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# The returns to occupation-specific human capital - Evidence from mobility after training

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**Abstract**

Using a longitudinal dataset based on the PISA 2000 survey, we analyze the effect of inter-firm and occupational mobility on post-training wages in Switzerland to assess the transferability of the human capital acquired in training. We show that OLS provides a lower bound estimate of the wage effects of inter-firm and occupational mobility. Inter-firm mobility has no significant wage effect in OLS regressions. However, those who stay in their occupational field earn about 5 percent more than their colleagues who change occupation. We find no evidence for adverse selection when accounting only for apprentices' level of ability. Accounting for the endogeneity of mobility tends to increase the estimated wage differential between occupation stayers and changers, but not between firm stayers and movers. We conclude that occupation-specific human capital is an important component of apprenticeship training and accounts for a part of the returns to training.

JEL classification: C25, J24, J31, J62

Keywords: apprenticeship, endogenous treatment, human capital, mobility, PISA, occupation, school-to-work transition, training

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# 1 Introduction

In this paper, we study the specificity and transferability of human capital by analyzing inter-firm and occupational mobility of trainees after the conclusion of training. Several articles have recently pointed to the importance of industry-specific and occupation-specific human capital, whereas the classical treatment focuses on the dichotomy between firm-specific and general human capital (Becker, 1962). Many studies have used firm tenure and experience within the industry, the occupation and on the labor market to distinguish among different types of human capital (Dustmann and Meghir, 2005; Kambourov and Manovskii, 2009; Neal, 1995; Parent, 2000; Sullivan, 2010; Zangelidis, 2008). Other studies have analyzed occupational and industrial mobility directly (Kambourov and Manovskii, 2008; Longhi and Brynin, 2010; Moscarini and Thompson, 2007; Parrado et al., 2007; Shaw, 1987).

We investigate the inter-firm and occupational mobility of a sample of trainees who have just completed several years of training in firms (combined with vocational school) in a particular occupation. After training, trainees must decide whether to continue working for their training firm as a skilled worker, change firms within the learned occupation, or even change firms and move out of the learned occupation.[1] Analyzing the causal wage effect of trainees' mobility decisions by addressing the endogeneity of mobility allows us to assess the transferability of the newly acquired human capital to other firms and occupations.

Vocational training and apprenticeship programs lend themselves to the study of human capital transferability and mobility because they are structured along a multitude of well-defined occupations and corresponding educational tracks. Apprenticeships are at the core of the educational system in some countries such as Germany and Switzerland (Wolter and Ryan, 2011). In the US, calls for more vocational education tracks are a subject of public debate (see Symonds et al., 2011), while policy initiatives have been proposed in the UK to reinvigorate the apprenticeship system (see UK Parliament, 2009: the Apprenticeships, Skills, Children and Learning Act of 2009).

The question of the transferability of human capital is of utmost importance for any vocational education system: the main economic rationale of such a system is to provide trainees with a set of clearly defined and nationally tested occupational skills that are transferable to other firms after graduation. This promises specialization gains due to more specialized skills than would be acquired in a purely general education system.

[1] We restrict attention to these three alternatives. Occupation change always implies a firm change since we observe virtually no cases of occupation changes within the training firm after training.

Apprentices acquire occupation-specific human capital that enables them to immediately begin work as skilled workers after training; in a general education system, they would need to go through a period of on-the-job training when taking up employment at a firm. However, this early specialization, which typically occurs at the age of 16 years in Switzerland, may also be detrimental if the allocative efficiency of apprenticeship systems is inferior to that of general education systems. Specific human capital may impede workers from making efficiency-enhancing firm or occupation changes and lead to wage losses for those who want or have to leave the training firm or the learned occupation.[2] This barrier becomes particularly important when job prospects on the labor market are deteriorating due to the business cycle or changes in the skills needed in the economy (e.g., due to technological change or macroeconomic reallocation, see Bassanini et al., 2007, and Wasmer, 2006). Some studies have indicated that occupational mobility has generally been increasing during the last decades (Kambourov and Manovskii, 2008; Lalé, 2012; Parrado et al., 2007).

The potential for gains from specialization and the allocative inefficiencies associated with apprenticeship systems depend on the transferability of the human capital acquired in apprenticeships. To empirically assess the transferability of this human capital, we study the incidence of inter-firm and occupational mobility[3] of apprentices shortly after their training and the effect of these types of mobility on wages.

There is a small set of studies analyzing mobility and wages for German apprenticeship graduates. Concerning inter-firm mobility, von Wachter and Bender (2006) found causal evidence of initial wage losses for graduates leaving (middle- and large-sized) training firms at the time of graduation; however, they also observed that the wages of these individuals make up this gap after some years. In addition, they showed that initial sorting, adverse selection and endogenous job mobility bias OLS results such that short-run wage losses are underestimated on average. Negative wage effects associated with leaving the training firm have also been found by Acemoglu and Pischke (1998), and Bougheas and Georgellis (2004). However, Goeggel and Zwick (2012), Harhoff and Kane (1997), and Werwatz (1996) found some evidence for positive wage effects of leaving the training firm. Dustmann et al. (1997) found no significant mover-stayer wage differential, neither did Euwals and Winkelmann (2004) once they consider movers staying in the same firm size class. Winkelmann (1996) analyzes mobility patterns and finds that apprentices' human capital is not less portable than that of graduates from other educations.

The effects reported for switching out of the learned occupation are similarly heteroge-

[2] Furthermore, Lamo et al. (2011) compare the economic transitions in Poland and Estonia and conclude that overly specific training may increase unemployment.

[3] The terms "occupational change" and "occupational mobility" are used interchangeably in this paper.

neous. Dustmann and Schoenberg (2007, p. 6) analyzed self-assessments of the utility of skills, concluding that "apprenticeship training has only a small firm-specific component (about 5%), but a substantial occupation-specific component (as high as 35%)." Werwatz (2002) found wage losses only for those occupational movers who ended up in unskilled jobs, showing that apprentices' human capital is largely general. While Clark and Fahr (2002) came to a similar conclusion, they also estimated a "worst case scenario" where only one-third of the human capital of exogenously displaced workers can be transferred beyond 1-digit occupations. Clark (2000) discussed occupational mobility in a matching framework and found that German apprenticeship training was highly transferable within a broad vocational field. Goeggel and Zwick (2012) have provided the only analysis focusing on the period immediately after graduation; they found that the effects of occupational changes are heterogeneous but negative on average. Fitzenberger and Spitz (2004) found positive effects from occupational changes even after addressing the selection problem. According to Fitzenberger and Kunze (2005), occupational mobility has reduced the gender wage gap over recent decades.

Many of the studies mentioned above addressed the endogenous nature of mobility, yet none of them analyzed employer and occupation changes simultaneously.[4] To our knowledge, the relative importance of these kinds of skills for wages in early careers of apprenticeship graduates has not yet been investigated within a unified framework.

In the context of Switzerland, Bertschy et al. (2009) analyzed whether apprentices in a subset of training occupations three years in duration find an adequate job after graduation. They found that the aspiration level of the vocational education track (i.e., the learned occupation) is highly important in finding an adequate job. Wage effects of mobility at the transition to the first job have not yet been analyzed for Switzerland.

We use the longitudinal data set that is based on the Swiss cohort 2000 of the *Programme for International Student Assessment (PISA)* and matches employer and employee data. We exploit the employment information of workers one year after apprenticeship graduation, along with information on their training period. In addition, we have information about training firms. One advantage of this sample is that all trainees are at the same stage of their labor market career; mobility immediately after training is not influenced by

[4] For example, von Wachter and Bender (2006) and Werwatz (1996) dropped occupational changers when analyzing the causal wage effect of employer changes; Clark (2000) and Clark and Fahr (2002) focused on displaced workers when analyzing occupational changes; the other studies ignored the possibility that the wage effect of firm (occupation) changes might be partly driven by a loss of occupation-specific (firm-specific) human capital. An exception is Longhi and Brynin (2010) who study inter-firm and occupational mobility in Britain and Germany where occupation changes have been restricted to cases with simultaneous employer changes, as we do. They do, however, not address the potential endogeneity of mobility with respect to wages.

years of labor market experience. Some confounding factors associated with years on the labor market include job-shopping, multiple changes and internal promotions. By avoiding these factors, the wage effects of mobility after training provide a "purer" measure of the transferability of human capital acquired in training than analyses that compare learned and current occupation for employees with many years of labor market experience. Furthermore, the dataset contains open text information on the learned and current occupation (in addition to occupation codes) that we use to ensure accurate coding of occupation change. The wealth of background variables available in PISA allows us to control for important dimensions of individual heterogeneity such as socio-economic background and ability. Finally, we address several sources of endogeneity of inter-firm and occupational mobility by means of a control function approach.
Our findings are that 49 percent of those who have a job one year after graduation have moved away from their training firm and that 7 percent moved away from their broadly defined learned occupation. According to log wage regressions, the firm movers staying in their occupation show no wage difference compared to firm stayers; however, occupation changers earn about 5 percent less than their colleagues. We show that these OLS estimates provide a lower bound on the wage differential due to non-transferable firm- or occupation-specific human capital. Accounting for graduates' ability does not change the results. However, when we account for the endogeneity of job and occupation changes, the estimated wage losses for occupation changers are higher. This is consistent with the predictions of human capital theory and confirms that the OLS estimates represent a lower bound. We conclude that occupation-specific human capital is a non-negligible component of apprenticeship training in Switzerland; we do not find evidence that firm-specific human capital is an important component of such programs.

The paper is structured as follows. The relevant economic theories and our empirical model are discussed in section 2. Section 3 discusses the estimation strategy. The data are presented in section 4. Section 5 is dedicated to the results of the empirical analyses. Section 6 concludes.

# 2 Theory and empirical model

## 2.1 Theory

Several labor market theories have to be considered when analyzing the transferability of acquired skills to a new firm or occupation. We will briefly discuss these in turn and then incorporate the main ideas in an empirical model.

The idea of firm-specific human capital (Becker, 1962) readily extends to occupation-specific human capital: occupation-specific human capital is transferable to other jobs within the same occupation, but it cannot be used in jobs outside the occupation. Changing occupation should, *ceteris paribus*, entail a wage loss because the occupation-specific human capital cannot be put to use anymore.

The concept of occupation-specific human capital seems particularly pertinent in the context of a labor market that is structured along an apprenticeship training system. Young Swiss can choose from roughly 250 apprenticeship occupations after completing compulsory schooling at age 16. Two-thirds of every cohort in Switzerland completes a firm-based apprenticeship training program. These programs combine general and occupation-specific training in vocational schools (one to two days a week) with general, occupation-specific and, possibly, firm-specific training in training firms (three to four days a week). Within each occupation, federal training ordinances regulate the details concerning title, duration, skills to be acquired, final exam and diploma.[5] Apprentices and training firms sign a combined work and training contract for two, three or four years (depending on the training occupation). Apprentices become recognized as skilled workers when they successfully complete final exams, which consist of written, oral and practical parts that test general and occupation-specific knowledge and skills.

The occupation-specific human capital acquired during apprenticeship should be rewarded by the labor market; an exogenous move away from the learned occupation is expected to entail a wage loss. A causal wage difference between occupation changers and stayers can be interpreted as a measure for the transferability of training and, accordingly, as a measure for the specificity of the acquired human capital. In the same vein, the causal wage difference between firm stayers and firm movers is an indication of the importance of firm-specific human capital.

Job mobility is also at the heart of search theory (see Mortensen, 1986; Rogerson et al., 2005), but the focus is on the endogenous nature of inter-firm and occupational mobility with respect to wage. Search theory assumes that workers trade off the gains from accepting a job that offers a given wage with the expected gains from continuing search and waiting for a higher wage offer. Apprentices will search for a post-training job and compare wage offers from the training firm, from other firms within the same training occupation and from firms in other occupations altogether. Occupational or inter-firm changes are realized when the wage offer in another firm or occupation exceeds the asking

[5] For more information on the Swiss apprenticeship training system, see OECD (2009). For a comparative study on the German and Swiss VET system, see Muehlemann et al. (2010).

wage of the graduated apprentices. Because workers receive random draws from wage offer distributions, the theory predicts that those workers who accept a new job are more likely to have received a draw from the upper tail of the respective distribution. Therefore, the endogenously determined wage distribution of actual occupation changers differs from the overall wage offer distribution. Observed wage differentials among stayers, firm movers and occupation changers will not be identical to the differentials that are the result of exogenous changes; therefore, they do not correctly measure the transferability of human capital. Rather, wages and mobility are determined simultaneously in this framework.

Matching theory (Jovanovic, 1979) highlights the idea that job mobility is efficiency-enhancing when it improves worker-firm or worker-occupation matches. Assuming that apprentices and firms learn about match quality only some amount of time after signing the training contract, changing one's firm or occupation after training serves to dissolve bad matches. Individuals will receive a relatively higher wage outside their training firm or occupation when dissolving a bad match due to their higher productivity in the new firm or occupation.

In short, both search theory and matching theory suggest that firm and occupational mobility are results of individuals' optimizing behavior. Because individuals try to realize wage gains through firm and occupational changes, such behavior may mask the negative wage effect of mobility that is implied by human capital theory.

Another important strand of literature analyzes informational asymmetries about workers' innate abilities on the labor market (Gibbons and Katz, 1991). Workers' true productivity might be unobservable to employers in the labor market (and to the workers themselves). If firms can only learn about worker productivity by employing the workers and observing them over a period of time, the outside labor market will be characterized by adverse selection. In this framework, job movers are a negatively selected group. This idea has been applied to apprenticeship training (Franz and Soskice, 1995; Acemoglu and Pischke, 1998). Training firms have an informational advantage over other firms because they know the true productivity of their apprentices. In the model from Acemoglu and Pischke (1998), firms retain those apprentices after graduation whose ability is above some threshold value. This allows them to earn rents because they can pay apprentices a wage below their true productivity. Acemoglu and Pischke find empirical evidence that supports the predictions of their model in the context of the German apprenticeship system. In short, firm movers (and possibly occupation changers[6]) might earn lower wages simply

[6] The argument is less clear when comparing firm movers within the learned occupation to firm movers who leave their occupation. Intuitive reasoning suggests that occupational changers might be selected even more adversely.

because they are adversely selected based on their inferior ability levels.

## 2.2 Model

Our analytical model of wages earned by apprenticeship graduates accounts for the human capital, search, matching and ability components discussed so far. We assume that every apprentice receives three wage offers after graduation: one from his or her training firm (denoted $st$: the apprentice is a "stayer"), one from another firm for a job in his or her learned occupation ($fm$: the apprentice is a "firm mover"), and one from another firm for a job in a different occupation ($oc$: the apprentice is an "occupation changer").

The wage offer of the training firm $f$ to the firm's own graduated apprentice $i$ is given by (ignoring observable individual and firm characteristics for the moment):

$$lnw_i^{st} = r_j + \alpha_i + \mu_{ifj} + \epsilon_i^{st} \tag{1a}$$

The log wage offer for "stayers" depends on the return to apprenticeship training in occupation $j$ ($r_j$), individual ability ($\alpha_i$), a combined worker-firm and worker-occupation match ($\mu_{ifj}$) for the training firm $f$ and training occupation $j$, and a random error ($\epsilon_i^{st}$). Ability, match and error are all assumed to be distributed with zero mean.

The wage offer for a job in an outside firm, but in the same occupation is:

$$lnw_i^{fm} = (1 - \phi)r_j + \epsilon_i^{fm} \tag{1b}$$

For firm movers, the firm-specific share of training ($\phi$) is, by definition, not transferable to other firms and reduces the return to apprenticeship training. Because we assume that the outside firm does not know the ability of the apprentice nor his or her match quality, these components are not included in the outside firm's wage offer.

In the same vein, the apprenticeship graduate receives a wage offer for a job in an outside firm outside his or her learned apprenticeship occupation:

$$lnw_i^{oc} = (1 - \phi)(1 - \omega_{jk})r_j + \epsilon_i^{oc} \tag{1c}$$

For an occupation changer, the return to apprenticeship-acquired human capital is further reduced by the occupation-specific share of training ($\omega_{jk}$), in addition to the firm-specific share. More precisely, let $\Omega$ be a $J$x$K$ matrix that describes the transferability of human capital from occupation $j$ to occupation $k$, where $\omega_{jk}$ is the element in the $j$th row and the $k$th column. This captures the idea that occupations may vary in their distance from one another and that the human capital acquired in one occupation may be more or less transferable depending on the new occupation. The $\omega_{jk}$ lie between zero (full transferability) and unity (no transferability).

If apprenticeship graduates maximize earnings, or if they maximize utility and earnings increase utility, their decision among the three different wage offers is determined by all the elements in the wage equations: job choice depends on the transferability of human capital and on individuals' ability levels, firm- and occupation-specific matches and random draws from the three wage offer distributions.

# 3 Estimation strategy

The empirical identification strategy is to use inter-firm and occupational mobility of apprenticeship graduates to estimate the mean transferability of human capital acquired by apprentices. More precisely, we want to estimate the firm-specific and occupation-specific shares of the short-term returns to apprenticeship, i.e., $\overline{\phi}$ and $\overline{\omega_{jk}}$, measured one year after graduating from apprenticeship.
Wage differentials between stayers, firm movers and occupation changers can be estimated by an OLS wage regression:

$$lnw_i \quad = \quad \beta_j + \beta^{fm} FM_i + \beta^{oc} OC_i + \beta^X X_{if} + u_{ifj} \tag{2}$$

The combined error term $u$ contains the unobservable ability and match components as well as the random draw from the respective wage offer distribution. Our focus is on the wage differential estimates $\hat{\beta}^{fm}$ and $\hat{\beta}^{oc}$. However, these estimates will provide biased estimates of our parameters of interest for several reasons. We will discuss three potential sources of bias and our estimation strategy for addressing each one in turn.

First, the $FM$ and $OC$ dummies depend on individuals' unobserved ability and match quality in a sample with endogenously determined firm and occupation changes. Therefore, they are endogenous with respect to the observed wage. Our dataset contains detailed information on individuals' characteristics and their experiences during training. We will

use several observable proxy variables to eliminate (or at least reduce) the endogeneity bias due to ability and match quality.
Concerning ability, we control for individuals' grade in the final examination at the end of apprenticeship training and for reading literacy test scores at age 15 (i.e., before training) from the international PISA 2000 survey. The proxy solution assumes that ability and the firm mover and occupation change dummies are uncorrelated conditional on literacy test scores and final exam grades. The proxy variable for firm match quality is apprentices' general satisfaction with the training. The proxy for occupation match quality is how much the apprentices like to perform the typical tasks of their apprenticeship occupations as measured during training at least one year before graduation.

Second, the firm and occupational change dummies are supposed to measure the mean transferability of the human capital acquired in apprenticeship training (since $\phi$ and $\omega_{jk}$ are expected to lower earnings in our model, signs for the mobility dummies are negative in equation (2') an (3)):

$$lnw_i = \beta_j - \overline{\phi} FM_i - \overline{\omega_{jk}} OC_i + \beta^X X_{if} + u_{ifj} \tag{2'}$$

$\omega_{jk}$ in the wage offer equation (1c) is assumed to be a random coefficient because transferability depends on the learned and the current occupation.[7] Ignoring the ability and match components discussed in section 2.2 for the moment, the error term in (2') is therefore:

$$u_{ifj} = (\overline{\omega_{jk}} - \omega_{jk}) OC_i + \epsilon_i \tag{3}$$

Occupation changers are more likely to choose a new occupation that allows a high transfer of human capital from their learned occupation ($\omega_{jk} < \overline{\omega_{jk}}$). In this case, the resulting endogeneity bias drives the OLS coefficient upwards because the occupation change dummy and the error term in (2') are positively correlated. Assuming a constant transferability of human capital from any occupation to any other defines away this endogeneity problem, but the assumption seems implausible.

[7] The same argument could be made with respect to firm-specific human capital. If the firm-specific share of training varies by firms, $\phi$ becomes a random coefficient. The discussion on occupation-specific human capital in the text carries over to this case: the result is an upward bias in the OLS estimate of the firm mover dummy. We ignore this issue in the text for simplicity because our main focus is on occupation-specific human capital.

Third, the job choice decision depends on the random draws from the wage offer equations (1a) to (1c). This introduces a positive correlation between the firm mover and occupation change dummies and the error term in the OLS regression equation (2). This positive correlation again results in an upward bias of the OLS estimates.

Because the two latter sources of endogeneity induce an upward bias, the OLS estimates of our mobility dummies will underestimate the wage loss that would occur when we move an apprentice randomly (in a thought experiment) from one occupation (or firm) to another. We therefore conclude that the OLS estimates provide a lower bound in absolute terms for the effects of firm and occupation changes on wages and hence for the return to specific human capital.

Treating the OLS coefficients as baseline results, endogenous mobility can be directly addressed by means of an endogenous treatment model using a control function approach (Heckman, 1978; Maddala, 1983; Vella, 1998; Vella and Verbeek, 1999).
In our case, the endogenous regressor is not binary as in the standard case; it is a categorical variable with three categories (i.e., two dummy variables) for firm stayers, firm movers and occupation changers (on multiple treatments see Lee, 1983; Dubin and McFadden, 1984). The first stage of the model consists of a multinomial choice model for mobility decisions; the second stage is a wage regression augmented by control functions derived from the first stage:

$$y_{li}^* = \gamma_l + \gamma_l^X X_{if} + \gamma_l^Z Z_i + v_{li} \qquad l = st,fm,oc \tag{4}$$

$$lnw_i = \beta_j + \beta^{fm} FM_i + \beta^{oc} OC_i + \beta^X X_{if} + \sum_l \beta_l^\lambda \lambda_{li} + u_{ifj} \qquad l = st,fm,oc \tag{5}$$

In this setup, $l$ is the categorical variable that describes the choice of trainees among three alternatives based on the individual 'utilities' $y_{li}^*$. We use a standard multinomial logit specification to parameterize (4).
The Mills ratios are derived from a generalized version of the Dubin and McFadden (1984) approach. Bourguignon et al. (2007) showed that this version (dubbed "DMF1" in their paper) performs well in Monte Carlo simulations of selection bias correction models and is their preferred option in small samples. The DMF1 approach involves one control function per choice alternative in the first stage, i.e., three Mills ratios $\lambda_{li}$ in our case.[8] In

[8] Dubin and McFadden (1984) originally used one fewer Mills ratio, based on the additional assumption that the correlations between the error term in the second stage and error terms in the multinomial choice equation sum to zero. Bourguignon et al. (2007) showed that this assumption leads to inferior results in Monte Carlo simulations when it does not hold, as is likely to be the case in empirical applications.

the second stage wage regression, we assume that the treatment effect operates through the intercept; that is, we assume that the coefficient vector $\beta^X$ is the same for all groups.[9] The reduced form multinomial mobility estimation in the first stage should include a vector of variables $Z$ that are excluded from the independent variables in the wage regression. If these variables are correlated with mobility but uncorrelated with wages (after vector $X$ has been controlled for), the estimates identify the causal effect of mobility.

We will use three such variables[10] that exploit regional variation in job offer rates. The variables are calculated from the firm census data and matched to the apprentices based upon their place of residence during apprenticeship training. The relevant individual regions encompass all municipalities that can be reached within twenty minutes by car from the apprentice's residential municipality. The first variable is the share of training firms in the region where the apprentice lives. The share of training firms will affect job offers from outside firms upon graduation. Some training firms will try to retain their apprentices after the training period to recoup their investment cost. Thus, these firms will offer fewer open posts for skilled workers on the outside labor market. A higher share of training firms in the region should lead to fewer job offers for the individual job-seeker after he or she completes the apprenticeship. A second variable is the difference between the share of apprentices in the workforce in the region between the years 2005 and 2001. These years represent the time period during which the apprentices began and completed their training. As the number of competitors on the labor market increases (the variation is driven mainly by demography), we expect that the number of job offers to an individual apprentice would decrease. Finally, we include the change in a Herfindahl-type firm concentration index that accounts for the change in firm structure in the region in the industry of the training firm. We expect that a higher number of firms with similar skill needs, i.e. a less concentrated industry, leads to more job offers and thus increases firm changes. Because the variables are derived from the firm census, they are by construction independent of the individual characteristics and productivities of the apprentices.[11]

This approach accounts for the endogeneity of the firm mover and occupation change dummies; if the dummy coefficients are assumed to be random due to self-selection of individuals based on heterogeneous and unobserved idiosyncratic gains, the effect is identified for the subpopulation who are led to change jobs or occupations by the instruments

[9] Due to the limited sample size, we are not able to allow for differences in the $\beta^X$ coefficients across mobility groups as in a full switching regression.

[10] For more details on the variables, see table A1 in the appendix.

[11] As is typical for non-experimental exclusion restrictions, a concern might be that regional differences in the structure of firms, training firms and apprentices affect trainees' wages. As we will show, the main results of the model also hold when identification relies on the non-linearity of the control functions alone.

(compliers).

Deb and Trivedi (2006) provided an alternative estimation approach for endogenous multinomial treatment that uses simulated maximum likelihood to accommodate non-normal and nonlinear outcome equations. Because results tend to vary substantially depending on starting values for maximization and the number of random draws for simulation (see Deb and Trivedi, 2006, p. 318), we prefer the two-step control function method outlined above. Nonetheless, we compared the two approaches and found that the Deb-Trivedi results support the results of our control function approach.[12]

To sum up, we would expect that (i) the wage effects of exogenous firm and occupational change are negative (specific human capital effect), (ii) the observed changes are endogenously chosen and the wage effects of firm and occupational changes in an OLS estimation are therefore biased upwards, and (iii) changers are a negatively selected group that might earn less anyway, such that an observed wage loss might not be caused by the change.

# 4 Data

We use Swiss data from the PISA 2000 survey and the longitudinal dataset TREE[13] *(TRansitions from Education to Employment)* that follows the pupils surveyed in PISA 2000 (in their last year of compulsory schooling) during their first years thereafter (TREE, 2008; Bertschy et al., 2007). These datasets enable us to observe the PISA literacy test score and other background variables for individuals, along with detailed information about their training and working career on a yearly basis. We use data from the years 2000 to 2005. This time period allows us to include the vast majority of all individuals in the PISA 2000 cohort who enter an apprenticeship because these programs typically start immediately after compulsory school and end after 2 to 4 years.

The PISA 2000 survey *(Programme for International Student Assessment)* was organized by the OECD in 43 participating countries (OECD, 2002) and focused on testing the reading literacy of 15 year olds, who are typically in their final year of compulsory school. The average test score in reading literacy for Swiss pupils is not significantly different from the OECD mean (FSO, 2002). The 6343 students tested in PISA 2000 were also surveyed by TREE in 2001. Due to sample attrition of about 6.5 percent per year, 4509

[12] Results are available from the authors.

[13] As of 2008, TREE is co-funded by the Swiss National Science Foundation (SNSF) and the University of Basel. From 2000 to 2007, the project has been financed and/or carried out by SNSF, the Departments of Education of the three cantons Berne, Geneva and Ticino, the Federal Office for Professional Education and Technology (OPET), and the Swiss Federal Statistical Office (FSO).

observations remain in 2005. Of these, we drop those students who have not started and completed an apprenticeship and those who were already enrolled in an upper-secondary educational program at the time of PISA. This leaves us with 1618 pupils for whom we observe the transition from apprenticeship to work or to another activity within a year after graduation. Of the graduates, 72 percent took up work, 15 percent were enrolled in further education, 4 percent were serving in the military, 3 percent were temporarily out of labor force due to travelling or doing language studies abroad, and 6 percent were unemployed. The final figure confirms the comparatively low youth unemployment rate in Switzerland reported by OECD (2011). We exclude observations with missing values in the wage, mobility, or control variables. Our final sample of employed individuals is 878 observations for the wage regressions: 514 women and 364 men. Due to the limited sample size, we do not split the sample between men and women. This seems justified for two reasons. First, female labor participation is not smaller than male participation at this age for apprenticeship graduates.[14] Second, we control for occupation dummies to account for the occupational segregation by gender in the labor market.

A variable of primary interest is the occupational change dummy that indicates whether an apprentice has moved away from his or her apprenticeship occupation after the apprenticeship period.[15] Identifying occupational changes is not trivial; we made use of different information in the dataset to construct a valid coding scheme. Apprenticeship occupations were pre-coded according to the official classification (BIS)[16] of the Federal Statistical Office that is designed to categorize apprenticeship occupations. However, the occupations of the jobs that were accepted after the apprenticeships were coded according to the Swiss Occupation Classification (SBN)[17]; this classification system is typically used for labor market analysis. To compare the learned and current occupations, we converted the vocational training occupations (BIS) into the Swiss Occupation Classification using the official "thesaurus" developed by the Federal Statistical Office. Making use of the digit structure of this classification, we have defined occupational change as a change on 2-digit level. There are thirty-nine 2-digit occupation categories: thus, we have adopted a rather broad definition of an occupation to exclude changes between occupations entailing

[14] In our data, female labor market participation of apprenticeship graduates is even higher (77% versus 66%). While both genders show very similar shares of unemployment (6%) and spells of being temporarily out of labor force due to travelling or language studies abroad (3%), only male participants are in military service (9%). The share of those who attend further certifying education (e.g., university of applied sciences) is slightly higher for male graduates as well (16% versus 14%).

[15] Note that industry changes occur almost exclusively together with occupation changes in our data. Because all apprenticeship regulations refer to clearly defined occupations and not to industries, occupations are the relevant dimension in our context.

[16] *Bildungsstatistisches Informationssystem BIS.*

[17] *Schweizerische Berufsnomenklatur SBN 2000*

a very similar set of skills.[18]

A problem inherent in all classification-based analyses is that there remains some arbitrariness in assigning an occupational description obtained from a respondent to one specific code. This is another reason why we look at 2-digit changes and not at 3- or 5-digit changes; the more finely grained definitions would identify more spurious occupation changes. The problem may be exacerbated if the assignment process is not consistent; for instance, different coders may use different assignment rules (Kambourov and Manovskii, 2009; Lalé, 2012; Sullivan, 2009). An advantage of our data set is that we know the original open-text answer the respondents provided when asked about their current occupation. We were thus able to check all coding and improve its coherence by applying dependent coding (Lalé, 2012). We found that about half of the changes that would have resulted from using the initially assigned codes were spurious.[19] Cross-checking codes for learned and current occupations with open text information on both, we consider our conservative measure of occupational change to be superior to an operationalization that is based on given classification codes alone.

Another important variable is the firm stayer variable that allows us to analyze the effects of firm change and occupation change separately. The firm information comes from the firm census of the Swiss Federal Statistical Office. We identified stayers by comparing the firm identification numbers that are included in the data set for training firms and for current firms. One advantage of the data is that we make use of a firm ID at the enterprise level, not the establishment level. We define a stayer as a person who remains within the same enterprise as opposed to the same establishment. This is the preferred distinction because information on workers' ability is likely to be available to the enterprise as a whole.[20] Variables on regional differences in firm and training structure are constructed from the firm census as well (see section 3).

Measures that account for individuals' ability are PISA reading test scores as well as

[18] In this respect, the recent task-based or skill weights approaches (Gathmann and Schoenberg, 2010; Geel and Backes-Gellner, 2009; Lazear, 2009) allow one to analyze the distance between occupations directly. The more classical approach based on formal occupations remains relevant because all state regulations (on training ordinances, curricula and diplomas) are based on these.

[19] Detailed information on the corrections applied is available from the authors. The majority of spurious occupational changes occurred between the two 1-digit categories *"5. Handels- und Verkehrsberufe"* (commerce) and *"7. Berufe des Managements und der Administration, des Bank- und Versicherungsgewerbes und des Rechtswesens"* (management, administration, banking, insurance and law). This is due to an imprecision in the German language: the classical notion of *"Kaufmann"* refers to merchants who are assigned to category 5. However, the modern designation of *"Kaufmann/Kauffrau"* does refer to commercial employees, and these are assigned to category 7. Using the open-text information, we were able to eliminate pseudo-changes between category 7 (apprenticeship occupation = commercial employee) and category 5 (current occupation coded as merchant).

[20] Other firm data sets often do not allow one to identify stayers on enterprise level; see Euwals and Winkelmann (2004), for a short discussion.

final grades of apprenticeship. In all of our specifications, we condition on several groups of covariates; we include variables on personal characteristics (sex, immigrant), family background (parental education), the apprenticeship training program (occupation, size of training firm, obtained professional baccalaureate), and the language region. Variable definitions can be found in table A1; descriptive statistics for all variables are presented in table A2 in the appendix.

# 5 Results

The mobility behavior of employed apprenticeship graduates is described in table 1: roughly one-half of them continue to work in their training firms, while the other half changes firms. For 14.7 percent of the firm movers, we simultaneously observe a move out of the occupation in which they were trained. The share of occupation changes (as defined in section 4) is rather low one year after completing apprenticeship training.

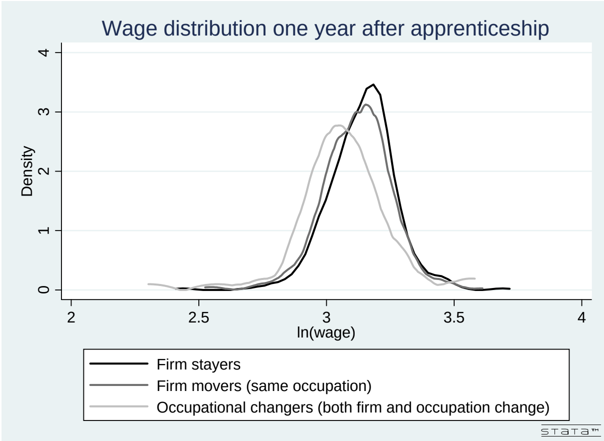
Table 1: Mobility patterns after training (status one year after graduation)

| Firm | Share | Occupation | | % in category |
|---|---|---|---|---|
| Job in training firm | 51.03% | learned occupation | | 51.03% |
| Job in a new firm | 48.97% | learned occupation | 85.35% | 41.80% |
| | | occupational change | 14.65% | 7.18% |
| | 100.00% | Total | | 100.00% |

As for the wage offers (see equations 1a to 1c in section 2.2), we expect to observe the highest wages for stayers, followed by firm movers and occupation changers due to a loss of specific human capital. The wage distributions are likely to be broader for movers than for stayers and even broader for occupation changers because the offers come from very different firms. The observed wage distributions in figure 1 mirror this description, although they necessarily differ from the underlying wage offer distributions due to endogenous job choice. It can be seen that occupation changers earn the least on average: they earn 21.74 CHF per hour, compared with 22.86 CHF for firm movers and 23.31 CHF for stayers (see table A2 in the appendix).

The OLS wage regression in table 2 shows no significant difference in wages between stayers and firm movers, but wages for occupation changers are lower by 4.7 percent, and the difference is statistically significant. As described in section 3, the OLS estimate provides a lower bound for the short-term wage effect of occupation-specific human capital acquired during apprenticeship training. We thus find that occupation-specific human capital is an

Figure 1: Distribution of hourly wages by mobility status after graduation




important element of apprenticeship training, but we find no evidence that firm-specific human capital is similarly important.

The wage regression includes the proxy variables for ability and the match quality with the training occupation and firm. The PISA literacy test score measured at age 15 turns out to be significant: an increase by one standard deviation increases wage by 1.8 percent. Still, it the results for the mover and occupation change dummies do not change when the literacy test score variable is included or excluded. In addition, we do not find a significant interaction effect between mobility and test score (not shown). These regressions provide some evidence that an ability measure (which is hard to observe for outside firms) plays a role in determining wages, but they provide no evidence that it affects the wage differential between stayers, firm movers and occupation changers. The other ability and match proxy variables are not significant. Other significant effects are in line with results well known from the literature: women earn less, employees in larger firms earn more, and there are wage differences across language regions and occupations.[21]

Table 2: Wage estimations

| | ln(wage) OLS | ln(wage) CF estim. | MLOGIT Coefficients (Base: Occ. change) | | MLOGIT Average marginal effects | | |
|---|---|---|---|---|---|---|---|
| | | | Mover | Stayer | Mover | Occ. change | Stayer |
| Occupational change | −0.047** | −0.128+ | | | | | |
| | (0.017) | (0.072) | | | | | |
| Firm stayer | 0.002 | 0.010 | | | | | |
| | (0.009) | (0.079) | | | | | |
| Likes tasks of training occupation | 0.001 | −0.002 | 0.494* | 0.632** | −0.010 | −0.032* | 0.042 |
| | (0.007) | (0.009) | (0.226) | (0.234) | (0.027) | (0.013) | (0.027) |
| Satisfaction with training | 0.004 | 0.001 | 0.246+ | 0.590** | −0.054** | −0.024** | 0.078** |
| | (0.004) | (0.007) | (0.135) | (0.142) | (0.016) | (0.008) | (0.016) |
| Professional baccalaureate | −0.013 | −0.014 | −0.188 | 0.315 | −0.095* | −0.003 | 0.098* |
| | (0.011) | (0.014) | (0.440) | (0.439) | (0.042) | (0.024) | (0.041) |
| GPA in apprenticeship training | −0.014 | −0.018 | 0.803 | 0.710 | 0.040 | −0.043 | 0.003 |
| | (0.014) | (0.015) | (0.514) | (0.513) | (0.053) | (0.028) | (0.053) |
| PISA test score reading literacy | 0.018** | 0.018* | 0.295 | 0.194 | 0.027 | −0.014 | −0.013 |

[21] Controlling for 13 industry dummies does not change the reported results.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (0.006) | (0.007) | (0.201) | (0.201) | (0.023) | (0.011) | (0.022) |
| Parental education: upper-secondary | −0.005 | −0.005 | −0.355 | −0.143 | −0.048 | 0.014 | 0.034 |
| | (0.010) | (0.011) | (0.362) | (0.361) | (0.039) | (0.020) | (0.039) |
| Parental education: tertiary | −0.002 | −0.007 | 0.795+ | 0.894+ | 0.006 | −0.048+ | 0.043 |
| | (0.011) | (0.013) | (0.467) | (0.469) | (0.043) | (0.026) | (0.043) |
| Parental education: no information | 0.041+ | 0.035 | 2.045+ | 1.948 | 0.077 | −0.114 | 0.037 |
| | (0.024) | (0.023) | (1.230) | (1.252) | (0.090) | (0.070) | (0.093) |
| Female | −0.043** | −0.046** | 0.374 | 0.189 | 0.044 | −0.016 | −0.028 |
| | (0.011) | (0.012) | (0.377) | (0.380) | (0.041) | (0.021) | (0.041) |
| Immigrant: second-generation | 0.028 | 0.028 | 0.039 | 0.013 | 0.006 | −0.001 | −0.004 |
| | (0.018) | (0.024) | (0.562) | (0.564) | (0.067) | (0.031) | (0.067) |
| Immigrant: first-generation | −0.001 | −0.003 | −0.031 | 0.595 | −0.112+ | −0.016 | 0.128* |
| | (0.016) | (0.022) | (0.581) | (0.562) | (0.064) | (0.031) | (0.061) |
| French speaking part of Switzerland | 0.006 | 0.007 | −0.140 | −0.570 | 0.072+ | 0.020 | −0.092* |
| | (0.010) | (0.012) | (0.385) | (0.389) | (0.039) | (0.021) | (0.039) |
| Italian speaking part of Switzerland | −0.107** | −0.102** | −1.730** | −1.721** | −0.052 | 0.099** | −0.046 |
| | (0.017) | (0.022) | (0.590) | (0.590) | (0.069) | (0.033) | (0.069) |
| Agriculture and Forestry (3) | −0.103** | −0.088** | −1.439* | −2.157** | 0.085 | 0.102** | −0.188* |
| | (0.022) | (0.034) | (0.625) | (0.664) | (0.083) | (0.035) | (0.085) |
| Production, Manufacturing (3) | −0.032+ | −0.027 | −0.379 | −0.783 | 0.061 | 0.033 | −0.094 |
| | (0.018) | (0.021) | (0.580) | (0.586) | (0.067) | (0.032) | (0.067) |
| Production, Manufacturing (4) | −0.007 | −0.008 | 0.418 | 0.210 | 0.049 | −0.018 | −0.031 |
| | (0.021) | (0.022) | (0.791) | (0.796) | (0.079) | (0.044) | (0.079) |
| Technicians, IT (4) | 0.007 | 0.001 | 1.885+ | 1.953+ | 0.043 | −0.110+ | 0.067 |
| | (0.017) | (0.018) | (1.100) | (1.094) | (0.071) | (0.063) | (0.069) |
| Construction (3) | 0.023 | 0.020 | −0.084 | 0.541 | −0.113 | −0.013 | 0.126 |
| | (0.023) | (0.029) | (0.818) | (0.789) | (0.092) | (0.044) | (0.089) |
| Construction (4) | 0.004 | 0.003 | −0.005 | 0.595 | −0.107 | −0.016 | 0.123 |
| | (0.026) | (0.037) | (0.950) | (0.909) | (0.107) | (0.051) | (0.103) |
| Retail and wholesale, transport (2) | −0.145** | −0.146** | −0.098 | 0.404 | −0.092 | −0.008 | 0.100 |
| | (0.019) | (0.024) | (0.742) | (0.723) | (0.074) | (0.041) | (0.071) |
| Retail and wholesale, transport (3) | −0.045* | −0.043* | −0.739 | 0.102 | −0.171* | 0.019 | 0.152* |
| | (0.018) | (0.021) | (0.660) | (0.636) | (0.069) | (0.036) | (0.066) |
| Catering and restaurant (2) | −0.105** | −0.099** | −0.366 | −1.124 | 0.124 | 0.042 | −0.166 |
| | (0.038) | (0.033) | (1.184) | (1.281) | (0.146) | (0.067) | (0.154) |
| Catering and restaurant (3) | −0.090** | −0.085** | −0.085 | −1.082+ | 0.175** | 0.033 | −0.207** |
| | (0.017) | (0.026) | (0.561) | (0.598) | (0.066) | (0.032) | (0.069) |
| Office worker (2) | −0.051 | −0.035 | −3.176** | −2.024* | −0.298+ | 0.150** | 0.148 |
| | (0.040) | (0.046) | (1.173) | (0.977) | (0.179) | (0.057) | (0.165) |
| Health and welfare (3, 4) | −0.011 | −0.012 | 0.567 | 0.448 | 0.038 | −0.029 | −0.009 |
| | (0.018) | (0.018) | (0.854) | (0.862) | (0.065) | (0.048) | (0.066) |
| Firm size of training firm: 11-100 | 0.014 | 0.013 | −0.211 | 0.280 | −0.093* | −0.002 | 0.095** |
| | (0.010) | (0.014) | (0.356) | (0.359) | (0.037) | (0.020) | (0.037) |
| Firm size of training firm: 100+ | 0.015 | 0.014 | −0.333 | 0.071 | −0.082 | 0.008 | 0.074 |
| | (0.014) | (0.015) | (0.503) | (0.503) | (0.054) | (0.028) | (0.054) |
| Firm size of current firm: 11-100 | 0.018+ | 0.018 | −0.256 | −0.027 | −0.048 | 0.008 | 0.040 |
| | (0.010) | (0.012) | (0.384) | (0.386) | (0.038) | (0.021) | (0.038) |
| Firm size of current firm: 100+ | 0.061** | 0.063** | −0.856+ | −0.115 | −0.157** | 0.028 | 0.129* |
| | (0.014) | (0.020) | (0.471) | (0.467) | (0.052) | (0.026) | (0.051) |
| Firm size of current firm: Missing | 0.034 | 0.047 | −0.624 | −2.998** | 0.404** | 0.102* | −0.505** |
| | (0.026) | (0.048) | (0.635) | (0.944) | (0.140) | (0.040) | (0.157) |
| Change reg. share apprentices | | | −1.361** | −1.274* | −0.056 | 0.076** | −0.020 |
| | | | (0.500) | (0.503) | (0.051) | (0.028) | (0.052) |
| Reg. share of training firms 2001 | | | −0.210* | −0.211* | −0.006 | 0.012* | −0.006 |
| | | | (0.091) | (0.091) | (0.009) | (0.005) | (0.009) |
| Change industry concentration | | | −1.251+ | −0.416 | −0.185* | 0.048 | 0.137+ |
| | | | (0.755) | (0.760) | (0.076) | (0.042) | (0.076) |
| Constant | 3.206** | 3.257** | −0.474 | −2.831 | | | |
| | (0.070) | (0.079) | (2.864) | (2.871) | | | |
| Mills "firm mover" | | 0.007 | | | | | |
| | | (0.030) | | | | | |
| Mills "occ. change" | | 0.038+ | | | | | |
| | | (0.022) | | | | | |
| Mills "firm stayer" | | 0.003 | | | | | |
| | | (0.032) | | | | | |
| N | 878 | 878 | 878 | | | | |
| R-sq / Pseudo R-sq | 0.285 | 0.290 | 0.155 | | | | |

+ p<0.10, * p<0.05, ** p<0.01; CF (control function) estimates: bootstrapped standard errors (2000 replications) in parentheses to account for generated regressors.
Reference group: Firm mover, no professional baccalaureate, highest parental education: compulsory school, male, Swiss, German speaking part of Switzerland, training occupation: commercial employee (3), firm size: 1-10 fulltime-equivalents.

The other columns in table 2 show the results for the two-step control function estimation

(CF) that accounts for the endogeneity of job and occupation changes. For the first-stage multinomial logit, the coefficients and corresponding average marginal effects are presented.[22] Test scores and final grades have no significant effects on job choice, which means that we find no evidence of adverse selection. Parental education has a weak effect: apprentices whose parents have obtained a tertiary educational degree are less likely to change occupation. The match variables have the expected effects on job choice: general satisfaction with training increases the likelihood that an apprentice stays in the firm after completing training. An apprentice who likes the tasks of the training occupation is less likely to change occupation after the training period. Further, there are significant mobility differences across occupations and regions.

The three variables excluded in the second stage are all statistically significant in the mobility equation. As expected, an increase in industry concentration decreases firm changes. An increase in the regional share of apprentices in the workforce or a higher share of training firms increases occupational mobility, which is likely because the number of wage offers in the learned occupation is reduced and job search costs increase.

The second column shows the results for the second-stage regression. For most covariates, the results are very similar to the OLS results. The wage loss of an occupation changer relative to a firm changer still working in his or her learned occupation increases from 4.7 percent in the OLS estimates to 12.8 percent in the CF model. This result is in line with our theoretical prediction that OLS provides a lower bound for the importance of occupation-specific human capital and is biased due to endogeneity problems. The point estimate for firm stayers remains low and insignificant. The Mills ratio from the first-stage alternative "occupation change" is marginally significant, indicating that endogeneity is an issue.

To check the sensitivity of these results to alternative specifications, table A3 in the appendix provides results using all possible combinations of the three exclusion restrictions, including none, one, two or all of the variables. The main lessons from table A3 are the following:

- The occupation change dummy varies between -.08 and -.15. The point estimates thus indicate higher wage differentials than those provided by OLS for occupation change (but not for firm change).
- This is even true for the specification without exclusion restriction that is identified only by parametric assumptions (the nonlinearity of the Mills ratios).
- Bootstrapped standard errors are clearly higher than the OLS estimates that do not

[22] Both sets of results are interesting for inference because the coefficients' standard errors allow one to test one alternative against the reference choice (occupation change in our case), while standard errors for marginal effects allow one to test one alternative against all others.

account for the two-stage procedure. The occupation change and mills1 coefficients move from statistically significant to insignificant in some specifications.

Because the confidence intervals for the occupation change dummy in table A3 always contain the OLS point estimate (table 2), the control function estimates do not allow us to make exact statements about the "true" size of the wage penalty for occupation changes and thus the short-term return to occupation-specific human capital. The merit of the control function point estimate is to empirically confirm that OLS estimates are a lower bound as was deduced from theory. This result is fairly robust to the specification of the exclusion restrictions (although significance levels of the point estimates are rather low); the results even hold without applying exclusion restrictions.

# 6 Conclusion

Firm-based apprenticeships have been suspected of transferring an overly specific, narrow set of skills. However, several studies have found a high transferability of apprenticeships in Germany. We have shown for the case of Switzerland that firm mobility within one year after finishing an apprenticeship is high (49 percent of all apprenticeship graduates), whereas occupational mobility is very limited (7 percent). In OLS wage regressions, firm movers earn the same wages as firm stayers, controlling for ability and match quality proxies. This result does not point to an important role for firm-specific human capital in apprenticeships on average. Occupation changers, however, earn about 5 percent less than those staying in their learned occupation. As shown in the model, this OLS estimate provides a lower bound for the short-term return to occupation-specific human capital. Accounting for unobserved ability using PISA test scores has no influence on the mobility wage differentials and provides no evidence for adverse selection (Acemoglu and Pischke, 1998). Applying a control function approach to account for endogenous mobility decisions, we find a wage differential of roughly 8 to 15 percent between occupations stayers and changers. This result empirically confirms that the wage effect of the loss of occupation-specific human capital due to occupation change is higher than suggested by the OLS estimate.

We can thus conclude that firm-specific human capital does not play a major role for Swiss apprenticeships on average, while occupation-specific human capital is an important component of apprenticeship training and accounts for a part of the returns to training. This is in line with several studies (Kambourov and Manovskii, 2008; Neal, 1995; Parent, 2000; Sullivan, 2010) that highlight the importance of industry- and occupation-specific human capital in labor market analyses. Because the majority of Swiss workers complete an apprenticeship, this certainly holds true for Switzerland.

The implications of these results for the broader economy have yet to be investigated. The irrelevance of firm-specific human capital shows that apprenticeships are not restricted to a very narrow set of skills that hinder apprentices' mobility and flexibility on the labor market. Still, the importance of occupation-specific human capital raises the question whether apprentices' flexibility is reduced compared to students in a general education system that does not require a choice of an occupation at the age of 16. At the same time, the importance of occupation-specific human capital can also be interpreted as evidence for gains that accrue from specialization, both at the individual level and for the economy as a whole. Relatively high rates of (lifetime) returns to apprenticeships (Weber et al., 2001) and the high Swiss per capita GDP support the view that the apprenticeship system is successful in supplying the skills needed by the Swiss economy. More empirical studies are required to analyze the relative costs and benefits of education systems that rely on vocational education with early specialization.

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# A Appendix

Table A1: Variable definition

| **Variable** | **Definition** |
|---|---|
| Female | Equals 1 if female; 0 if male. |
| Nationality | Dummies representing 3 categories: "Swiss" (trainee born in Switzerland with at least one parent born in Switzerland), "second-generation immigrant" (trainee born in Switzerland but parents born outside Switzerland), "first-generation immigrant" (trainee and parents foreign-born). |
| Professional baccalaureate | Equals 1 if apprentice obtained a professional baccalaureate (additional schooling) while serving his apprenticeship; 0 otherwise. |
| Parental education | Dummies representing 3 categories of highest parental education: compulsory school, upper-secondary education, tertiary education. |
| Language region | Dummies representing Swiss language regions (German, French, Italian). |
| Training occupation | Dummies representing apprenticeship tracks. Training occupations are coded according to the nomenclature of occupations (Schweizerische Berufsnomenklatur SBN) at the 1-digit level, additionally split along the official duration of the corresponding apprenticeship training (2, 3 or 4 years). |
| Firm size of training firm | Dummies for 3 firm size categories (firm = establishment). |
| Firm size of current firm | Dummies for 3 firm size categories (firm = establishment) and a dummy for missing current firm size information. |
| PISA test score reading literacy | Reading literacy test score from the PISA 2000 survey, standardized with mean=0 and std. dev.=1 for the estimations. |
| GPA in apprenticeship training | The average grade in the final apprenticeship examination. Metric scale: 4 - 6 (4 = sufficient, 6 = excellent). |
| Satisfaction with training | Level of general satisfaction with education reported during apprenticeship, ranging from 1 (not satisfied at all) to 7 (extremely satisfied). |
| Likes tasks of training occupation | Level of how much the apprentice likes to perform the pertinent tasks of the apprenticeship occupation. Reported during training, ranging from 1 (don't like them at all) to 4 (like them very much). |
| Ln(hourly wage) in current job | Natural logarithm of hourly gross wage in the current job (one year after graduation). |
| Change in regional share of apprentices | The change in the regional* share of apprentices in the workforce between 2001 and 2005, i.e., between the time the apprentices started and completed their training. Source: Swiss firm census. |
| Regional share of training firms | The regional* share of training firms among all firms 2001, i.e. when the youngsters started apprenticeship training. Source: Swiss firm census. |
| Change in industry concentration | The change in the regional* firm concentration (ln-Herfindahl) between 2001 and 2005, i.e., between the time the apprentices started and completed their training. Calculated separately for 13 industries and matched to apprentices based on his/her region of residence and the industry of his/her training firm. Source: Swiss firm census. |

* Definition of regions: individual regions encompass all municipalities that can be reached within 20 minutes by car from the apprentice's residential municipality. The computation is based on a distance matrix provided by the Federal Statistical Office (FSO).

Table A2: Descriptive statistics

| | Freq | Stayer | Mover | Occ. change | Overall |
|---|---|---|---|---|---|
| Total | 878 | 100.00 | 100.00 | 100.00 | 100.00 |
| Male | 364 | 44.64 | 36.51 | 47.62 | 41.46 |
| Female | 514 | 55.36 | 63.49 | 52.38 | 58.54 |
| Swiss | 752 | 84.82 | 87.19 | 82.54 | 85.65 |
| Immigrant: second-generation | 55 | 5.58 | 6.54 | 9.52 | 6.26 |
| Immigrant: first-generation | 71 | 9.60 | 6.27 | 7.94 | 8.09 |
| No professional baccalaureate | 676 | 71.65 | 82.29 | 84.13 | 76.99 |
| Professional baccalaureate | 202 | 28.35 | 17.71 | 15.87 | 23.01 |
| Parental education: compulsory schooling | 272 | 30.58 | 30.79 | 34.92 | 30.98 |
| Parental education: upper-sec. education | 345 | 39.06 | 38.15 | 47.62 | 39.29 |
| Parental education: tertiary education | 232 | 27.23 | 27.25 | 15.87 | 26.42 |
| Parental education: no information | 29 | 3.13 | 3.81 | 1.59 | 3.30 |
| German speaking part of Switzerland | 607 | 72.77 | 65.94 | 61.90 | 69.13 |
| French speaking part of Switzerland | 207 | 20.31 | 27.52 | 23.81 | 23.58 |
| Italian speaking part of Switzerland | 64 | 6.92 | 6.54 | 14.29 | 7.29 |
| Training occupation (duration in years): | | | | | |
| Agriculture and Forestry (3) | 43 | 2.68 | 6.27 | 12.70 | 4.90 |
| Production, Manufacturing (3) | 62 | 5.58 | 7.90 | 12.70 | 7.06 |
| Production, Manufacturing (4) | 51 | 5.58 | 6.27 | 4.76 | 5.81 |
| Technicians, IT (4) | 82 | 12.28 | 7.08 | 1.59 | 9.34 |
| Construction (3) | 39 | 5.80 | 2.72 | 4.76 | 4.44 |
| Construction (4) | 28 | 4.24 | 1.91 | 3.17 | 3.19 |
| Retail and wholesale, transport (2) | 54 | 7.59 | 4.63 | 4.76 | 6.15 |
| Retail and wholesale, transport (3) | 61 | 8.93 | 4.63 | 6.35 | 6.95 |
| Catering and restaurant (2) | 11 | 0.67 | 1.91 | 1.59 | 1.25 |
| Catering and restaurant (3) | 73 | 4.24 | 12.81 | 11.11 | 8.31 |
| Office worker (2) | 10 | 1.34 | 0.54 | 3.17 | 1.14 |
| Commercial employee (3) | 293 | 34.60 | 32.43 | 30.16 | 33.37 |
| Health and welfare (3, 4) | 71 | 6.47 | 10.90 | 3.17 | 8.09 |
| Firm size of training firm: 1-10 | 357 | 33.93 | 49.05 | 39.68 | 40.66 |
| Firm size of training firm: 11-100 | 381 | 46.65 | 38.96 | 46.03 | 43.39 |
| Firm size of training firm: 100+ | 140 | 19.42 | 11.99 | 14.29 | 15.95 |
| Firm size of current firm: 1-10 | 340 | 33.04 | 46.32 | 34.92 | 38.72 |
| Firm size of current firm: 11-100 | 354 | 43.30 | 37.33 | 36.51 | 40.32 |
| Firm size of current firm: 100+ | 159 | 23.21 | 11.44 | 20.63 | 18.11 |
| Firm size of current firm: Missing | 25 | 0.45 | 4.90 | 7.94 | 2.85 |
| PISA test score reading literacy | 878 | 505.69 | 509.62 | 481.30 | 505.58 |
| | | (77.88) | (70.08) | (83.58) | (75.39) |
| GPA in apprenticeship training | 878 | 4.81 | 4.83 | 4.72 | 4.81 |
| | | (0.32) | (0.33) | (0.34) | (0.32) |
| Satisfaction with training | 878 | 5.76 | 5.43 | 4.95 | 5.57 |
| | | (0.96) | (1.08) | (1.13) | (1.05) |
| Likes tasks of training occupation | 878 | 3.49 | 3.41 | 3.11 | 3.43 |
| | | (0.59) | (0.65) | (0.82) | (0.64) |
| ln(hourly wage) in current job | 878 | 3.14 | 3.12 | 3.06 | 3.13 |
| | | (0.13) | (0.14) | (0.19) | (0.14) |
| Hourly wage in current job | 878 | 23.31 | 22.86 | 21.74 | 23.01 |
| | | (3.04) | (3.10) | (4.07) | (3.17) |
| Change reg. share apprentices | 878 | 0.38 | 0.37 | 0.45 | 0.38 |
| | | (0.30) | (0.32) | (0.30) | (0.31) |
| Reg. share of training firms | 878 | 15.48 | 15.43 | 15.72 | 15.48 |
| | | (1.96) | (2.03) | (1.74) | (1.97) |
| Change industry concentration | 878 | 0.01 | −0.03 | 0.02 | −0.01 |
| | | (0.22) | (0.21) | (0.19) | (0.21) |

Table A3: Overview on key results varying the exclusion restrictions in the first stage

| | 0) | 1a) | 1b) | 1c) | 2a) | 2b) | 2c) | 3) |
|---|---|---|---|---|---|---|---|---|
| **Wage regression (2nd stage)** | | | | | | | | |
| Occupational change | −0.102 | −0.127 | −0.118 | −0.083 | −0.146 | −0.096 | −0.112 | −0.128 |
| | (0.061)+ | (0.059)* | (0.059)* | (0.057) | (0.057)* | (0.055)+ | (0.055)* | (0.053)* |
| | (0.085) | (0.082) | (0.082) | (0.081) | (0.078)+ | (0.077) | (0.077) | (0.073)+ |
| Firm stayer | −0.026 | −0.001 | −0.059 | 0.020 | −0.034 | −0.003 | 0.033 | 0.010 |
| | (0.081) | (0.080) | (0.081) | (0.068) | (0.080) | (0.068) | (0.068) | (0.068) |
| | (0.092) | (0.097) | (0.089) | (0.076) | (0.092) | (0.074) | (0.080) | (0.077) |
| Mills "firm mover" | 0.006 | 0.010 | −0.010 | 0.021 | −0.007 | 0.008 | 0.021 | 0.007 |
| | (0.032) | (0.032) | (0.032) | (0.028) | (0.031) | (0.027) | (0.027) | (0.027) |
| | (0.035) | (0.035) | (0.034) | (0.029) | (0.034) | (0.029) | (0.030) | (0.029) |
| Mills "occ. change" | 0.025 | 0.038 | 0.023 | 0.027 | 0.037 | 0.025 | 0.039 | 0.038 |
| | (0.017) | (0.016)* | (0.017) | (0.017) | (0.016)* | (0.017) | (0.016)* | (0.016)* |
| | (0.024) | (0.023)+ | (0.024) | (0.024) | (0.022)+ | (0.024) | (0.023)+ | (0.022)+ |
| Mills "firm stayer" | 0.027 | 0.013 | 0.033 | 0.010 | 0.019 | 0.013 | 0.001 | 0.003 |
| | (0.033) | (0.032) | (0.032) | (0.030) | (0.032) | (0.030) | (0.030) | (0.030) |
| | (0.035) | (0.037) | (0.034) | (0.031) | (0.036) | (0.030) | (0.033) | (0.032) |
| **Multinomial Logit (1st stage)** | | | | | | | | |
| *Reg. share of training firms* | | | | | | | | |
| Coeff. outcome "firm mover" | | −0.166+ | | | −0.206* | | −0.171+ | −0.210* |
| | | (0.087) | | | (0.091) | | (0.087) | (0.091) |
| Coeff. outcome "firm stayer" | | −0.175* | | | −0.214* | | −0.173* | −0.211* |
| | | (0.087) | | | (0.091) | | (0.087) | (0.091) |
| AME outcome "firm mover" | | −0.003 | | | −0.005 | | −0.005 | −0.006 |
| | | (0.009) | | | (0.009) | | (0.009) | (0.009) |
| AME outcome "occ. change" | | 0.010* | | | 0.012* | | 0.010* | 0.012* |
| | | (0.005) | | | (0.005) | | (0.005) | (0.005) |
| AME outcome "firm stayer" | | −0.007 | | | −0.007 | | −0.005 | −0.006 |
| | | (0.009) | | | (0.009) | | (0.009) | (0.009) |
| *Change reg. share of apprentices* | | | | | | | | |
| Coeff. outcome "firm mover" | | | −1.055* | | −1.318** | −1.100* | | −1.361** |
| | | | (0.454) | | (0.497) | (0.458) | | (0.500) |
| Coeff. outcome "firm stayer" | | | −0.978* | | −1.246* | −1.012* | | −1.274* |
| | | | (0.458) | | (0.500) | (0.462) | | (0.503) |
| AME outcome "firm mover" | | | −0.045 | | −0.052 | −0.048 | | −0.056 |
| | | | (0.052) | | (0.052) | (0.051) | | (0.051) |
| AME outcome "occ. change" | | | 0.059* | | 0.074** | 0.061* | | 0.076** |
| | | | (0.025) | | (0.028) | (0.026) | | (0.028) |
| AME outcome "firm stayer" | | | −0.014 | | −0.022 | −0.013 | | −0.020 |
| | | | (0.052) | | (0.052) | (0.052) | | (0.052) |
| *Change industry concentration* | | | | | | | | |
| Coeff. outcome "firm mover" | | | | −1.052 | | −1.184 | −1.114 | −1.251+ |
| | | | | (0.724) | | (0.737) | (0.739) | (0.755) |
| Coeff. outcome "firm stayer" | | | | −0.213 | | −0.344 | −0.279 | −0.416 |
| | | | | (0.733) | | (0.746) | (0.745) | (0.760) |
| AME outcome "firm mover" | | | | −0.181* | | −0.184* | −0.181* | −0.185* |
| | | | | (0.075) | | (0.075) | (0.076) | (0.076) |
| AME outcome "occ. change" | | | | 0.038 | | 0.045 | 0.041 | 0.048 |
| | | | | (0.041) | | (0.041) | (0.042) | (0.042) |
| AME outcome "firm stayer" | | | | 0.143+ | | 0.139+ | 0.140+ | 0.137+ |
| | | | | (0.076) | | (0.076) | (0.076) | (0.076) |

+ p<0.10, * p<0.05, ** p<0.01
Unadjusted and bootstrapped standard errors (2000 replications) in parentheses.
All model specifications are identical to the model in table 2 (except for the exclusion restrictions).
AME = Average marginal effect.