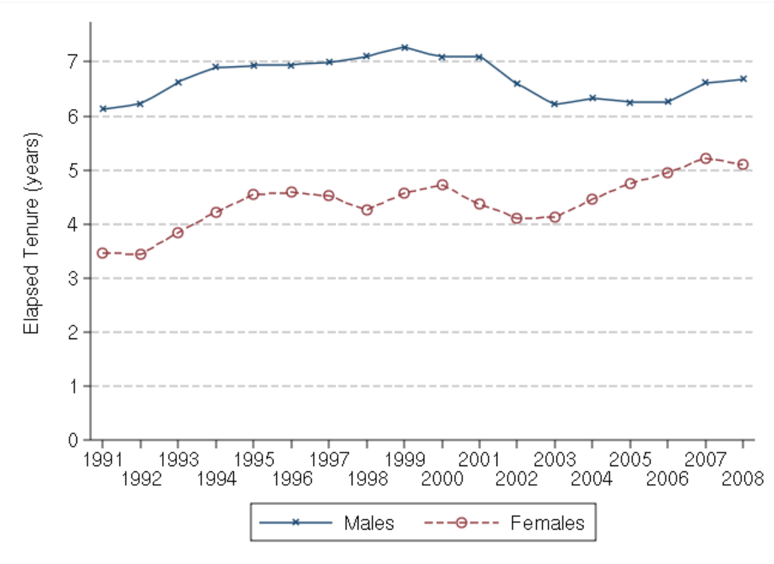
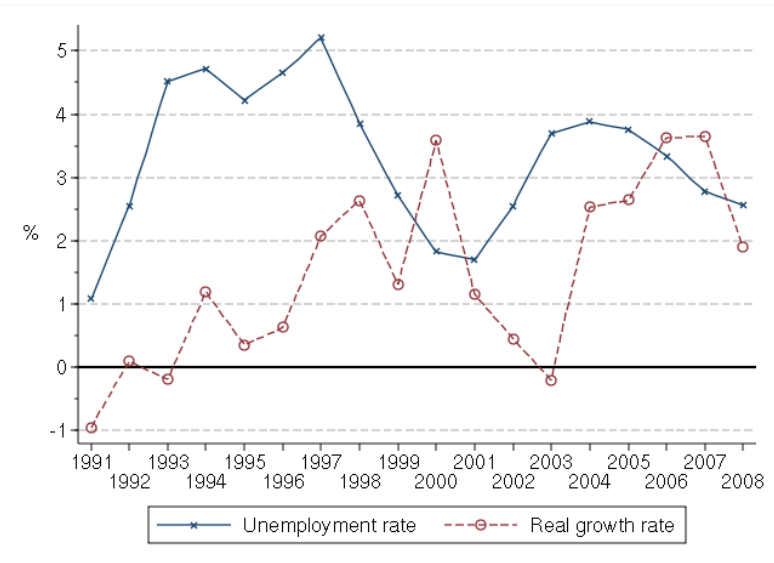


Figure 2: Annual rate of unemployment and real GDP growth rate in Switzerland



for instance remain unaltered for several decades, with more frequent layoffs being offset by fewer quits. This distinction is pivotal to the discussion on job *stability* and job *security*, the former being associated to the size of turnover and the length of jobs, while the latter implies that job terminations have undesired consequences for workers.

Figures 3 and 4 display the evolution of median elapsed tenure for some age groups. It shows that tenure obviously rises with age. The difference between old age and youth is more pronounced for men than women. The latter having more frequent career interruptions, their chances to stay in very long job spells are obviously reduced. In other words, there is no difference in median tenure between young men and young women. We only observe significantly longer median tenures for men in groups older than 35. This clearly coincides with the age at which many women are still in a child rearing period,[4] and will quit a job either temporarily or permanently.

Between 1991 and 2008, it appears that median tenure is virtually constant. For each age group, median tenure has almost the same value in 2008 than it had in 1991. For men however, the picture does change. For the older age groups, median tenure is clearly on the decline, with 5 years less in 2008 than in 1991 for workers over 45.

Figures 5 and 6 display median tenure for some selected sectors. We again observe that the shape of tenure is much more similar for women across different sectors than for men. In the public sector, men have a much longer median tenure than in the other sectors. Both for men and women, the housing and real estate sector appears to be on the low side.

Figures 7 and 8 split individuals on the basis of hours worked. Men working part-time have lower median tenure than those working full-time. Quite surprisingly, women working part-time appear to have a slightly longer tenure than their counterparts working full-time. We note however that men working part-time are very rare in Switzerland, and it could well be that they are less attached to the labor market. The fraction of men working part-time increased from 3% to 7% between 1991 and 2008, which could explain the upward trend in the median tenure of this group. On the other side, part-time is very widespread among women, with almost one out of two female jobs being part-time in 2008.

One final decomposition is shown in Figures 9 and 10 with the evolution of median tenure for some education groups, an unusual separation in this literature, even though the differences across these groups are substantial. Here also, the various female groups are much more compact than the male

[4]The average age for women giving birth to their first child is between 27 and 30 over the period 1991-2008 (SFSO, 2009a).

Figure 3: Median elapsed tenure for men by age groups, SLFS

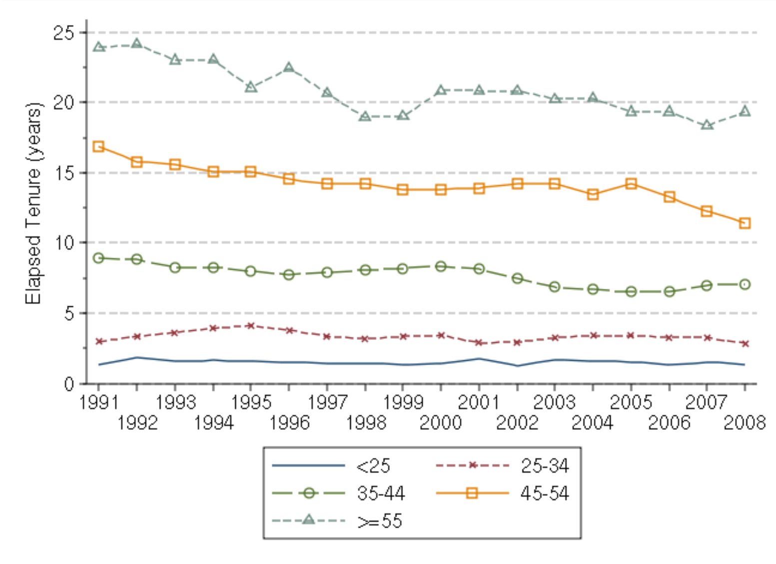


Figure 4: Median elapsed tenure for women by age groups, SLFS

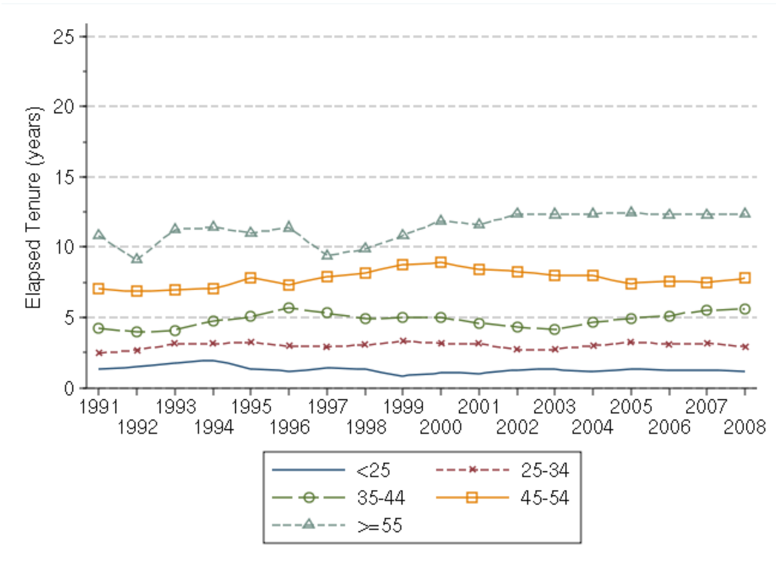


Figure 5: Median elapsed tenure for men by sectors, SLFS

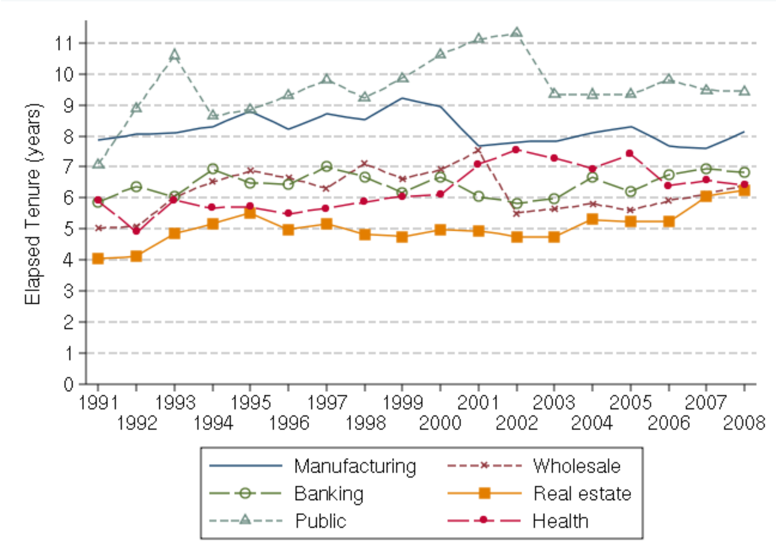


Figure 6: Median elapsed tenure for women by sectors, SLFS

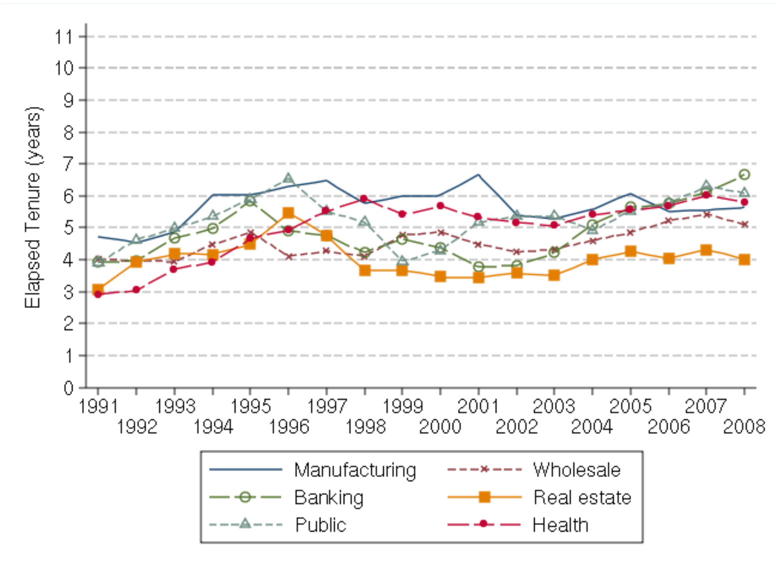


Figure 7: Median elapsed tenure for men by hours worked, SLFS

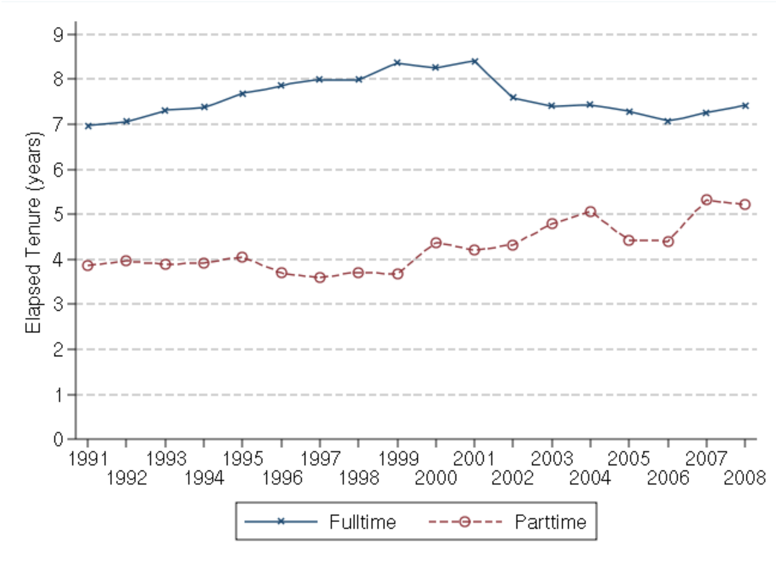


Figure 8: Median elapsed tenure for women by hours worked, SLFS

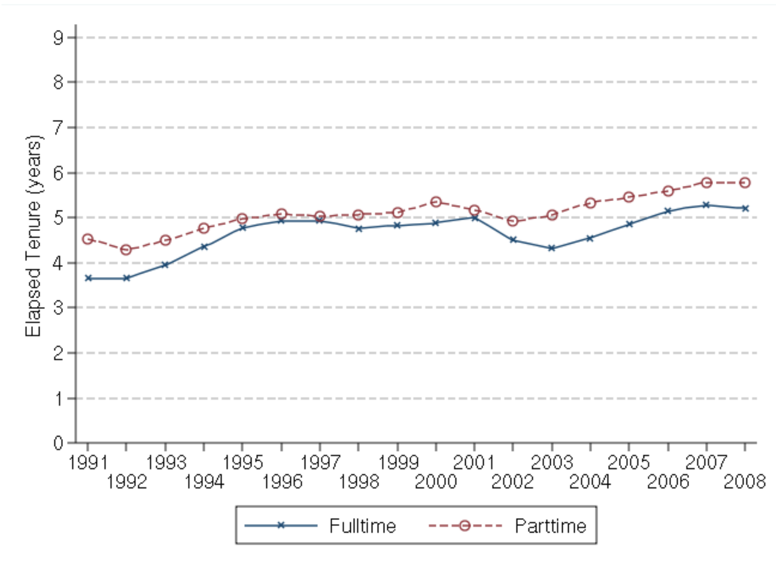


Figure 9: Median elapsed tenure for men by education groups, SLFS

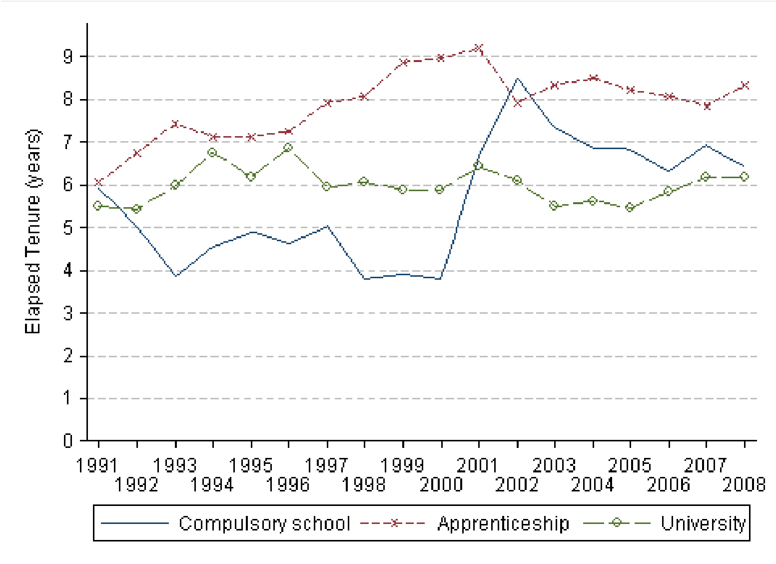
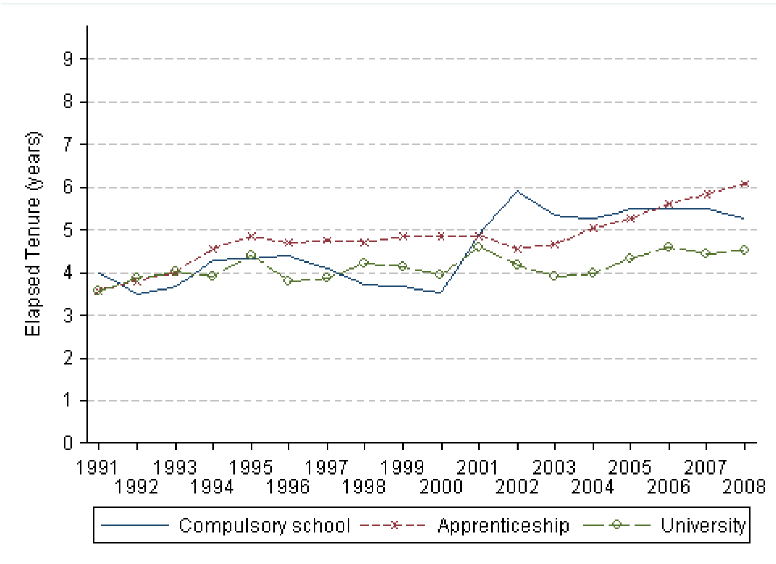


Figure 10: Median elapsed tenure for men by education groups, SLFS



ones for whom the spread in median tenure is larger. More interestingly, we observe that median tenure follow opposite paths depending on whether workers have no skills beyond compulsory schooling or hold an apprenticeship. This is particularly pronounced for men. Hence, it appears that median tenure for apprenticeship holders is particularly countercyclical, whereas it is *procyclical* for the compulsory school group.

Another interesting feature is that the relationship between median tenure is non-monotonic along education levels. The most educated group exhibits less tenure than the apprentices during the whole observation period, and, from 2002 onwards, tenure for these workers is even less than the least educated group. Median tenure is nevertheless much less volatile for the university degree holders than for any other group. These workers are thus less affected by the business cycle.

3 Modeling Tenure Data

Some problems must be addressed with panel tenure data because respondents are selected from a stock of people who occupy a state at the moment they are interviewed. In the terminology of duration models, this process is known as *stock sampling* (Lancaster, 1990) and it raises a serious statistical issue labeled *left-truncation*. “This creates a sample selection bias for the period before the observation window. The earlier the starting time of the episode and the shorter the durations, the less likely it is that these episodes will appear in the observation window” (Blossfeld & Rohwer, 2002). Long tenure spells will therefore be over-represented in the sample, and statistics based on the latter will overestimate the actual distribution of tenure.

Another way to look at this problem is to think about the difference between jobs and workers. What we wish to model is the distribution of job tenures. However, the unit of observation is the worker. Since “most jobs are short, but most workers are in long jobs” (Burgess & Rees, 1996), there is an obvious difference between what is observed and what is to be analyzed.

An effective solution to left-truncation consists in analyzing only the part of the duration that reaches into the observation window (see for example Guo, 1993). However, a proper statistical analysis of tenure is seldom used as most researchers simply use elapsed or completed tenure to make inference, even though both measures suffer from the left truncation problem.

There is no doubt that survival analysis is the most appropriate tool to analyze tenure. First, it allows to retrieve information from all the observed job spells, completed or not. Right-censoring is readily handled in duration models, but many researchers ignore this problem and use inaccurate econometric techniques like OLS on elapsed tenure spells (Mumford & Smith, 2004; Farber, 2009) or logit regressions on the probability of having held a job for less than one year (Burgess & Rees, 1998; Gregg & Wadsworth, 2002; Farber, 2009; Bratberg, Salvanes, & Vaage, 2010).[5] When using such models, one should discard the uncompleted job spells (i.e. most of the observations) in order to have clean data, but elapsed tenure is used without taking into account the fact that such job spells might last for many additional years. Another practical advantage of duration models over traditional regression models is that the whole distribution can be described with a single estimation without resorting to separate estimations for several cuts of the tenure distribution.[6]

Among the many different variants of the duration approach, the semi-parametric Cox proportional hazard model (Cox, 1972, 1975) is quite appealing. It leaves the baseline hazard unspecified and the duration dependence is therefore free to evolve non-monotonically over the job spell. The duration dependence of the hazard of job termination is certainly non-monotonic and we do not want to impose any restriction on its shape, which will be determined by the data alone.

In what follows, $S(t)$ is the survivor function, $f(t) = dS(t)/dt$ is the probability density function, and $h(t) = f(t)/S(t)$ is the hazard function. The Cox model specifies the hazard function as:[7]

$$h(t|x) = h_0(t) \cdot \exp(x'\beta) \tag{1}$$

where $h_0(t)$ is the baseline hazard function, x is a matrix of possibly time-dependent covariates, and β are the parameters of interest. This model is said to be semi-parametric since the baseline hazard function $h_0(t)$ is left unparameterized and the covariates enter the model log-linearly and multiplicatively.

Another advantage of the Cox model is the ease of interpretation of the β parameters. The ratio of the hazards of two individuals i and j is indeed time-independent and given by:

$$\frac{h_i(t|x_i)}{h_j(t|x_j)} = \exp(x'_i - x'_j)\beta \tag{2}$$

[5] Running a logit regression on the likelihood that a person has held a job for less than some threshold is obviously problematic if the job is still in progress. Such a measure pools job spells that will actually end very shortly with job spells that will in fact last many additional years.

[6] In most papers of the literature, the likelihood that a worker has held a job for a very short time (usually up to one year) is modeled, as well as the likelihood of having held a job for at least several years (usually five, ten or even twenty).

[7] For a detailed presentation of duration models, see among others Kiefer (1988), Lancaster (1990), or Kalbfleisch & Prentice (2002).

Hence, the exponential of a parameter gives the hazard ratio of two individuals differing by one unit in the corresponding variable. For example, if x contains a nationality dummy for Non-Swiss, then $\exp(\beta_{\text{Non-Swiss}})$ gives the transition hazards' ratio of foreign to Swiss workers. A positive (negative) β indicates a higher (lower) hazard rate and therefore shorter (longer) job spell.

Consider now individual $i = 1, \dots, n$ with the trivariate response $(t_{0i}; t_i; \delta_i)$, representing a period of observation $(t_{0i}; t_i]$, ending in either failure ($\delta_i = 1$) or right-censoring ($\delta_i = 0$). This structure enables us to account for two features present in our data, namely left-truncation and right-censoring.

An observation i known to fail at time t_i contributes to the likelihood function the value of the density at time t_i conditional on the entry time t_{0i}, $f(t_i|x_i)/S(t_{0i}|x_i)$. A right-censored observation, known to survive only up to time t_i, contributes $S(t_i|x_i)/S(t_{0i}|x_i)$, which is the probability of surviving beyond time t_i conditional on the entry time, t_{0i}. The log-likelihood is thus given by:

$$\log L = \sum_{i=1}^{n} \delta_i \log h(t_i|x_i) + \log S(t_i|x_i) - \log S(t_{0i}|x_i) \tag{3}$$

The β parameters are implicitly included in (3). For individuals under observation when their job spell starts, $S(t_{0i}|x_i) = 1$ and the likelihood simplifies to a more usual form. In our data though, most job spells have already started when the individuals enter the panel survey and the spells are thus left-truncated. In such case, the period before the first interview must not be considered as a period at risk since, had the job ended, we would never have known it. The starting date being asked retrospectively, we condition on time spent in the job but not in the panel. This methodology is the best way to retrieve information from such spells (Guo, 1993).

The likelihood function not only contains the β parameters to be estimated but also the baseline hazard $h_0(t)$ which is unknown and unspecified. It is thus not possible to proceed directly to the maximization. Cox (1972, 1975) shows that the likelihood function can be decomposed in order to rule out the baseline hazard. The estimation of the model is then made by maximizing the following partial likelihood function:[8]

$$\log PL = \sum_{j=1}^{k} \left[\sum_{i \in D_j} x_i'\beta - d_j \log \left\{ \sum_{\ell \in R(t_j)} \exp(x_\ell'\beta) \right\} \right] \tag{4}$$

[8]The original Cox model assumes no ties in the durations. Since tenure is measured in months, we obviously have ties in our data, and we use Breslow's (1974) method to handle them.

where j indexes the ordered failure times $t_{(j)}$, $j = 1; \ldots ; k$, D_j is the set of d_j observations that fail at time $t_{(j)}$, d_j is the number of failures at $t_{(j)}$; and $R(t_j)$ is the set of observations ℓ which are at risk at time $t_{(j)}$ (i.e., all ℓ such that $t_{0\ell} < t_{(j)} \leq t_\ell$).

The partial likelihood contains no unknown elements and can therefore be maximized to retrieve the parameters of interest. The attendant cost is a loss in efficiency: if we knew the functional form of $h_0(t)$, we could do a better job at estimating β. Nevertheless, it can be shown that maximum partial likelihood estimates have all the standard asymptotic properties (see Kalbfleisch & Prentice, 2002, pp. 101-104).

Since we consider several possible exits from a job, competing risks models must be used. The methodology is the same as the one just described, except that a specific hazard rate is specified for each possible exit e:

$$h_e(t|x) = h_{0e}(t) \cdot \exp(x'\beta), \qquad e = 1, \ldots, m. \tag{5}$$

The overall hazard rate is given by the sum of all the specific hazard rates:

$$h(t) = \sum_{e=1}^{m} h_e(t) \tag{6}$$

and the overall log-likelihood and partial likelihood of the model are given by:

$$\log L = \sum_{e=1}^{m} \log L_e \qquad \text{and} \qquad \log PL = \sum_{e=1}^{m} \log PL_e \tag{7}$$

From this latter equation, it is straightforward to see that the estimation of the competing risks model is simply achieved by estimating a separate equation for each possible exit. For each exit-specific estimation, spells ending in a different exit than the one under study are considered as right-censored.

4 The Determinants of Job Tenure

Our empirical findings from the Cox proportional hazard model enable us to unravel the determinants of job tenure and to make some inference about the evolution of job stability and job insecurity in Switzerland over the period 1991-2008.

In Table 1, all tenure spells are pooled in the same regression, ignoring destination states and reasons for job termination. This is the typical tenure regression used to analyze “job stability”. One should however recall that the estimates are difficult or even impossible to interpret since the way a job ends may tell radically different stories. To illustrate this point, note that the coefficients for both education groups are negative, indicating that apprenticeship holders and university graduates have shorter job spells than the least educated. Whether the worker's position has improved or not following a separation will clearly depend on the nature of the separation. With a voluntary quit, chances are his position improved, whereas the situation may have worsened if the worker lost his job. In subsequent sets of estimations, we therefore use competing risks models to account for these possible different paths.

To evaluate a possible tendency of increased job instability, we include the year as a covariate. The coefficient is slightly positive (and significant for men), which tends to indicate that employment has become less stable between 1991 and 2008. However, including a single trend variable imposes a linear evolution of the hazard. To account for potential non-linearities, in alternative estimations, we replace this single variable by a complete set of time fixed effects. The results are presented graphically in Appendix A. Figures A.1 and A.2 display the time fixed effects obtained with estimations that are similar to those in Table 1. They depict the evolution of job instability for men and women. Because no clear pattern emerges from the estimated parameters, we cannot assess if job instability has decreased or increased.

Such an assessment does not imply that job insecurity has not increased though. It could be that the overall risk of job termination has remained more or less constant, but that the risk of being laid off has increased, compensated by a decrease in the risk of quits. This possibility once again underlines the need to distinguish between the several possible exits from a job. If one is investigating job insecurity, then modeling tenure without consideration of the subsequent status after the current job is not entirely satisfactory.

This crucial distinction is highlighted in Tables 2 and 3 which provide separate estimations by destination state (new job, unemployment, and inactivity) with completely different coefficients across them. In these estimations, all the coefficients are interesting per se with a straightforward interpretation.

As expected, older workers exhibit less job-to-job mobility on the labor market, since age reduces monotonically the hazard toward a new job. For the other destinations however, the effect of age is completely different. For men, the hazard rate towards unemployment is lowest for the 25-35 age group and is largest for individuals over 55. Towards inactivity, the hazard is U-shaped, being low for individuals between 25 and 45 and increasing thereafter, probably because of retirement. For women, the risk of inactivity is highest for the 25-35 age group, which corresponds to the period during which most of them give birth to their first child.

Education tends to increase the chances of moving job-to-job, and sharply

Table 1: Hazard of job termination

	Men	Women
Education: apprenticeship	-0.100^{***}	-0.097^{***}
	(0.036)	(0.034)
Education: university	-0.047	0.010
	(0.041)	(0.043)
Age 25-35 years	-0.283^{***}	-0.331^{***}
	(0.044)	(0.043)
Age 35-45 years	-0.478^{***}	-0.595^{***}
	(0.049)	(0.047)
Age 45-55 years	-0.689^{***}	-0.804^{***}
	(0.056)	(0.052)
Age > 55 years	-0.055	-0.474^{***}
	(0.055)	(0.057)
Year	0.006^{**}	0.004
	(0.003)	(0.003)
Non-Swiss	-0.047	-0.088^{***}
	(0.029)	(0.032)
Married	-0.150^{***}	0.087^{**}
	(0.031)	(0.036)
Part-time	0.346^{***}	0.191^{***}
	(0.059)	(0.042)
Part-time × Married	0.180^{**}	-0.202^{***}
	(0.086)	(0.053)
Number of children	-0.047^{***}	-0.062^{***}
	(0.017)	(0.017)
Firm > 100 co-workers	-0.210^{***}	-0.185^{***}
	(0.027)	(0.029)
Regional unemployment rate	0.038^{***}	0.020
	(0.013)	(0.012)
Regional vacancy rate	0.181^{**}	0.146^{*}
	(0.088)	(0.088)
Industry wage premium	-0.610^{***}	-0.150
	(0.149)	(0.151)
Canton dummies	yes	yes
Sector dummies	yes	yes
# spells	29,445	24,766
# individuals	25,682	21,420
# failures	6,584	6,317
LogL	−50,657	−49,538
AIC	101,417	99,181
BIC	102,013	99,765

Swiss Labor Force Survey, 1991-2008.
Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

Table 2: Hazards of job termination by destination state, Men

	Newjob	Unemployment	Inactivity
Education: apprenticeship	0.168***	−0.295***	−0.402***
	(0.051)	(0.090)	(0.073)
Education: university	0.311***	−0.604***	−0.564***
	(0.055)	(0.115)	(0.095)
Age 25-35 years	−0.157***	−0.318**	−0.643***
	(0.054)	(0.129)	(0.216)
Age 35-45 years	−0.358***	−0.132	−0.620***
	(0.060)	(0.137)	(0.218)
Age 45-55 years	−0.694***	0.126	−0.106
	(0.070)	(0.142)	(0.213)
Age > 55 years	−1.212***	0.576***	1.769***
	(0.097)	(0.149)	(0.196)
Year	−0.004	0.017**	0.040***
	(0.003)	(0.008)	(0.007)
Non-Swiss	−0.131***	0.482***	−0.002
	(0.037)	(0.081)	(0.069)
Married	−0.116***	−0.486***	0.056
	(0.041)	(0.089)	(0.072)
Part-time	0.157*	0.337**	0.678***
	(0.083)	(0.168)	(0.151)
Part-time × Married	0.070	0.237	0.278
	(0.133)	(0.244)	(0.181)
Number of children	−0.013	−0.088*	−0.145**
	(0.020)	(0.050)	(0.057)
Firm > 100 co-workers	−0.314***	−0.268***	0.116**
	(0.035)	(0.078)	(0.058)
Regional unemployment rate	0.003	0.198***	0.057*
	(0.016)	(0.034)	(0.033)
Regional vacancy rate	0.451***	−0.428	−0.358
	(0.103)	(0.273)	(0.241)
Industry wage premium	−0.769***	−0.841**	−0.180
	(0.188)	(0.425)	(0.352)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	29,444	29,445	29,445
# individuals	25,681	25,682	25,682
# failures	4,317	876	1,235
LogL	−34,220	−6,731	−7,581
AIC	68,544	13,563	15,267
BIC	69,140	14,136	15,863

Swiss Labor Force Survey, 1991-2008.

Standard errors in parentheses. ***/**/*: Significant at the 0.01/0.05/0.10 level.

Table 3: Hazards of job termination by destination state, Women

	Newjob	Unemployment	Inactivity
Education: apprenticeship	0.180^{***}	-0.291^{***}	-0.254^{***}
	(0.051)	(0.090)	(0.061)
Education: university	0.398^{***}	-0.460^{***}	-0.381^{***}
	(0.061)	(0.120)	(0.090)
Age 25-35 years	-0.334^{***}	-0.139	0.315^{**}
	(0.053)	(0.135)	(0.134)
Age 35-45 years	-0.480^{***}	-0.279^{*}	-0.222
	(0.058)	(0.145)	(0.141)
Age 45-55 years	-0.758^{***}	-0.090	-0.362^{**}
	(0.067)	(0.151)	(0.146)
Age > 55 years	-1.172^{***}	0.091	0.697^{***}
	(0.098)	(0.173)	(0.145)
Year	-0.005	0.047^{***}	0.003
	(0.004)	(0.009)	(0.005)
Non-Swiss	-0.167^{***}	0.375^{***}	-0.115^{*}
	(0.044)	(0.087)	(0.064)
Married	-0.259^{***}	0.215^{**}	0.877^{***}
	(0.051)	(0.094)	(0.077)
Part-time	0.101^{*}	-0.007	0.540^{***}
	(0.054)	(0.128)	(0.095)
Part-time × Married	-0.150^{**}	-0.357^{**}	-0.407^{***}
	(0.075)	(0.154)	(0.110)
Number of children	-0.054^{**}	-0.016	-0.037
	(0.023)	(0.045)	(0.034)
Firm > 100 co-workers	-0.261^{***}	-0.150^{*}	-0.027
	(0.040)	(0.083)	(0.054)
Regional unemployment rate	-0.015	0.152^{***}	0.039
	(0.017)	(0.036)	(0.024)
Regional vacancy rate	0.105	-0.476	0.333^{**}
	(0.119)	(0.311)	(0.160)
Industry wage premium	-0.122	-1.133^{**}	0.027
	(0.204)	(0.455)	(0.285)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	24,765	24,766	24,766
# individuals	21,420	21,420	21,420
# failures	3,619	831	1,716
LogL	−28,899	−6,384	−12,478
AIC	57,900	12,871	25,060
BIC	58,473	13,455	25,644

Swiss Labor Force Survey, 1991-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

reduces the risk of transiting towards unemployment or inactivity, both for men and women. It thus seems that if educated workers have shorter overall tenure, this is because they switch job more often in search of a better match.

Married men appear to be less mobile, as their hazard toward a new job is reduced by about 10% compared to single men. Their unemployment risk is also much lower. On the other hand, married women appear to become much more often unemployed or inactive than single ones. These results are in line with several other studies on the Swiss labor market (Ferro Luzzi & Flückiger, 1998; Flückiger & Ramirez, 2001; Weber, 2006).

Workers in large firms appear to suffer less separations. One possible explanation is given by the larger set of career opportunities offered to employees within the firm. Another possible reason is that large firms are certainly less sensitive to business cycle. Large firms provide some security to their employees, and can reduce turnover more easily by offering increasing wage tenure profiles.

Among the three possible destination states we consider, unemployment is the one that might be related to job insecurity. If the hazard towards this exit has increased, then we could infer that job insecurity has increased. Both for men and women, the coefficient attached to sample year is positive and significant. On this basis, it appears that transition from employment to unemployment have become more frequent and therefore that job insecurity has increased. However, with time fixed effects replacing the trend variable, the evidence is less clear-cut (see Figures A.3 and A.4). Once again, no clear pattern emerges from the coefficients, and it is hard to firmly conclude that job insecurity has increased.

In Tables 4 and 5, exits are separated according to termination reasons: layoffs, quits, and other reasons. Again, we obtain very different results across the possible exits. Of greater interest are layoffs and quits, since the “other reasons” is a residual group where several possible exits cannot easily be classified in either firm or worker initiated separations.

As expected, our results indicate that older workers are more likely to be laid off but also that they quit much less frequently. A higher level of education decreases the layoff risk and increases the quit probability. As for the previous set of results, married men are found to keep their job longer than single ones, as they quit less and are less frequently laid off. The hazard rates for employees of large firms are lower for any of the exits considered. Notice finally that the regional unemployment rate raises the layoff hazard rate and decreases the hazard rate of quits.

Like the hazard rate towards unemployment, the hazard rate towards layoff might be considered as an indicator of job insecurity. The coefficient on year for men is unsignificant, whereas those for women is slightly positive

Table 4: Hazards of job termination by termination reason, Men

	Layoffs	Quits	Other reasons
Education: apprenticeship	-0.144^{**}	0.158^{**}	0.001
	(0.073)	(0.076)	(0.072)
Education: university	-0.583^{***}	0.437^{***}	0.105
	(0.099)	(0.081)	(0.082)
Age 25-35 years	-0.034	-0.279^{***}	-0.265^{**}
	(0.126)	(0.078)	(0.112)
Age 35-45 years	0.159	-0.624^{***}	-0.571^{***}
	(0.130)	(0.086)	(0.122)
Age 45-55 years	0.444^{***}	-1.112^{***}	-0.838^{***}
	(0.132)	(0.107)	(0.138)
Age $>$ 55 years	0.705^{***}	-2.049^{***}	0.633^{***}
	(0.142)	(0.169)	(0.116)
Year	-0.001	-0.012	0.013
	(0.010)	(0.008)	(0.009)
Non-Swiss	0.266^{***}	-0.224^{***}	0.017
	(0.068)	(0.053)	(0.059)
Married	-0.270^{***}	-0.179^{***}	-0.082
	(0.072)	(0.061)	(0.061)
Part-time	0.230	0.185^{*}	0.362^{***}
	(0.171)	(0.109)	(0.122)
Part-time $\times$ Married	0.389^{*}	-0.194	0.178
	(0.220)	(0.209)	(0.162)
Number of children	0.010	-0.009	-0.138^{***}
	(0.037)	(0.030)	(0.039)
Firm $>$ 100 co-workers	-0.333^{***}	-0.265^{***}	-0.038
	(0.065)	(0.050)	(0.053)
Regional unemployment rate	0.249^{***}	-0.127^{***}	0.111^{***}
	(0.034)	(0.026)	(0.031)
Regional vacancy rate	-0.082	0.434^{**}	0.408^{**}
	(0.258)	(0.183)	(0.206)
Industry wage premium	-1.554^{***}	-0.937^{***}	0.030
	(0.375)	(0.290)	(0.324)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	25,632	25,632	25,632
# individuals	22,510	22,510	22,510
# failures	1,278	2,081	1,651
LogL	$-9,425$	$-15,964$	$-11,604$
AIC	18,954	32,031	23,313
BIC	19,540	32,617	23,899

Swiss Labor Force Survey, 1996-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

Table 5: Hazards of job termination by termination reason, Women

	Layoffs	Quits	Other reasons
Education: apprenticeship	-0.191^{**}	0.119^{*}	0.002
	(0.079)	(0.071)	(0.074)
Education: university	-0.424^{***}	0.454^{***}	0.159^{*}
	(0.112)	(0.082)	(0.088)
Age 25-35 years	-0.313^{**}	-0.464^{***}	-0.288^{***}
	(0.130)	(0.075)	(0.095)
Age 35-45 years	-0.147	-0.764^{***}	-0.681^{***}
	(0.132)	(0.082)	(0.105)
Age 45-55 years	0.262^{*}	-1.160^{***}	-1.243^{***}
	(0.135)	(0.095)	(0.122)
Age > 55 years	0.418^{***}	-1.603^{***}	-0.179
	(0.151)	(0.140)	(0.115)
Year	0.020^{*}	0.006	-0.031^{***}
	(0.011)	(0.008)	(0.009)
Non-Swiss	0.357^{***}	-0.200^{***}	-0.190^{***}
	(0.078)	(0.058)	(0.067)
Married	0.084	-0.087	0.281^{***}
	(0.085)	(0.067)	(0.077)
Part-time	0.158	0.124	0.210^{**}
	(0.102)	(0.078)	(0.089)
Part-time × Married	-0.516^{***}	-0.177^{*}	-0.132
	(0.131)	(0.102)	(0.112)
Number of children	-0.026	-0.084^{***}	-0.091^{**}
	(0.042)	(0.031)	(0.036)
Firm > 100 co-workers	-0.301^{***}	-0.225^{***}	-0.123^{**}
	(0.075)	(0.053)	(0.058)
Regional unemployment rate	0.211^{***}	-0.145^{***}	0.067^{**}
	(0.037)	(0.028)	(0.028)
Regional vacancy rate	0.400	0.240	0.251
	(0.281)	(0.204)	(0.199)
Industry wage premium	-0.109	-0.451	-0.443
	(0.392)	(0.292)	(0.336)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	21,654	21,654	21,654
# individuals	18,896	18,896	18,896
# failures	1,072	1,956	1,579
LogL	−7,956	−15,120	−11,782
AIC	16,015	30,342	23,661
BIC	16,578	30,906	24,203

Swiss Labor Force Survey, 1996-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

and significant at 10%. The time fixed effects of the alternative estimation are displayed in Figures A.5 and A.6. Once again, there is no clear tendency. If any, there seems to be a slight decrease of the time fixed effects. Taken as a whole, our analysis therefore does not bring any clear evidence of an increasing job insecurity.

4.1 The Impact of Wages on Tenure

One variable of particular interest in modeling tenure is the wage rate. This variable has a definite influence on expected tenure: a higher wage provides incentives to stay longer in the same job. This relationship has been extensively analyzed from a theoretical and empirical point of view. Employers manipulate wage profiles and make them steeper with tenure to reduce turnover or provide effort incentives. But the reverse causality is also true, since wages will increase as workers acquire specific skills through tenure. For this reason, long tenured workers earn higher wages and job tenure often appears as a determinant in wage regressions. Some authors like Hirsch & Schnabel (2010) include the wage rate as a regressor in their estimations without questioning the validity of such an approach but, as stated by Gottschalk & Moffitt (1999, p. S116), "wage changes and job dynamics are clearly jointly determined", which obviously raises an endogeneity problem. Topel & Ward (1992) also include the worker's current wage in their proportional hazards model for job mobility. As expected, they find that wage has a strong negative impact on mobility.

In order to account for the effect of earnings on job tenure while avoiding the endogeneity problem, we use inter-industry wage differentials (Krueger & Summers, 1988) instead of individual wages per se. They were obtained by regressing individual wages on a set of personal characteristics and two-digit industry dummies. The coefficients on industry dummies are normalized, and therefore give the industry "premiums". They are to be interpreted as the proportionate wage difference between an employee of a given industry and the average employee. Our contention is that the industry "rent" associated to some industrial wage policy is set exogenously by employers to reduce turnover or attract the best workers, and therefore it is not affected by an individual employee's tenure.

In order to have a measure as exogenous as possible, the industry premiums were computed using the Swiss Wage Structure Survey (SWSS).[9] This representative and nation-wide survey is conducted every two years since

[9]We thank Roman Graf who kindly computed the industry premiums for us. The results of this first step are available on request.

1994. It is an establishment survey, i.e., the questionnaires are filled out by personnel officers in each firm. The SWSS is known to provide more accurate information on wages than the SLFS.

Because the SWSS is only available every even year since 1994 while the data are annual since 1991 in the SLFS, we match each year of the SLFS with the closest following year available in the SWSS.[10]

The industry wage differentials are highly correlated over time. As expected, financial services or insurance companies systematically pay an extra premium of around 20%. On the other side, retail and hotels and restaurants “underpay” their employees by more than 20%.

We observe that industry wage premiums have an unambiguously negative impact on the hazard rate whatever the exit considered, even though the estimates are not all significantly different from zero. This indicates that separation occur less frequently in industries where wages are higher in average. In those industries, workers are less tempted to move. Turnover is also more costly to firms, which are therefore less willing to dismiss employees.

To take an example, the coefficient on the industry premium in first column of Table 4 is -1.6. A worker moving to an industry where the premium is 10 percentage points higher will see his hazard rate towards layoff drop by 16 percent. This is quite sizeable considering that a difference of similar magnitude is observed between workers with only compulsory school and those with apprenticeship training.

4.2 Duration Dependence of the Hazard Rate

Based on the estimations in Tables 1 to 5, we plot the hazard functions, which shows how the hazard rate evolves with tenure. All hazard functions are drawn for the mode of the overall sample covariates distribution, namely for a Swiss individual aged 35-45, married, without children, with apprenticeship training, working full-time in a firm of the manufacturing sector with less than 100 co-workers, in the canton of Zürich, in 2007. Keeping the covariates at the same values allows for level comparisons between different exits as well as between men and women. We cut the time axis at 30 years of seniority because longer job spells are scarce and the trajectories would fluctuate strongly afterwards.

The hazard functions corresponding to the pooled estimations in Table 1 are plotted in Figure 11. It first confirms the well-known fact that women have shorter job spells that men, their hazard being always larger. The differ-

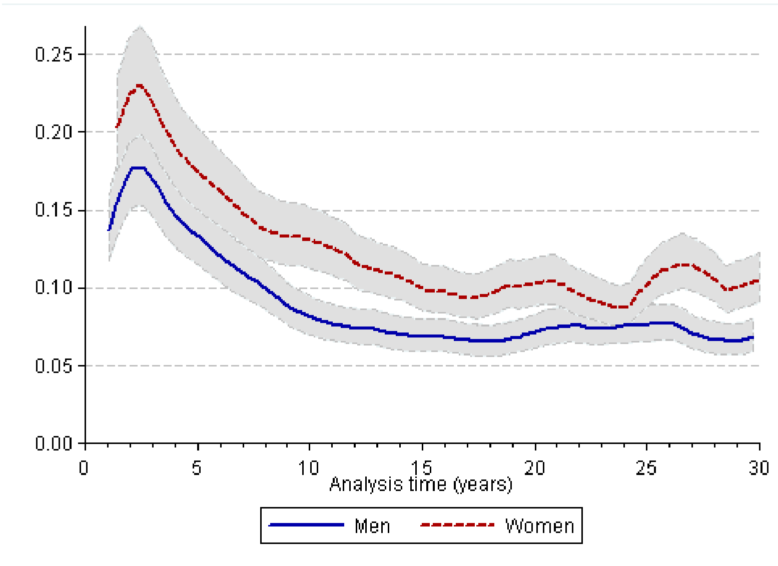
[10]The years 1991-1994 are all assigned the 1994 industry premiums, 1995-1996 are assigned the 1996 values, etc.

ence however appears to be weakly significant, with the confidence intervals at 90% sometimes slightly overlapping.

We then observe that the hazard of job termination peaks within the first few years of a job spell and then decreases monotonically with tenure. It indicates that jobs have a high risk of ending early, and many jobs will last no more than a few years or even a few months. This is perfectly consistent with the results of Booth et al. (1999). Gregg & Wadsworth (2002) also reached a similar conclusion: "job survival chances rise sharply with duration. Whilst half of new jobs break down in just over a year, the remaining fifty percent will last, on average, a total of 4 years".

This non-monotonic relationship between the transition rate and tenure can be explained if jobs are "experience goods".[11] In this case, Jovanovic (1979) demonstrates that the probability of leaving a job may initially rise with tenure. The reason is that it pays to remain and collect information on a new job. Before dissolving their match, the worker and the employer must

Figure 11: Hazard rate by gender



Notes: Hazard rates are drawn for the mode of the covariates distribution, i.e., for a Swiss individual aged 35-45, married, without children, with apprenticeship training, working full-time in a firm of the manufacturing sector, with less than 100 co-workers, in the canton of Zürich, in 2007 (the last complete year under observation).
Shaded areas are confidence intervals at 90%.

[11] A job is an "experience good" if the only way to determine the quality of a particular match is to form the match and "experience it".

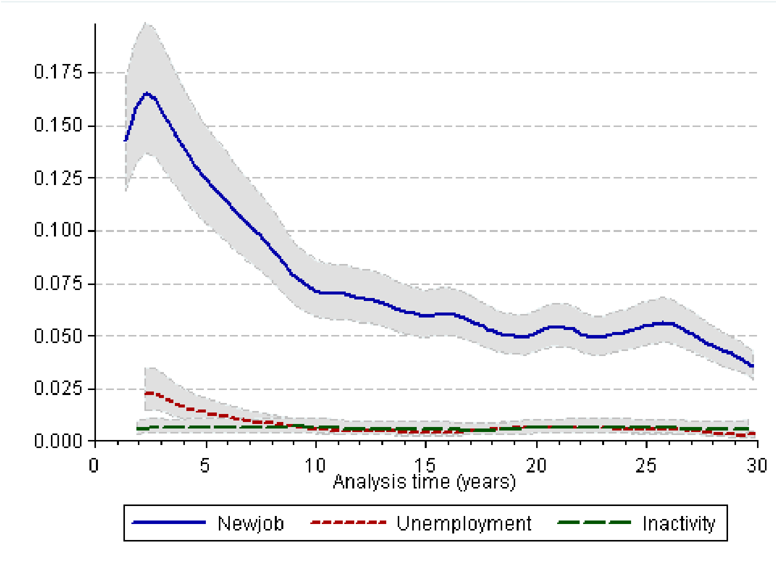
accumulate some critical amount of information to determine whether it is worth continuing their collaboration or not. This results in a transition rate that increases at the beginning of a job. Eventually, however, the probability of separation must decline with tenure.

Between 15 and 30 years of tenure, the hazard rate remains virtually flat. Beyond 30 years of tenure (not shown in the graph), the hazard rate would increase very sharply, because jobs end mechanically as workers reach retirement age.

Figures 12 and 13 draws the hazard functions towards the different destination states. The hazard rate towards a new job is by far the largest, at least for men. It peaks during the first few years of a job spell and then decreases until 30 years of tenure. The risk of transition towards unemployment is comparatively low and it is always decreasing during. A large and significant difference between men and women is observed for the hazard rate towards inactivity: while it is virtually nil for men, this transition rate is considerable for women. There is no apparent duration dependence for this destination state.

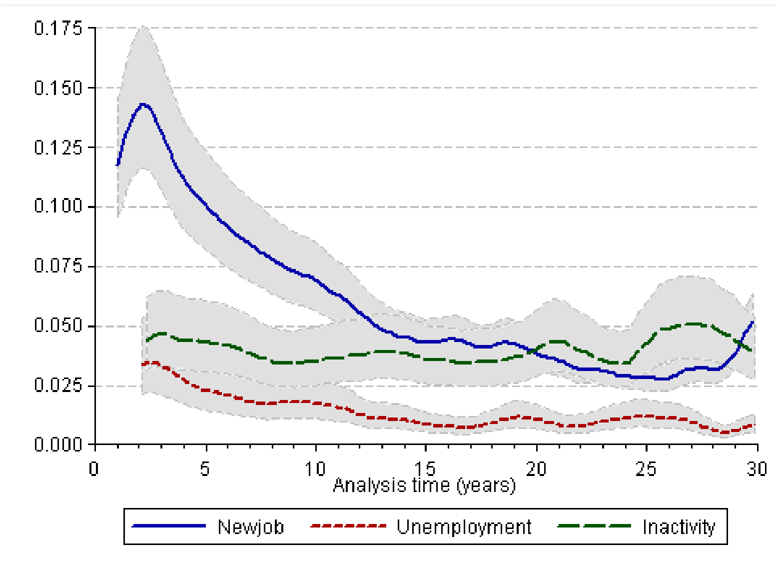
Figures 14 and 15 display the duration dependence of the hazard rates for the different termination reasons. The largest risk transition is found for quits. This hazard rate is of a similar magnitude for men and women, and its duration dependence once again shows a peak early in the spell and a continuous decrease thereafter. The hazard of layoff seems slightly higher for women than for men (even though the difference is not statistically significant), and it is always decreasing with tenure.

Figure 12: Hazard rate by destination state, Men



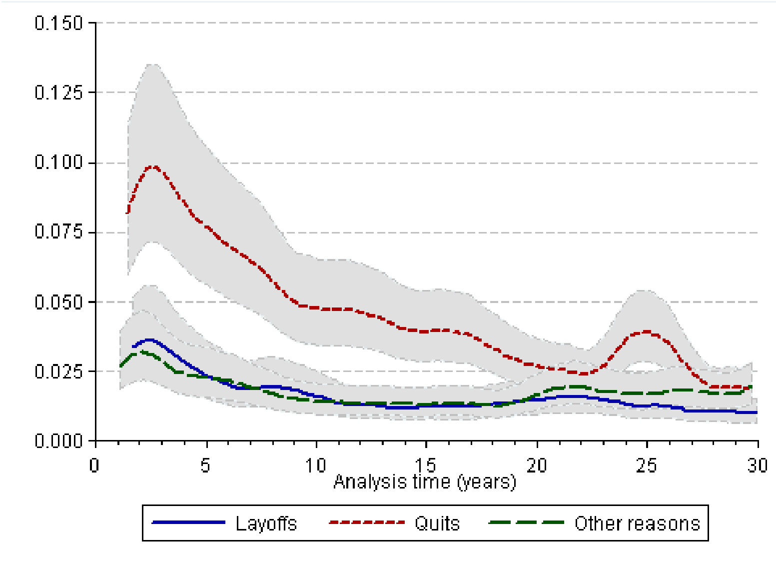
Notes: see Figure 11.

Figure 13: Hazard rates by destination state, Women



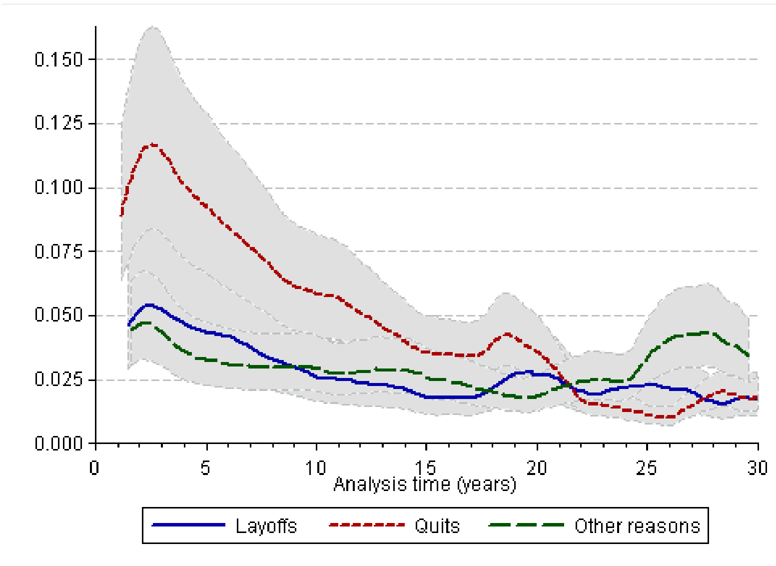
Notes: see Figure 11.

Figure 14: Hazard rates by termination reason, Men



Notes: see Figure 11.

Figure 15: Hazard rates by termination reason, Women



Notes: see Figure 11.

5 Conclusions

This chapter investigates the determinants of tenure through the estimation of a series of Cox proportional hazards models. Job stability has been extensively studied in the literature, though often without the appropriate econometric model. We argue that duration analysis is a much more efficient technique to analyze tenure than OLS or logit models. Moreover, we allow individuals to move towards several destination states and jobs to terminate for various reasons by making use of competing risks models. The effects of the covariates are diametrically different across the competing risks, which not only demonstrates the importance of such separations, but also enriches our understanding of the employer-employee relationship.

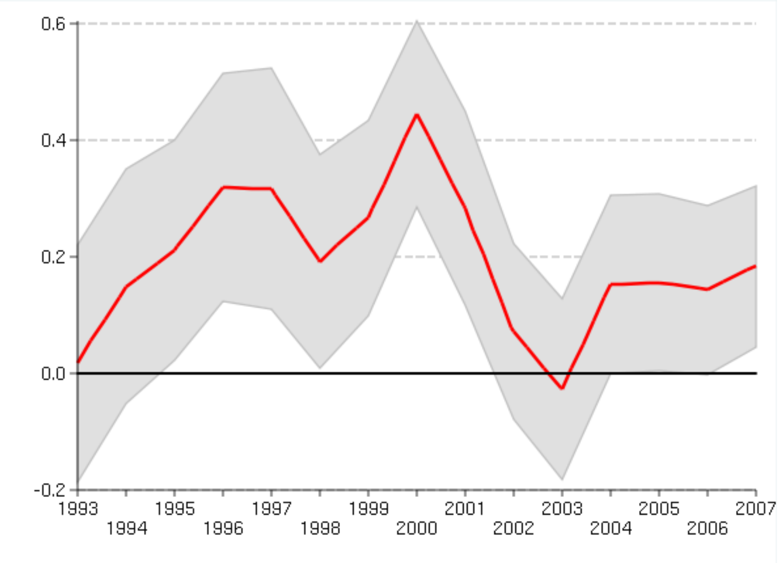
Job stability can be investigated through a regression on tenure without regard to the state of the worker after his job has ended. Our estimates do not show any clear tendency towards either increasing or decreasing tenure. However, we argue that such analysis is of rather limited interest. In our view, the concept of job insecurity is clearly more attractive, since the worker's subsequent state and/or the reason of job termination are taken into account. The evolution of transition rate towards unemployment and that of layoff separations provide useful insights into a potential rise or decline in job insecurity.

Another original contribution of this chapter lies in our suggestion for solving the obvious (but often neglected) endogeneity problem associated to individual earnings in tenure regressions. We use inter-industry wage differentials as regressors, and our contention is that these "premiums" are determined, as in the efficiency wage literature, by sectoral factors like the workers' effort monitoring technology. These rents are therefore independent of individual workers' tenure, but they can clearly motivate workers to stick longer with their firm. In accordance with this hypothesis, we find this variable to have a large negative effect (though not always significant) on the hazard rates, whichever the destination state and the job termination reason.

Finally, let us mention that it would be interesting to combine both destination states and termination reasons, since these are two complementary decompositions. One could indeed imagine, for example, that the probabilities of quitting towards a new job and quitting towards unemployment or inactivity are different. The transition rate from a quit to a new job could also differ from the transition rate from a layoff to a new job. Our dataset does unfortunately not contain sufficient observations to estimate such models, which we leave in the agenda of future research.

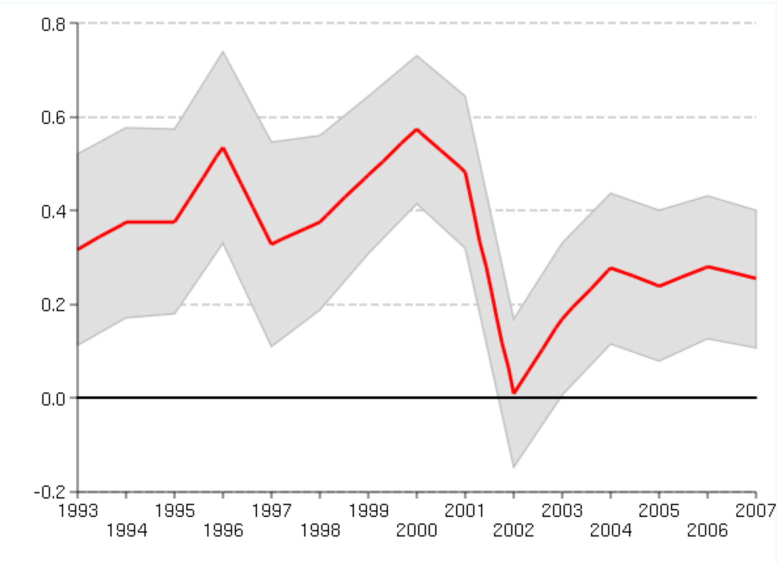
Appendix A: Evolution of Job Stability and Job Insecurity

Figure A.1: Evolution of job instability, Men



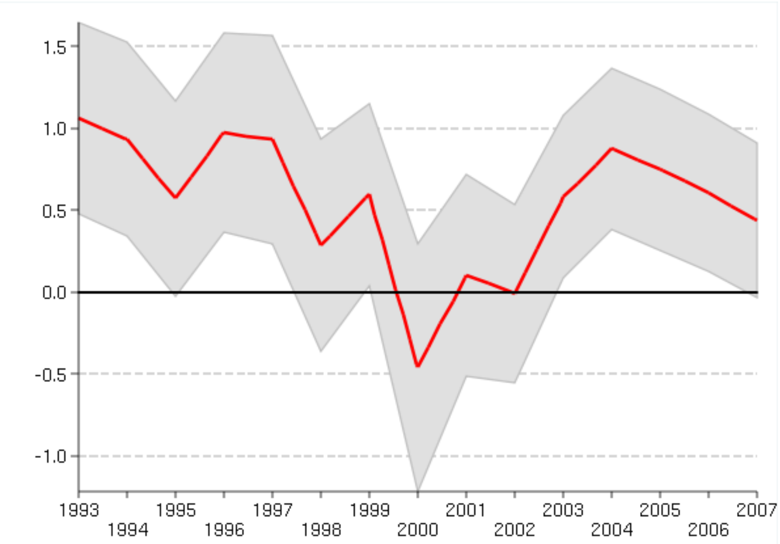
Notes: The plot displays time fixed effects from a regression similar to that in column "Men" of Table 1, where the variable "Year" has been replaced by time fixed effects.
Shaded area is confidence interval at 95%.

Figure A.2: Evolution of job instability, Women



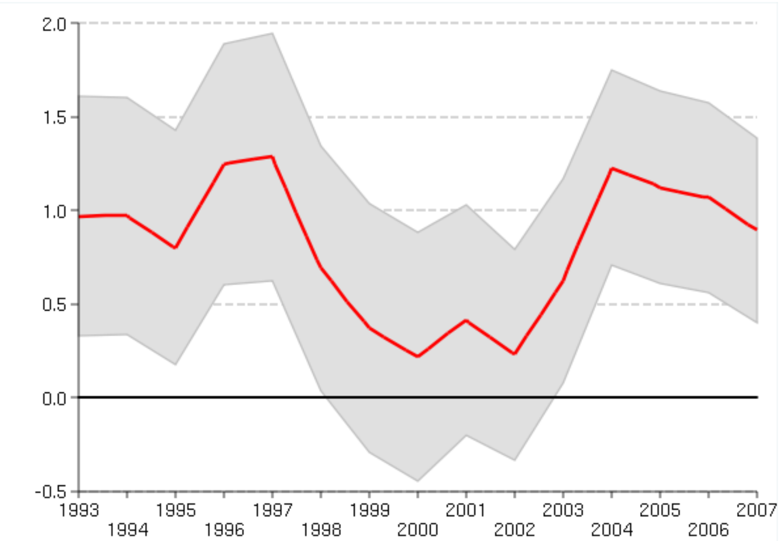
Notes: The plot displays time fixed effects from a regression similar to that in column "Women" of Table 1, where the variable "Year" has been replaced by time fixed effects.
Shaded area is confidence interval at 95%.

Figure A.3: Evolution of job insecurity (unemployment hazard rate), Men



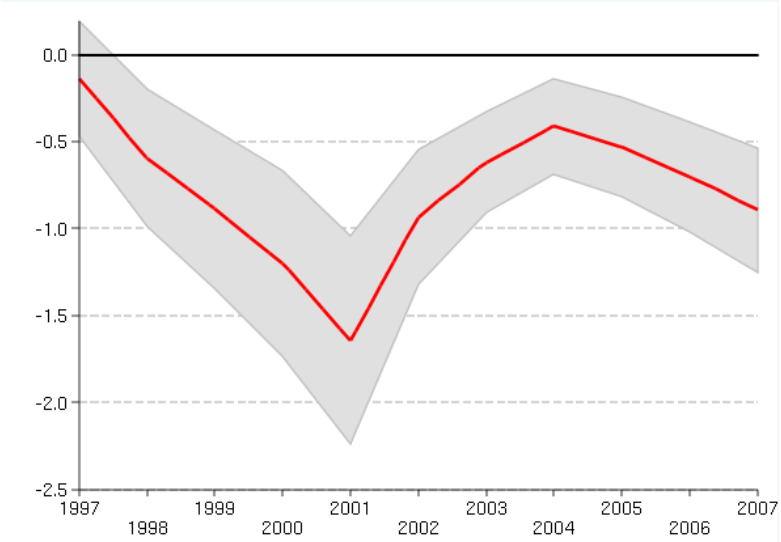
Notes: The plot displays time fixed effects from a regression similar to that in column "Unemployment" of Table 2, where the variable "Year" has been replaced by time fixed effects. Shaded area is confidence interval at 95%.

Figure A.4: Evolution of job insecurity (unemployment hazard rate), Women



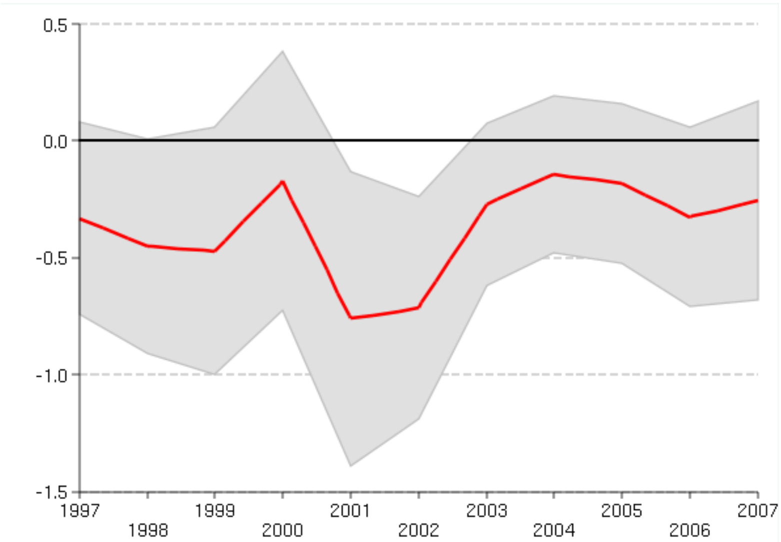
Notes: The plot displays time fixed effects from a regression similar to that in column "Unemployment" of Table 3, where the variable "Year" has been replaced by time fixed effects. Shaded area is confidence interval at 95%.

Figure A.5: Evolution of job insecurity (layoff hazard rate), Men



Notes: The plot displays time fixed effects from a regression similar to that in column "Layoff" of Table 4, where the variable "Year" has been replaced by time fixed effects. Shaded area is confidence interval at 95%.

Figure A.6: Evolution of job insecurity (layoff hazard rate), Women



Notes: The plot displays time fixed effects from a regression similar to that in column "Layoff" of Table 5, where the variable "Year" has been replaced by time fixed effects. Shaded area is confidence interval at 95%.

Appendix B: Did Things Become Worse for Old Workers?

Figure 3 (p. 82) seems to indicate that median tenure has declined for male workers over 45 years old. If this decrease in tenure for old workers is due to undesired job losses, it could explain the popular feeling of growing job insecurity. For workers over 45, losing a job might in fact have serious consequences.

Even if job instability and job insecurity do not seem to have increased for the entire active population, it could be the case for some specific groups. In order to determine if the situation has worsened for old workers over time, we use interaction terms between the year and the age group indicators. Tables B.1 to B.5 display the same estimations as in Tables 1 to 5, with the addition of these interaction terms.

In Table B.1, the coefficients on "Year $\times$ Age 45-55" and "Year $\times$ Age $>$ 55" are positive and highly significant. This shows that employment has become less stable for men over 45 years old. However, it does not necessarily mean that employment has become more insecure.

In fact, Tables B.2 and B.4 do not reveal any increase in the hazard rate towards unemployment or layoff for old male workers. The hazard rate towards inactivity and towards the "other reasons" (not classified as quits nor layoffs) has increased. Therefore, it does not seem that the growing job instability for old men was accompanied by a growing job insecurity. A possible explanation for the decline in their median tenure is that a growing share of them has taken advantage of early retirement plans, which cannot be unambiguously associated to job insecurity.

Tables B.1, B.3 and B.5 display the results for female workers, but no firm conclusion can be drawn for this group, as most of the interaction terms are unsignificant. The only strong effect is observed for prime age workers (25-55), who seem to quit more often than before, which may be due to social changes: more part-time work, more demand for leisure, etc.

Table B.1: Hazard of job termination

	Men	Women
Education: apprenticeship	-0.101^{***}	-0.098^{***}
	(0.036)	(0.034)
Education: university	-0.047	0.010
	(0.041)	(0.043)
Age 25-35 years	-0.281^{***}	-0.325^{***}
	(0.044)	(0.043)
Age 35-45 years	-0.472^{***}	-0.612^{***}
	(0.050)	(0.048)
Age 45-55 years	-0.759^{***}	-0.820^{***}
	(0.059)	(0.054)
Age > 55 years	-0.091	-0.461^{***}
	(0.057)	(0.057)
Year	-0.006	0.006
	(0.007)	(0.006)
Year × Age 25-35	0.005	-0.008
	(0.008)	(0.008)
Year × Age 35-45	0.008	0.006
	(0.009)	(0.008)
Year × Age 45-55	0.040^{***}	0.007
	(0.010)	(0.010)
Year × Age > 55	0.024^{***}	-0.010
	(0.009)	(0.010)
Non-Swiss	-0.043	-0.088^{***}
	(0.029)	(0.032)
Married	-0.147^{***}	0.088^{**}
	(0.032)	(0.036)
Part-time	0.349^{***}	0.192^{***}
	(0.059)	(0.042)
Part-time × Married	0.173^{**}	-0.201^{***}
	(0.086)	(0.053)
Number of children	-0.049^{***}	-0.063^{***}
	(0.017)	(0.017)
Firm > 100 co-workers	-0.209^{***}	-0.184^{***}
	(0.027)	(0.029)
Regional unemployment rate	0.039^{***}	0.019
	(0.013)	(0.012)
Regional vacancy rate	0.181^{**}	0.142
	(0.087)	(0.088)
Industry wage premium	-0.613^{***}	-0.146
	(0.150)	(0.151)
Canton dummies	yes	yes
Sector dummies	yes	yes
# spells	29,445	24,766
# individuals	25,682	21,420
# failures	6,584	6,317
LogL	−50,646	−49,535
AIC	101,403	99,182
BIC	102,045	99,811

Swiss Labor Force Survey, 1991-2008.
Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

Table B.2: Hazards of job termination by destination state, Men

	Newjob	Unemployment	Inactivity
Education: apprenticeship	0.167***	−0.289***	−0.401***
	(0.051)	(0.090)	(0.073)
Education: university	0.309***	−0.595***	−0.568***
	(0.056)	(0.115)	(0.095)
Age 25-35 years	−0.156***	−0.228	−0.648***
	(0.054)	(0.140)	(0.223)
Age 35-45 years	−0.355***	−0.015	−0.730***
	(0.061)	(0.150)	(0.238)
Age 45-55 years	−0.746***	0.191	−0.259
	(0.073)	(0.158)	(0.228)
Age > 55 years	−1.170***	0.676***	1.769***
	(0.100)	(0.164)	(0.201)
Year	−0.013	0.068***	−0.051
	(0.008)	(0.024)	(0.036)
Year × Age 25-35	0.008	−0.058**	0.089**
	(0.010)	(0.028)	(0.043)
Year × Age 35-45	0.008	−0.065**	0.126***
	(0.010)	(0.028)	(0.044)
Year × Age 45-55	0.033***	−0.044	0.139***
	(0.013)	(0.030)	(0.041)
Year × Age > 55	−0.017	−0.059*	0.086**
	(0.017)	(0.031)	(0.036)
Non-Swiss	−0.132***	0.480***	−0.002
	(0.037)	(0.081)	(0.069)
Married	−0.114***	−0.485***	0.058
	(0.041)	(0.089)	(0.072)
Part-time	0.161*	0.317*	0.693***
	(0.083)	(0.167)	(0.151)
Part-time × Married	0.068	0.261	0.265
	(0.133)	(0.244)	(0.180)
Number of children	−0.015	−0.090*	−0.149***
	(0.020)	(0.050)	(0.057)
Firm > 100 co-workers	−0.313***	−0.269***	0.116**
	(0.035)	(0.078)	(0.058)
Regional unemployment rate	0.003	0.197***	0.060*
	(0.016)	(0.034)	(0.033)
Regional vacancy rate	0.450***	−0.433	−0.357
	(0.103)	(0.274)	(0.240)
Industry wage premium	−0.765***	−0.857**	−0.166
	(0.188)	(0.426)	(0.351)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	29,444	29,445	29,445
# individuals	25,681	25,682	25,682
# failures	4,317	876	1,235
LogL	−34,215	−6,728	−7,574
AIC	68,541	13,564	15,260
BIC	69,183	14,183	15,901

Swiss Labor Force Survey, 1991-2008.

Standard errors in parentheses. ***/**/*: Significant at the 0.01/0.05/0.10 level.

Table B.3: Hazards of job termination by destination state, Women

	Newjob	Unemployment	Inactivity
Education: apprenticeship	0.174***	−0.285***	−0.245***
	(0.051)	(0.089)	(0.061)
Education: university	0.396***	−0.457***	−0.385***
	(0.061)	(0.121)	(0.090)
Age 25-35 years	−0.325***	−0.143	0.315**
	(0.053)	(0.145)	(0.135)
Age 35-45 years	−0.479***	−0.177	−0.313**
	(0.059)	(0.156)	(0.145)
Age 45-55 years	−0.793***	0.031	−0.371**
	(0.071)	(0.157)	(0.147)
Age > 55 years	−1.192***	0.045	0.737***
	(0.103)	(0.193)	(0.144)
Year	−0.008	0.079***	0.019
	(0.008)	(0.021)	(0.023)
Year × Age 25-35	−0.006	−0.013	−0.014
	(0.009)	(0.026)	(0.025)
Year × Age 35-45	0.004	−0.052*	0.021
	(0.010)	(0.027)	(0.026)
Year × Age 45-55	0.024*	−0.069**	−0.014
	(0.012)	(0.027)	(0.026)
Year × Age > 55	0.016	0.002	−0.047*
	(0.019)	(0.034)	(0.025)
Non-Swiss	−0.162***	0.378***	−0.132**
	(0.044)	(0.087)	(0.064)
Married	−0.260***	0.213**	0.881***
	(0.051)	(0.094)	(0.077)
Part-time	0.103*	−0.016	0.538***
	(0.054)	(0.128)	(0.095)
Part-time × Married	−0.148**	−0.355**	−0.404***
	(0.075)	(0.154)	(0.110)
Number of children	−0.056**	−0.013	−0.043
	(0.023)	(0.045)	(0.035)
Firm > 100 co-workers	−0.259***	−0.153*	−0.029
	(0.040)	(0.083)	(0.054)
Regional unemployment rate	−0.015	0.151***	0.040
	(0.017)	(0.036)	(0.024)
Regional vacancy rate	0.098	−0.480	0.315**
	(0.119)	(0.313)	(0.161)
Industry wage premium	−0.120	−1.152**	0.052
	(0.204)	(0.454)	(0.285)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	24,765	24,766	24,766
# individuals	21,420	21,420	21,420
# failures	3,619	831	1,716
LogL	−28,895	−6,377	−12,468
AIC	57,900	12,861	25,048
BIC	58,517	13,456	25,677

Swiss Labor Force Survey, 1991-2008.
Standard errors in parentheses. ***/**/*: Significant at the 0.01/0.05/0.10 level.

Table B.4: Hazards of job termination by termination reason, Men

	Layoffs	Quits	Other reasons
Education: apprenticeship	-0.141^{*}	0.157^{**}	-0.003
	(0.073)	(0.077)	(0.072)
Education: university	-0.575^{***}	0.436^{***}	0.105
	(0.099)	(0.081)	(0.082)
Age 25-35 years	0.220	-0.257^{***}	-0.293^{**}
	(0.184)	(0.097)	(0.132)
Age 35-45 years	0.490^{***}	-0.627^{***}	-0.653^{***}
	(0.190)	(0.109)	(0.150)
Age 45-55 years	0.680^{***}	-1.230^{***}	-1.134^{***}
	(0.195)	(0.151)	(0.194)
Age > 55 years	0.808^{***}	-2.047^{***}	0.406^{***}
	(0.212)	(0.242)	(0.141)
Year	0.073^{**}	-0.011	-0.035
	(0.036)	(0.021)	(0.027)
Year × Age 25-35	-0.082^{**}	-0.008	0.015
	(0.040)	(0.023)	(0.031)
Year × Age 35-45	-0.104^{***}	0.001	0.037
	(0.040)	(0.024)	(0.033)
Year × Age 45-55	-0.075^{*}	0.033	0.095^{**}
	(0.041)	(0.032)	(0.039)
Year × Age > 55	-0.038	-0.002	0.076^{**}
	(0.043)	(0.053)	(0.030)
Non-Swiss	0.270^{***}	-0.222^{***}	0.029
	(0.068)	(0.053)	(0.059)
Married	-0.271^{***}	-0.178^{***}	-0.076
	(0.072)	(0.061)	(0.062)
Part-time	0.225	0.185^{*}	0.368^{***}
	(0.171)	(0.109)	(0.122)
Part-time × Married	0.392^{*}	-0.194	0.163
	(0.220)	(0.209)	(0.162)
Number of children	0.009	-0.010	-0.141^{***}
	(0.037)	(0.030)	(0.039)
Firm > 100 co-workers	-0.332^{***}	-0.265^{***}	-0.035
	(0.065)	(0.050)	(0.053)
Regional unemployment rate	0.248^{***}	-0.128^{***}	0.103^{***}
	(0.034)	(0.026)	(0.031)
Regional vacancy rate	-0.107	0.426^{**}	0.388^{*}
	(0.258)	(0.183)	(0.205)
Industry wage premium	-1.565^{***}	-0.939^{***}	0.033
	(0.376)	(0.291)	(0.326)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	25,632	25,632	25,632
# individuals	22,510	22,510	22,510
# failures	1,278	2,081	1,651
LogL	−9,419	−15,962	−11,596
AIC	18,950	32,036	23,304
BIC	19,581	32,667	23,935

Swiss Labor Force Survey, 1996-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

Table B.5: Hazards of job termination by termination reason, Women

	Layoffs	Quits	Other reasons
Education: apprenticeship	-0.195^{**}	0.116	0.007
	(0.079)	(0.071)	(0.074)
Education: university	-0.424^{***}	0.445^{***}	0.162^{*}
	(0.112)	(0.082)	(0.088)
Age 25-35 years	-0.322^{*}	-0.595^{***}	-0.263^{**}
	(0.166)	(0.091)	(0.108)
Age 35-45 years	-0.068	-0.929^{***}	-0.662^{***}
	(0.171)	(0.107)	(0.123)
Age 45-55 years	0.196	-1.328^{***}	-1.233^{***}
	(0.174)	(0.129)	(0.147)
Age $>$ 55 years	0.322	-1.673^{***}	-0.081
	(0.201)	(0.190)	(0.134)
Year	0.013	-0.044^{**}	-0.015
	(0.031)	(0.018)	(0.022)
Year $\times$ Age 25-35	0.004	0.057^{***}	-0.014
	(0.037)	(0.022)	(0.025)
Year $\times$ Age 35-45	-0.020	0.066^{***}	-0.012
	(0.036)	(0.023)	(0.027)
Year $\times$ Age 45-55	0.021	0.067^{**}	-0.009
	(0.036)	(0.028)	(0.033)
Year $\times$ Age $>$ 55	0.029	0.037	-0.040
	(0.042)	(0.044)	(0.029)
Non-Swiss	0.363^{***}	-0.201^{***}	-0.196^{***}
	(0.078)	(0.058)	(0.067)
Married	0.085	-0.088	0.281^{***}
	(0.085)	(0.067)	(0.077)
Part-time	0.157	0.130^{*}	0.208^{**}
	(0.102)	(0.078)	(0.089)
Part-time $\times$ Married	-0.514^{***}	-0.178^{*}	-0.132
	(0.131)	(0.102)	(0.112)
Number of children	-0.027	-0.084^{***}	-0.092^{***}
	(0.042)	(0.032)	(0.036)
Firm $>$ 100 co-workers	-0.301^{***}	-0.224^{***}	-0.124^{**}
	(0.075)	(0.053)	(0.058)
Regional unemployment rate	0.211^{***}	-0.149^{***}	0.069^{**}
	(0.037)	(0.028)	(0.029)
Regional vacancy rate	0.391	0.222	0.255
	(0.281)	(0.204)	(0.200)
Industry wage premium	-0.107	-0.430	-0.447
	(0.393)	(0.291)	(0.336)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	21,654	21,654	21,654
# individuals	18,896	18,896	18,896
# failures	1,072	1,956	1,579
LogL	$-7,955$	$-15,115$	$-11,780$
AIC	16,019	30,340	23,667
BIC	16,627	30,948	24,253

Swiss Labor Force Survey, 1996-2008.
Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

Appendix C: Results with a Piecewise Constant Exponential Model

The piecewise constant exponential model constitutes an alternative to the Cox model. Both are proportional hazard models, as they specify the same hazard function:

$$h(t) = h_0(t) \cdot \exp(x'\beta) \tag{C.1}$$

The only difference between the two models lies in the way the baseline hazard $h_0(t)$ is modelled. In the Cox model, the baseline hazard is left completely unspecified. In the piecewise constant exponential model, the baseline hazard is assumed to be constant within time intervals (arbitrarily defined), but it can change across intervals. Hence, the hazard function becomes:

$$h(t) = \left\{ \sum_{m=1}^{M} h_m \cdot \delta_m \right\} \cdot \exp(x'\beta) \tag{C.2}$$

where δ_m is a dummy variable indicating the m^{th} time interval defined by the cutoff points c_{m-1} and c_m:

$$\delta_m = \begin{cases} 1 & \text{if } c_{m-1} \leq t < c_m \\ 0 & \text{otherwise} \end{cases} \qquad m = 1, 2, \ldots, M. \tag{C.3}$$

For the empirical estimations, we use one-year length intervals between 0 and 10 years of tenure, two-years intervals between 10 and 20 years, and five-years intervals after 20 years. Different partitionings have been tested and lead to very similar results. As expected, the coefficients estimated are extremely close to those obtained with a Cox model (see Tables C.1 to C.5). Figures C.1 to C.4 show the hazard rates obtained with the piecewise constant exponential models. They are naturally very similar to the ones obtained with the Cox model. One observation that is made clearer with the piecewise constant exponential model is that the peak in the hazard rates occurs in the second year of a job spell. This is consistent across all estimations.

Table C.1: Piecewise exponential hazard model for job tenure

	Men	Women
Education: apprenticeship	-0.099^{***}	-0.092^{***}
	(0.035)	(0.033)
Education: university	-0.049	0.010
	(0.041)	(0.043)
Age 25-35 years	-0.279^{***}	-0.326^{***}
	(0.044)	(0.042)
Age 35-45 years	-0.472^{***}	-0.589^{***}
	(0.049)	(0.046)
Age 45-55 years	-0.686^{***}	-0.797^{***}
	(0.056)	(0.052)
Age > 55 years	-0.052	-0.466^{***}
	(0.055)	(0.056)
Year	0.006^{**}	0.004
	(0.003)	(0.003)
Non-Swiss	-0.045	-0.081^{**}
	(0.029)	(0.032)
Married	-0.152^{***}	0.089^{**}
	(0.031)	(0.036)
Part-time	0.344^{***}	0.190^{***}
	(0.059)	(0.041)
Part-time × Married	0.194^{**}	-0.201^{***}
	(0.085)	(0.053)
Number of children	-0.047^{***}	-0.062^{***}
	(0.017)	(0.017)
Firm > 100 co-workers	-0.211^{***}	-0.183^{***}
	(0.027)	(0.029)
Regional unemployment rate	0.030^{**}	0.014
	(0.013)	(0.012)
Regional vacancy rate	0.166^{*}	0.136
	(0.088)	(0.088)
Industry wage premium	-0.617^{***}	-0.149
	(0.149)	(0.150)
Canton dummies	yes	yes
Sector dummies	yes	yes
# spells	29,445	24,766
# individuals	25,682	21,420
# failures	6,584	6,317
LogL	−9,510	−9,740
AIC	19,166	19,626
BIC	20,006	20,449

Swiss Labor Force Survey, 1991-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

The time axis is split every year between 0 and 10 years of tenure, every two years between 10 and 20 years of tenure, and every five years after 20 years of tenure.

Table C.2: Piecewise exponential hazard model for job tenure by destination state (Men)

	Newjob	Unemployment	Inactivity
Education: apprenticeship	0.171***	−0.293***	−0.418***
	(0.051)	(0.090)	(0.073)
Education: university	0.313***	−0.606***	−0.578***
	(0.055)	(0.115)	(0.095)
Age 25-35 years	−0.150***	−0.326**	−0.653***
	(0.053)	(0.129)	(0.216)
Age 35-45 years	−0.348***	−0.139	−0.631***
	(0.059)	(0.138)	(0.218)
Age 45-55 years	−0.687***	0.119	−0.120
	(0.069)	(0.143)	(0.213)
Age > 55 years	−1.205***	0.566***	1.750***
	(0.097)	(0.150)	(0.197)
Year	−0.006*	0.018**	0.043***
	(0.003)	(0.008)	(0.007)
Non-Swiss	−0.122***	0.480***	−0.022
	(0.037)	(0.081)	(0.069)
Married	−0.116***	−0.492***	0.049
	(0.040)	(0.090)	(0.072)
Part-time	0.155*	0.341**	0.672***
	(0.083)	(0.168)	(0.150)
Part-time × Married	0.071	0.242	0.317*
	(0.132)	(0.245)	(0.178)
Number of children	−0.013	−0.087*	−0.145**
	(0.020)	(0.050)	(0.057)
Firm > 100 co-workers	−0.315***	−0.274***	0.118**
	(0.035)	(0.078)	(0.058)
Regional unemployment rate	−0.003	0.192***	0.035
	(0.015)	(0.034)	(0.032)
Regional vacancy rate	0.438***	−0.439	−0.393
	(0.102)	(0.274)	(0.239)
Industry wage premium	−0.769***	−0.840**	−0.216
	(0.187)	(0.425)	(0.349)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	29,444	29,445	29,445
# individuals	25,681	25,682	25,682
# failures	4,317	876	1,235
LogL	−8,827	−2,763	−1,466
AIC	17,799	5,672	3,078
BIC	18,639	6,512	3,918

Swiss Labor Force Survey, 1991-2008.

Standard errors in parentheses. ***/**/*: Significant at the 0.01/0.05/0.10 level.

The time axis is split every year between 0 and 10 years of tenure, every two years between 10 and 20 years of tenure, and every five years after 20 years of tenure.

Table C.3: Piecewise exponential hazard model for job tenure by destination state (Women)

	Newjob	Unemployment	Inactivity
Education: apprenticeship	0.187***	−0.291***	−0.254***
	(0.050)	(0.090)	(0.061)
Education: university	0.399***	−0.462***	−0.378***
	(0.060)	(0.120)	(0.090)
Age 25-35 years	−0.325***	−0.144	0.312**
	(0.052)	(0.136)	(0.134)
Age 35-45 years	−0.467***	−0.287**	−0.228
	(0.057)	(0.145)	(0.141)
Age 45-55 years	−0.743***	−0.103	−0.368**
	(0.066)	(0.152)	(0.145)
Age > 55 years	−1.159***	0.081	0.693***
	(0.097)	(0.173)	(0.145)
Year	−0.006*	0.047***	0.003
	(0.004)	(0.009)	(0.005)
Non-Swiss	−0.156***	0.372***	−0.114*
	(0.043)	(0.087)	(0.064)
Married	−0.258***	0.211**	0.880***
	(0.051)	(0.094)	(0.077)
Part-time	0.096*	−0.002	0.544***
	(0.053)	(0.128)	(0.095)
Part-time × Married	−0.147**	−0.358**	−0.409***
	(0.074)	(0.154)	(0.110)
Number of children	−0.055**	−0.012	−0.037
	(0.023)	(0.045)	(0.034)
Firm > 100 co-workers	−0.261***	−0.150*	−0.024
	(0.040)	(0.083)	(0.054)
Regional unemployment rate	−0.022	0.145***	0.036
	(0.016)	(0.036)	(0.024)
Regional vacancy rate	0.093	−0.486	0.329**
	(0.118)	(0.312)	(0.160)
Industry wage premium	−0.121	−1.145**	0.037
	(0.202)	(0.455)	(0.285)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	24,765	24,766	24,766
# individuals	21,420	21,420	21,420
# failures	3,619	831	1,716
LogL	−8,085	−2,616	−3,651
AIC	16,316	5,377	7,446
BIC	17,140	6,201	8,258

Swiss Labor Force Survey, 1991-2008.

Standard errors in parentheses. ***/**/*: Significant at the 0.01/0.05/0.10 level.

The time axis is split every year between 0 and 10 years of tenure, every two years between 10 and 20 years of tenure, and every five years after 20 years of tenure.

Table C.4: Piecewise exponential hazard model for job tenure by termination reason (Men)

	Layoffs	Quits	Other reasons
Education: apprenticeship	-0.150^{**}	0.142^{*}	-0.022
	(0.073)	(0.076)	(0.072)
Education: university	-0.601^{***}	0.393^{***}	0.081
	(0.099)	(0.080)	(0.082)
Age 25-35 years	-0.041	-0.233^{***}	-0.256^{**}
	(0.125)	(0.076)	(0.110)
Age 35-45 years	0.148	-0.567^{***}	-0.571^{***}
	(0.130)	(0.085)	(0.121)
Age 45-55 years	0.421^{***}	-1.075^{***}	-0.850^{***}
	(0.131)	(0.105)	(0.137)
Age > 55 years	0.676^{***}	-2.028^{***}	0.615^{***}
	(0.142)	(0.170)	(0.116)
Year	0.087^{***}	0.076^{***}	0.090^{***}
	(0.007)	(0.005)	(0.006)
Non-Swiss	0.182^{***}	-0.322^{***}	-0.069
	(0.067)	(0.052)	(0.059)
Married	-0.267^{***}	-0.198^{***}	-0.081
	(0.072)	(0.060)	(0.061)
Part-time	0.219	0.183^{*}	0.364^{***}
	(0.171)	(0.108)	(0.122)
Part-time × Married	0.396^{*}	-0.144	0.210
	(0.219)	(0.205)	(0.159)
Number of children	0.007	-0.005	-0.126^{***}
	(0.037)	(0.029)	(0.038)
Firm > 100 co-workers	-0.347^{***}	-0.272^{***}	-0.032
	(0.065)	(0.049)	(0.053)
Regional unemployment rate	0.285^{***}	-0.083^{***}	0.111^{***}
	(0.035)	(0.025)	(0.030)
Regional vacancy rate	0.296	0.439^{***}	0.486^{***}
	(0.236)	(0.157)	(0.188)
Industry wage premium	-1.426^{***}	-0.626^{**}	0.286
	(0.366)	(0.277)	(0.313)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	29,445	29,445	29,445
# individuals	25,682	25,682	25,682
# failures	1,294	2,142	1,680
LogL	−3,631	−5,510	−3,848
AIC	7,407	11,165	7,842
BIC	8,247	12,005	8,681

Swiss Labor Force Survey, 1996-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

The time axis is split every year between 0 and 10 years of tenure, every two years between 10 and 20 years of tenure, and every five years after 20 years of tenure.

Table C.5: Piecewise exponential hazard model for job tenure by termination reason (Women)

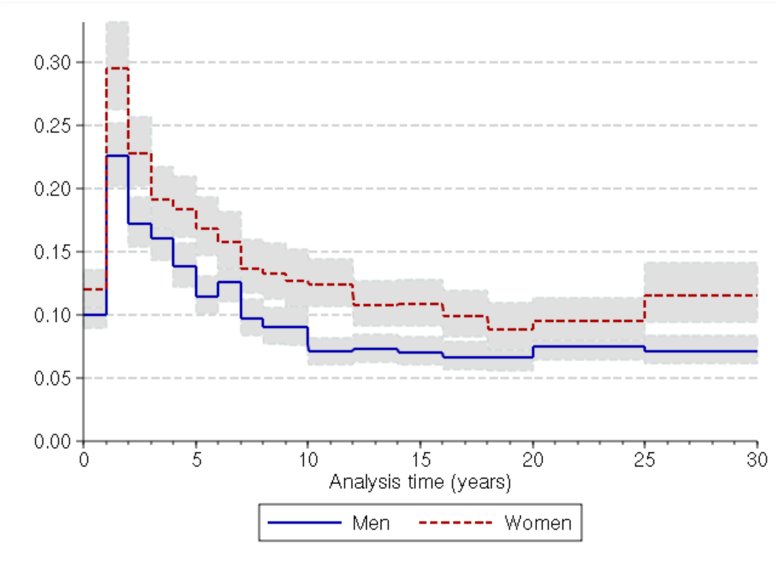
	Layoffs	Quits	Other reasons
Education: apprenticeship	-0.194^{**}	0.147^{**}	0.025
	(0.078)	(0.069)	(0.073)
Education: university	-0.458^{***}	0.419^{***}	0.127
	(0.112)	(0.081)	(0.087)
Age 25-35 years	-0.302^{**}	-0.416^{***}	-0.232^{**}
	(0.128)	(0.074)	(0.093)
Age 35-45 years	-0.152	-0.715^{***}	-0.658^{***}
	(0.130)	(0.081)	(0.104)
Age 45-55 years	0.249^{*}	-1.110^{***}	-1.181^{***}
	(0.133)	(0.094)	(0.122)
Age > 55 years	0.395^{***}	-1.576^{***}	-0.139
	(0.149)	(0.139)	(0.114)
Year	0.100^{***}	0.087^{***}	0.064^{***}
	(0.008)	(0.005)	(0.005)
Non-Swiss	0.287^{***}	-0.270^{***}	-0.278^{***}
	(0.077)	(0.057)	(0.066)
Married	0.061	-0.099	0.247^{***}
	(0.085)	(0.066)	(0.076)
Part-time	0.141	0.115	0.180^{**}
	(0.101)	(0.077)	(0.088)
Part-time × Married	-0.501^{***}	-0.164	-0.099
	(0.131)	(0.101)	(0.110)
Number of children	-0.021	-0.085^{***}	-0.077^{**}
	(0.042)	(0.031)	(0.036)
Firm > 100 co-workers	-0.306^{***}	-0.207^{***}	-0.124^{**}
	(0.075)	(0.052)	(0.057)
Regional unemployment rate	0.224^{***}	-0.118^{***}	0.102^{***}
	(0.037)	(0.027)	(0.028)
Regional vacancy rate	0.606^{**}	0.235	0.532^{***}
	(0.258)	(0.171)	(0.173)
Industry wage premium	0.065	-0.117	0.149
	(0.372)	(0.275)	(0.309)
Canton dummies	yes	yes	yes
Sector dummies	yes	yes	yes
# spells	24,766	24,766	24,766
# individuals	21,420	21,420	21,420
# failures	1,082	2,000	1,612
LogL	−3,199	−5,237	−4,413
AIC	6,545	10,620	8,972
BIC	7,368	11,444	9,796

Swiss Labor Force Survey, 1996-2008.

Standard errors in parentheses. $^{***}/^{**}/^{*}$: Significant at the 0.01/0.05/0.10 level.

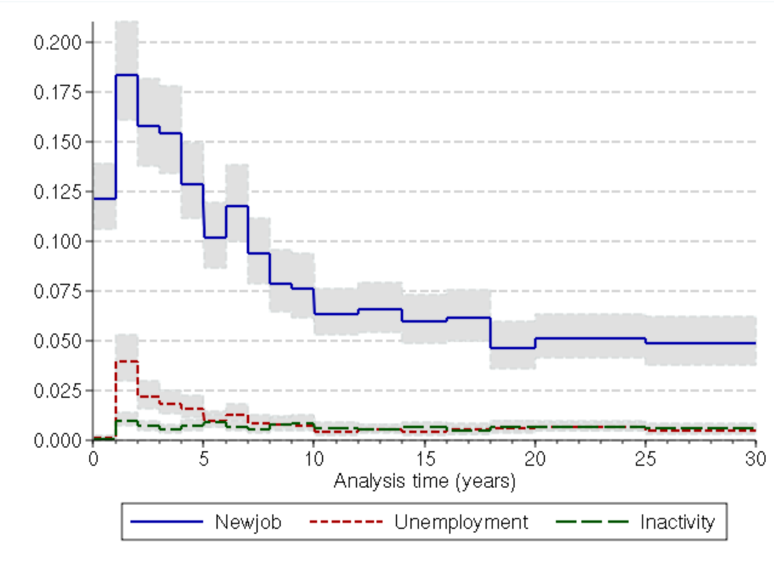
The time axis is split every year between 0 and 10 years of tenure, every two years between 10 and 20 years of tenure, and every five years after 20 years of tenure.

Figure C.1: Hazard rates by gender, piecewise exponential model



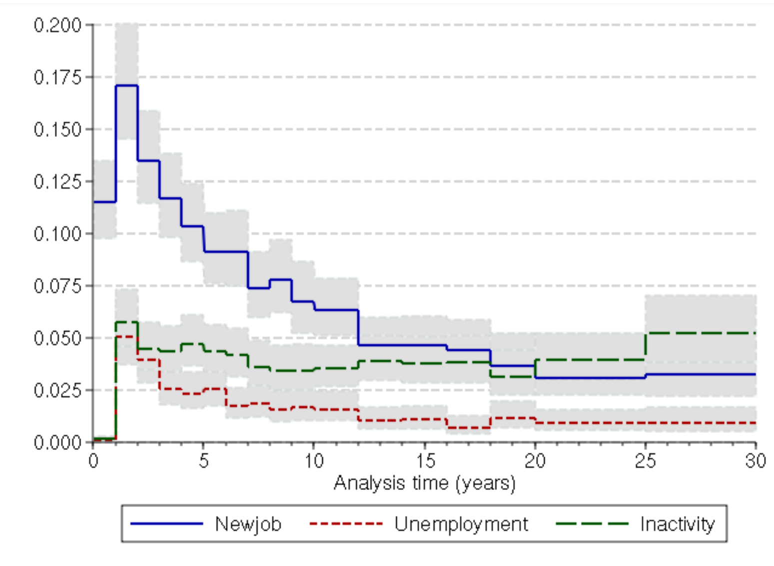
Notes: Hazard rates are drawn for the mode of the covariates distribution, i.e., for a Swiss individual aged 35-45, married, without children, with apprenticeship training, working full-time in a firm of the manufacturing sector, with less than 100 co-workers, in the canton of Zürich, in 2007 (the last complete year under observation).
Shaded areas are confidence intervals at 90%.

Figure C.2: Hazard rates by destination state, piecewise exponential model (Men)



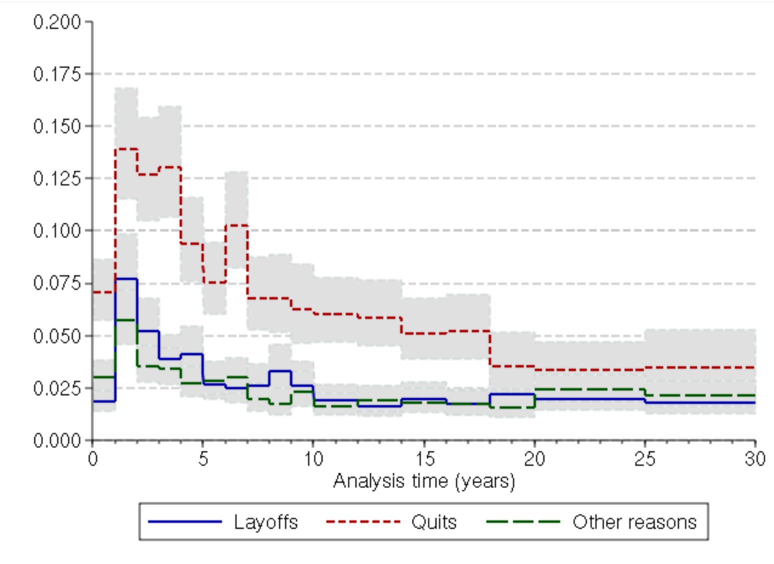
Notes: see Figure C.1.

Figure C.3: Hazard rates by destination state, piecewise exponential model (Women)



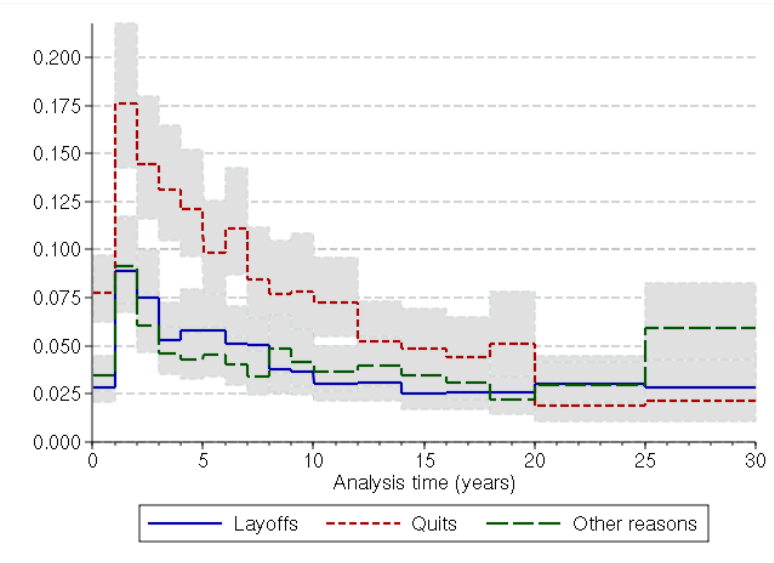
Notes: see Figure C.1.

Figure C.4: Hazard rates by termination reason, piecewise exponential model (Men)



Notes: see Figure C.1.

Figure C.5: Hazard rates by termination reason, piecewise exponential model (Women)



Notes see Figure C.1.

General Conclusion

1 Main Findings

This thesis investigates empirically three important aspects of the working life: human capital depreciation, wage growth, and tenure. In each case, the analysis is performed by separating workers by education level, taking advantage of the particular features of the Swiss educational system. This allows to compare the effects of general education (i.e., the academic track: high schools, universities) versus specific education (i.e., the vocational track: apprenticeships, professional and technical schools, universities of applied sciences). The results highlight that taking the qualitative aspects of education into account is more important than simply considering education length, how it is usually done in the literature. As a general finding, one may say that general education seems to have several advantages over specific education.

First, general education is found to protect workers against human capital depreciation better than specific human capital. A potential interpretation of this finding is that workers coming from the vocational track are more invested in specific technologies and therefore suffer more depreciation because of technological progress. Workers with a general human capital are able to move to a new technology or to a new job while taking with them most of their human capital. On the contrary, workers with mostly specific human capital are locked in a particular technology or a particular job. Were they to move, they would lose a substantial share of their human capital.

Second, wage growth over the career is found to be low for workers with apprenticeship training, as compared to other groups with more or less education. For all workers, wage growth mostly depends on general labor market experience. Occupational experience is also found to have a positive effect, but which is quantitatively weaker. The positive effect of tenure observed in traditional earnings equation virtually vanishes when occupational experience is included in the estimations.

The fact that workers with apprenticeship training benefit a lower wage growth than both the more- and the less-educated tends to indicate that vocational studies do not prepare workers to evolve during their career. Apprenticeship holders are in some way locked in their initial occupation. Because they are able to perform their job from the beginning of their working life, their experience-earnings profile is flatter than for workers with more general skills.

Third, we find that workers with specific education (apprenticeship) have longer job spells than the other education groups. This indicates that jobs are more stable for workers with apprenticeship training. But job stability is not necessarily a good thing. Indeed, longer job spells could either indicate that workers are better matched with their firm or that they are less mobile and that they are locked in their current job.

In fact, a concept more relevant than job stability for workers is job insecurity. To investigate job insecurity, one needs to consider why a job separation occurs (voluntary quit or involuntary layoff?) and what happens after the separation (new job, unemployment, or inactivity?). In this case, education is found to reduce job insecurity, in the sense that it decreases the hazard of unemployment, and the risk of being laid-off. The effect of education on job security appears more or less linear, and there is no clear separation between general and specific education. Workers with apprenticeship training benefit from more job security than workers with only compulsory school, and university graduates benefit from more job security than workers with apprenticeship training.

2 Policy Issues

The analyses conducted in this thesis should prove useful to policy makers acting in the fields of education and labor, two of the largest government spending items in many countries. Human capital depreciation is particularly relevant in advanced economies that increasingly rely on knowledge and which should therefore care about the evolution of their stock of human capital. Wage growth is an important aspect to consider when designing active labor market policies. Finally, job separations are heavily regulated, and sound analyses of job stability and job insecurity are necessary to take sensible decisions in this respect.

The recurrent result of the thesis indicates that workers benefit more from general skills than from specific skills. Workers possessing more general skills suffer a lower human capital depreciation rate, enjoy a larger wage growth over their career, and are more mobile. The policy implication to draw from those results is that general education should be promoted. Workers should be taught general notions so as to acquire the most general skills that will allow them to operate in a broad range of occupations and to adapt to changes in the labor market.

Hence, the thesis raises some concerns about the Swiss educational system. Each year, about 40% of the youth finishing compulsory school begin an apprenticeship. During three years, they spend 3 to 4 days a week in a firm where they acquire mostly occupation-specific skills. They only spend 1 to 2 days a week in a professional school. The question is therefore: does this dual education system provide individuals with the adequate skills to cope with the labor market during their entire life? Because the labor market rewards mostly general skills, it would certainly be worth discussing the possibility of increasing the proportion of time spent at school during apprenticeship. Given the substantial share of the Swiss workforce following vocational education training, it surely is a non-trivial question.

3 Further Research

The analyses conducted in this thesis obviously suffer some drawbacks. First of all, the dataset used is a rather short rotating panel of five years. The study of lifecycle earnings like that proposed in chapter 1 would clearly benefit from a longer observation period. A long panel with retrospective information is currently being build in the frame of the Swiss Household Panel, with data collected since 1999 on about 5,000 households. The SHP should soon contain enough observations to allow for robust analyses of the evolution of lifecycle earnings.

The analysis of chapter 2 suffers from data limitations as well. General experience is proxied by potential experience, occupational and industrial experiences are proxied by tenure in current job plus tenure at the end of previous job (if observed). General experience is thus upward biased, whereas occupational and industrial experiences are downward biased. Moreover, the latter two are almost identical. With retrospective data over the entire life of an individual, the researcher could account for delayed entries on the labor market, for career interruptions, and for non-consecutive job spells in the same occupation or in the same industry. The effects of occupational experience and industrial experience could then be estimated much more accurately.

In chapter 3, the determinants of tenure have been analyzed running separate competing risks models over the destination states and the termination reasons. It would in fact be worth taking account of both in a single model. Once again, such an analysis would call for many observations to obtain robust estimates.

All the mentioned drawbacks are definitely more serious for female workers. Their labor market behavior is more complex and more difficult to analyze, because women frequently interrupt their career and many of them work part-time. Nevertheless, all the analyses conducted in this thesis have been run on men as well as on women. Estimations on female workers surely must be interpreted with greater care, and have therefore been placed in appendices for the first two chapters concerned with earnings. It seems however clear that comparing the results across genders is enriching, and the fact that so many researchers concentrate on men and discard female workers underlines the necessity to provide analyses for the latter.

Labor market is a broad economic field that receives much attention from the academicians, but also from the media and from a general audience. Precisely because labor relations affect each one of us, studying labor economics is at the same time a delicate and exciting task. The impacts of labor market policies might be enormous at the individual and at the society's level. However, our understanding of the labor market remains far from perfect. Many additional analyses like this thesis are thus called for.

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