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Technological change and occupation mobility: A task-based approach to horizontal mismatch

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Abstract

Technological change and its impacts on labour markets are a much-discussed topic in economics. Economists generally assume that new technology penetrating the labour market shifts firms' task demand. Given individuals' acquired and supplied skills, these task demand shifts potentially foster horizontal skill mismatches, e.g. individuals not working in their learned occupations. In this paper, I first analyse the relation between task shifting technological change and individuals' horizontal mismatch incidence. Second, I estimate individuals' mismatch wage penalties triggered by this relation. The present paper proposes an instrumental variable (IV) approach to map this mechanism and to obtain causal estimates on mismatch wage penalties. Applying this empirical strategy yields a wage penalty of roughly 12% for horizontally mismatched individuals.

JEL classification: E24; J24; J62; O33
Keywords: horizontal mismatch; task-based approach; technological change; vocational education

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1 Introduction

Many economists claim that technological change has accelerated recently and transformed the labour market quite dramatically (Berger and Frey, 2016; Brynjolfsson and McAfee, 2012). Frey and Osborne (2017) estimate the probability of substitution for US occupations and postulate that 47% of the total US employment is at high risk. Using the same approach, Deloitte (2016) calculate similar numbers for Switzerland, Bonin *et al.* (2015) for Germany. However, Frey and Osborne (2017)'s approach might focus too narrowly on substitution effects of new technology and underestimate its complementarity to human capital. Autor (2015) and Acemoglu and Restrepo (2018) describe how this complementarity between automation and labour increases productivity, raises earnings, and augments demand for labour. Accordingly, they argue that new technologies do not lead to fewer jobs, but alter their nature (see also Bessen, 2016; Evangelista *et al.*, 2014; Graetz and Michaels, 2015; Gregory *et al.*, 2016; Hirsch-Kreinsen, 2016). In a labour market where the importance of certain occupations erodes and the characteristics of others change rapidly, occupational horizontal mismatches, i.e. individuals working in an occupation different from that they learned, become more likely.

In this paper, I first aim to analyse how recent technological change affects individuals' horizontal mismatch probabilities, and second the extent to which these horizontal mismatches translate into wage penalties. In order to trace this mechanism and to identify its causal effect on wages, I propose an instrumental variable (IV) approach. The task composition of individuals' learned occupation serves as the instrument for the endogenous mismatch variable in this case. This empirical strategy leans on the task-based approach developed by Autor *et al.* (2003), which shows that technology increases (decreases) demand for complementary (substitutable) tasks and occupations bundling them, respectively.

Applying this strategy to a sample of more than 10,000 observations of roughly 1,200 Swiss males in the years 1999-2016 reveals a mismatch wage penalty of roughly 12%. This estimated mismatch wage penalty pertains for individuals who primarily learned substitutable occupations and are thus negatively affected by task shifting technological change. Contrarily, I find no mismatch wage penalties for individuals who learned mostly complementary or unaffected occupations. Comparisons of different types of mismatches and different strategies (OLS, fixed-effect, and IV) to identify them, provided in this paper, suggest that these distinctions are relevant for any conclusion on mismatch wage penalties. Nevertheless, I discuss potential threats to the validity of the instrument – mainly the independence assumption and the exclusion restriction – and suggest potential improvements.

This paper relates to the existing mismatch literature, which can broadly be divided into two strands (for an overview see Somers *et al.* (2018)). One strand relies merely on ordinary least square

(OLS) estimations and generally associates horizontal mismatches with a wage penalty. Various personal characteristics and the strength of the mismatch thus determine the magnitude of this association. Robst (2007b) estimates wage penalties of roughly 11% for employees with formal qualifications that are 'not related' to their occupation and roughly 2% for employees with formal qualifications that are 'somewhat related'. Similarly, Bender and Heywood (2009), Nordin *et al.* (2010), Bender and Roche (2013), and Yakusheva (2010) find wage penalties that increase with individuals' mismatch intensity. Zhu (2014) explains the small wage penalty of 1.2% for Chinese males and 1.5% for Chinese females with an educational system that provides graduates with mostly general skills. Similarly, Nordin *et al.* (2010) show that employees holding degrees providing mostly job-specific skills suffer from the largest wage penalties when experiencing horizontal mismatch. Bender and Heywood (2009) highlights how the specificity of acquired human capital increases potential wage penalties at later stages of PhDs' career. Meanwhile, wage penalties seem to disappear over time as mismatched individuals acquire occupation specific human capital within their *new* occupation (Malamud, 2010).

Another strand of the mismatch literature applies fixed-effect estimations to account for unobservable personal characteristics, e.g. ability. Schweri *et al.* (2019) estimate no mismatch wage penalty for Swiss males either considering themselves as mismatched or being objectively mismatched (different learned and current occupations). Bender and Heywood (2009) apply fixed-effect estimations on a sample of US doctoral graduates and find a small wage penalty for males and a small but statistically insignificant wage penalty for females. I argue that these fixed-effect estimations suffer from one main shortcoming: while some individuals become mismatched due to lay-offs, others might chose voluntarily to become mismatched, e.g. because they concurrently realize a wage gain. Accordingly, Robst (2007a) attributes an overall negative effect for males of 10.2% and an overall negative effect for females of 8.9% for different types of mismatches: male employees experiencing a mismatch because 'no matching job is available' suffer from a wage loss of 26.5% (female employees: 18.5%) and employees experiencing a mismatch because of the 'job location' earn 29.3% (21.1%) less than their matched counterparts. Contrarily, males employees becoming mismatched because of payment or promotion opportunities realize a wage gain of 6.1% (9.1%).

The contribution of this paper to this existing mismatch literature is twofold. *First*, I propose a mismatch measurement that goes beyond a mere binary mismatch measurement. Instead, I use detailed survey data on occupational skill portfolios to estimate the strength of horizontal mismatches between any pair of learned and current occupations. Thus, I allow for wage penalties that vary with the magnitude of human capital loss induced by horizontal mismatches. Applying such a continuous horizontal mismatch measurement is motivated by the work of Bender and Heywood (2009), Nordin *et al.* (2010), Bender and Roche (2013), Robst (2007b), Yakusheva (2010), who argue that employees who can partly make use of their acquired skills despite being horizontally mismatched must only accept a small wage penalty. By comparing my results with estimated wage penalties based on a mismatch dummy, I show that understanding horizontal mismatch as a binary concept might overstate mismatch wage penalties. Moreover, the continuous mismatch measurement partly mitigates concerns arising from potential measurement error likely inherent to any occupational coding in survey data. *Secondly*, I propose an IV approach to estimate a wage penalty stemming causally from horizontal mismatches. To the best of my knowledge, all attempts to estimate *causal* mismatch wage penalties rely on fixed-effect estimations. However, Section 4 of this paper demonstrates theoretically how fixed-effect estimations merely reveal an effect on average that potentially underestimates wage effects for involuntary mismatched individuals. Comparisons of IV estimations and fixed-effect estimations applied on the same sample in Section 5 underpin this empirically.

The remainder of this paper is organised as follows. Section 2 introduces the task-based approach and relates it to the concept of horizontal mismatch. Section 3 describes the three data sources used in this paper. Section 4 outlines the empirical strategy. Section 5 presents the estimation results and Section 6 concludes.

2 The task-based approach and horizontal mismatches

The tasked based approach was introduced by Autor *et al.* (2003) "to study how computerization alters job skill demands." (p.1279) They argue that "present computer technology is more substitutable for workers in carrying out routine tasks than non-routine tasks, it is a relative complement to workers in carrying out non-routine tasks" (p. 1285). In light of falling computer prices, both these mechanisms increased the relative demand for workers executing non-routine tasks, typically college graduates. This was especially striking since most previous literature described an increasing college premium (for an overview see Katz, 1999) but failed to provide insights on technology related mechanisms enhancing it.

Beside substitutable "cognitive and manual routine tasks" and complementary "analytical and interactive non-routine tasks", Autor *et al.* (2003) introduced a fifth task category: manual non-routine tasks that are little affected by new technology. Either these tasks are not substitutable because they are too complex to be executed by machines (e.g. cleaning of different room types), or technology is barely complementary to the execution of these tasks because they require interpersonal communication which neither machines nor computers can deliver (e.g. psychological consultation). This general pattern displaying a strong increase in the demand for non-routine analytical and interactive tasks, a stable or slightly increasing demand for non-routine manual tasks, and a shrinking demand for cognitive and manual routine tasks was first described for the US by Autor *et al.* (2003), for Germany by Spitz-Oener (2006), and for the UK by Goos and Manning (2007); for an overview see Autor (2013). Hence, Autor *et al.*'s (2003) model "pertain primarily" to routine and complex problem-solving task types because "computers neither strongly substitute nor strongly complement non-routine manual tasks" (p. 1287).

In this paper, I strongly lean on the task categorisation introduced by Autor *et al.* (2003) but distinguish only three task types. I consider tasks in which technology supports people who carry them out to be *complementary*. This complementarity between humans and technology increases the efficiency of these tasks' execution and thus the return for individuals performing them. In Autor *et al.*'s (2003) categorisation these tasks are referred to as "analytical non-routine" and partly as "interactive non-routine" tasks. *Substitutable* tasks are executable by computers or machines without or with little help of humans, and hardly restricted by financial, legal, and ethical constraints. Humans performing these tasks tend to be replaced by machines, and their expected return decreases. The substitutability of these tasks is what classifies them as "cognitive routine" or "manual routine" tasks in Autor *et al.*'s (2003) categorisation. Finally, technology plays little or no role in the execution of *unaffected* tasks. This little impact accounts for both the demand for and the return to these tasks. Autor *et al.*'s (2003) categorises these tasks as "manual non-routine" and partly "interactive non-routine" tasks. Such a three-type categorisation, which is somewhat similar to that proposed above, can be found in Autor and Handel (2013).

[Figure 1 around here]

In order to categorise these three tasks types, I exploit the Swiss Job Market Monitor which contains a representative sample of job vacancies and lists for every vacant position the most important task requirements; for details see Subsection 3.3. Figure 1 displays the development of the three task types described above in the Swiss labour market between the years 1999 and 2016. As expected, tasks complementary to new technology increased their share by 8.8%, while tasks substitutable to new technology decreased their share in the labour market by 13.4%. The share of tasks unaffected by new technology increased slightly (+4.6%). This pattern fits the findings literature highlighted above. As for example Manning (2004) (for Switzerland: Oesch and Rodriguez Menés (2010) and Aepli *et al.* (2017)), I argue that technological change affecting firms production processes triggers – at least partly[1] – these task shifts.

[1]Section 2 introduces the task-based approach and describes how technological change is linked to shifts in task demands. However, technological change, understood in a narrow sense, might not be the only driver for these task shifts

Most task-based literature exploits these shifts in task demand to explain how technology either affects the employment structure (e.g. Acemoglu and Autor, 2011; Autor *et al.*, 2003; Autor, David and Dorn, 2013; Goos and Manning, 2007; Gregory *et al.*, 2016; Spitz-Oener, 2006) or shifts the earning distribution due to varying task returns (e.g. Acemoglu and Autor, 2011; Dustmann *et al.*, 2009; Firpo *et al.*, 2011). The present paper applies the task-based approach to an intersection of these two labour market developments: horizontal mismatches. Horizontal mismatches describe the situation of individuals whose educational field or learned occupation does not match their current occupation (for an overview see Somers *et al.*, 2018). More generally speaking, this refers to a mismatch between individuals' acquired skills (supply-side), i.e. their human capital, and the tasks demanded in the labour market (demand-side). These mismatches are presumably associated with wage losses and thus affect both the occupation people work in and how much they earn for their labour.

Technology affects these horizontal mismatches in two ways. Firstly, technology is considered to be the main demand-side driver for task shifts (Manning, 2004), whereas international trade or product demand shifts play a minor role (OECD, 2005). Thus, given supplied skills, task shifting technology change affects the match between demanded tasks and supplied skills. In the mismatch literature, Bender and Heywood (2011) report high mismatch probabilities for engineers and hard scientists which they attribute to rapid technological change within these fields. Similarly, Witte and Kalleberg (1995) argue that skills acquired during an apprenticeship that become obsolete due to changing task requirements foster occupational mismatches. Secondly, when technology alters returns to tasks, it triggers occupational mobility, i.e. individuals select into tasks displaying increasing returns (e.g. Autor and Handel, 2013). In general, this arguably increases the overall match quality, as task prices enhance their efficient allocation. However, high ability workers selecting into well paying positions might in return push other workers out of their traditional occupations and thus trigger mismatches among them.

Section 4.4 highlights – in what is the first stage in my IV approach – concretely how task shifts are related to horizontal mismatches. Section 5.1 estimates the direction and magnitude of this relation.

in labour markets across highly developed economies. For example, Goos *et al.* (2014), Harrison and McMillan (2011), and Pierce and Schott (2016) stress the importance of reallocation of industrial production to China or Eastern-European countries for the disappearance of relatively simple (manual routine) tasks in developed countries; for Switzerland see Waser and Hanisch (2011). However, the reallocation of industrial production to other countries also often requires some sort of new technology, e.g. transportation possibilities, ICT, or transfer of relatively new technology to these countries. Speaking of technological change thus includes (at least to some extent) outsourcing to other countries. Therefore, a more accurate term could be task-shifting technological change. Moreover, demand factors are likely to play a role, e.g. ageing societies increase the need for care professions (Degen and Hauri, 2017), which largely consist of unaffected (manual non-routine) tasks.

3 Data

The empirical analysis in this paper bases on three data sources. The Swiss Household Panel (SHP) observes the population of interest and is described in Section 3.1. I derive a continuous mismatch measurement between any occupation pair from the German BIBB/BAuA Employment Survey (BIBB/BAuA-ES). Section 3.2 presents this data source and highlights the benefits of such a continuous measurement. In order to determine the occupational exposure to technology, I rely on the Swiss Job Market Monitor introduced in Section 3.3.

3.1 Swiss Household Panel

The Swiss Household Panel (SHP) is the main data source used in this paper; it surveys a representative sample of Swiss households between the years 1999 and 2016. Although respondents were asked about other household members in some domains, I only rely on the actual respondent's information for the analysis below and thus my observation units are individuals. Beside detailed demographic information, the SHP covers various information on individualsÄô labour market status, such as individuals' wage, education, firm tenure, and hierarchical level (see table 1). These variables allow me to estimate a basic Mincer-equation which forms the basis of the econometric strategy introduced in Section 4. Moreover, the SHP collects a set of employer characteristics, including the overall number of employees and the firm's industry. To construct my main independent variable – the mismatch variable – I rely on a subsample of individuals for whom the SHP includes retrospective information on education and work episodes. This "biographic" subsample contains 28,469 observations stemming from 3,249 working individuals.

[Table 1 around here]

Due to womenÄôs participation in the labour market, which remains selective, I restrict the sample to males between the ages of 20 and 65 with either a VET, a tertiary-B (further education for individuals with a VET degree), or a tertiary-A (university or university of applied science) degree. Additionally, I exclude 410 individuals with a workload below 50%, and 468 individuals with an annual income below 24,000 or above 300,000 Swiss Francs, respectively. Overall, this lowers my sample to 10,471 observation stemming from 1,224 individuals. For roughly half of these person-year observations, the learned and the current occupation are not the same as table 1 highlights.[2]

[2]Additionally, figure A.2 and figure A.3 in the appendix display the temporal evolution of mismatches during the analysis period and the mismatch incidence by sex and age, respectively.

3.2 Occupational distance measurement

Lazear (2009) argued in a seminal paper that all skills are basically general, but firms combine ("weight") them differently in their production process. This varying skill demand across firms enhances specificity of skills and thus of human capital: the more specific an individual's skill combination, the more specific his or her human capital. Geel *et al.* (2011) apply this skill-weight approach of Lazear (2009) to three waves of the German BIBB/BAuA-ES dataset and determine occupations' specificity. The BIBB/BAuA-ES interviews employees – among other information – about how intensely they perform different tasks at their workplace. Geel *et al.* (2011) argue that these task items approximate the skill portfolio workers need to perform their jobs and – when aggregated among occupations – the skill portfolio of an occupation. In the empirical part of their paper, they then show how German graduates who learned a rather specific VET-occupation shy away from leaving this occupation; presumably because an expected wage loss is large due to their specific skill combination.

In the vein of Geel *et al.* (2011), I argue in this paper that the skill composition of two occupations determines the strength of a potential mismatch between them. This seems intuitive: The more similar the skill combination of two occupation is, the smaller the wage penalty for an individual who works in one of these occupations but has learned the other one. Accounting for the potential heterogeneity of mismatches is not new in the mismatch literature. Bender and Heywood (2009), Nordin *et al.* (2010), Bender and Roche (2013), Robst (2007b), and Yakusheva (2010)all show that the mismatch wage penalty increases with the strength of the perceived mismatch.

Besides accounting for potential heterogeneity of mismatches, such a continuous mismatch measurement is beneficial for another reason. Occupational coding in any survey likely contains some measurement error (Bound *et al.*, 2001, p.3802), e.g. different interviewers might assign similar information to different occupational codes. In case this measurement error is random, it biases the estimated wage penalty estimate towards zero (Angrist and Pischke, 2014; Bound *et al.*, 2001). Though any continuous mismatch measurement relying on learned and current occupation codes suffers from this measurement error as well, it seems plausible that wrongly coded individuals are misclassified into occupations being close to their true occupation. Measurement error in occupational classification appears thus less severe when relying on a continuous rather than a binary mismatch measurement that weights all mismatches equally.

[Table 2 around here]

For the concrete construction of my continuous mismatch measurement, I rely on the same data as

Geel *et al.* (2011) but employ the latest waves of 2006 and 2012,[3] and proceed as follows: (i) For each of 16 task-items (see table 2) I aggregate the answer ("How often does this task occur during your work?" 0=never; 0.5=seldom; 1=often) of 24,975 individuals[4] in the BIBB/BAuA-ES on the level of the 144 observed 3-digit German occupations. (ii) Within every occupation, I divide each task-item value by the sum of all sixteen task-item values. Thus, every German occupation consists of sixteen task-item shares that sum up to one. (iii) Based on occupational frequencies, I assign these task-item shares to a maximum of five learned occupations and to the current occupation of each individual at the 3-digit level of the Swiss Standard Classification of Occupations 2000 (SSCO 2000).[5] (iv) The occupational distance between any learned occupation ($locc = 1, 2, 3, 4, 5$) and any current occupation ($cocc$) equals the sum of their absolute differences across each of the sixteen occupational task-item shares, formally for individual i's learned and current occupation: $OccDist_{i,locc} = \sum_{j=1}^{16} |item_{i,j}^{locc} - item_{i,j}^{cocc}|$. (v) The relevant occupational distance for the mismatch analysis is the smallest difference between any of individual i's learned occupations at time t and individual i's current occupation at time t, formally: $OccDist_{it} = min\{OccDist_{it,locc=1}, ..., OccDist_{it,locc=5}\}$. (vi) Finally, I normalize this continuous mismatch measurement over the sample to mean one for all individuals considered mismatched, i.e. for $OccDist_{it} > 0$. Thus, any estimated wage penalty based on this continuous mismatch measurement can be interpreted as switching from a match to an *average* mismatch in terms of occupational distance $OccDist_{it}$. Figure 2 displays the distribution of this calculated occupational distance for the mismatched subpopulation, i.e. with $OccDist_{it} > 0$.

[Figure 2 around here]

For comparison purposes, I primarily display estimates based on a conventional mismatch dummy, D_{it}. However, I suggest focusing on estimations applying the occupational distance as a continuous measurement for horizontal mismatch.

[3] `https://www.bibb.de/veroeffentlichungen/de/publication/show/7094` and `https://www.bibb.de/veroeffentlichungen/en/publication/show/2274`.

[4] I exclude East-Germany, observations with wages in the bottom- or top-1 percentile, individuals working less than five hours per week, and observations with no occupational information.

[5] Concerning the transferability of task items from German to Swiss occupations, I argue that, due to similar economic structure and a similar education system (e.g. the importance of the vocational track), German occupations resemble Swiss occupations more than – for example – US-occupations. Consequently, Marsden (1999) argues in his "theory of employment systems" that the German labour market, which is based on occupational qualifications, allows a high inter-firm mobility of skilled workers and adjusts fast to technological change. Contrarily, the labour force in the US labour market receives more on-the-job training and stricter guidelines. According to Marsden (1999), the Swiss labour market belongs to the same category as the German labour market. The recoding scheme for German/Swiss occupations is available upon request.

3.3 Occupational task shares

In order to determine the occupational task composition in the Swiss labour market, I exploit the Swiss Job Market Monitor (SJMM) conducted annually by the University of Zurich. The SJMM is a representative monitor of vacant positions published by firms on online job portals, in newspapers, and on their websites. Beside general job requirements and characteristics, the SJMM lists the task considered to be the most relevant for a vacant position out of a set of 21 possible tasks. To the best of my knowledge, this is the only available information on the task content of Swiss occupations. The sample I use consists of 43,932 observations collected during the years 1995 and 2015. 42.4% of these job vacancy were published on firm websites, 36.5% in newspapers, and 21.1% on job portals.

[Table 3 around here]

The procedure of building broader task categories based on surveys collecting individual task data is called a survey-based[6] task-based approach, and was first introduced by Spitz-Oener (2006); moreover, it can be found in Autor and Handel (2013). Both these works are based on the conceptual framework of Autor *et al.* (2003), and they assign the observed task items into three broad categories. The task assignment in the present paper relies on the expertise of three labour market economists at the Swiss Federal Institute for Vocational Education and Training SFIVET.

I then proceeded as follows: (i) every expert independently assessed each of the 21 SJMM task items to one of the three task types introduced in Section 2 – complementary, substitutable, and unaffected tasks. (ii) After taking the mean of these experts' assignments every SJMM task items, and thus every job advertisement, is either considered as completely or partly complementary, substitutable, or unaffected *to* or *by* new technologies, respectively (Table 3).[7] (iii) I aggregate the three task types among the 43,932 job ads in my sample on the 3-digit SSCO 2000 level. Hence, every of the 87 occupations observed in the SJMM consists of a complementary, a substitutable, and an unaffected task share that sum up to one.

[Figure 3 around here]

Figure 3 illustrates that substitutable tasks represent a majority in agricultural (SSCO-1-digt: 1) and industrial occupations (2 and 4), while complementary tasks are frequent in IT and technical occupations (3). Unaffected tasks dominate in the remaining occupations together with sizeable shares

[6] Other task-based approaches rely on experts' assignments of tasks based on descriptions or curricula of occupations, e.g. Acemoglu and Autor (2011), Autor *et al.* (2006), and Goos and Manning (2007). For a discussion on the two different approaches see for example Autor and Handel (2013) and Rohrbach-Schmidt and Tiemann (2013).

[7] In fact, 9 task items were assigned to the same category by all three experts, while the other 12 items were assigned to two different categories, and none of the items was assigned to three distinct categories.

of substitutable tasks in trade (5) and hospitality occupations (6) and sizeable shares of complementary tasks in consulting (7) and social occupations (8), respectively. Aggregating over the whole sample, table 1 yields that substitutable tasks account for 42% of all tasks among learned occupations, while complementary and unaffected tasks are less relevant across learned occupations with a share of 37% and 21%, respectively. Current occupations display, however, higher shares of complementary tasks (44%) and unaffected tasks (26%) at the expense of substitutable tasks (30%).

4 Empirical strategy

4.1 Formalization of the hypothesis

To estimate the effect of horizontal mismatch on wages, I start with the following equation:[8]

$$log(Wage_{it}) = \alpha + \beta D_{it} + \gamma x_{it} + \psi z_{f[it]} + \phi_i + \theta_t + \epsilon_{it}$$

$Wage_{it}$ measures individual i's net monthly wage at time t. D_{it} is the mismatch dummy being one if person i's current occupation is not equal to any of this person's learned occupation(s) on the 3-digit SSCO 2000 level at time t. Individual i's characteristics entering x_{it} are age, age-square, a dummy for being foreign, a dummy for having children, a dummy for being married, a categorical variable for the main three linguistic regions of Switzerland (German, French, Italian), a dummy for receiving further education in the past year, firm tenure and its square term, degree of employment in percent, dummies for being in a director or a supervisor position, and a dummy for having a temporary contract. The term $z_{f[it]}$ captures the size of the firm f individual i is employed at time t by seven categories and an industry dummy for firm f (total twelve industries). The term ϕ_i represents unobserved person fixed effects for person i and the term θ_t time fixed effects for year t. Due to human capital losses in case of a horizontal mismatch, I expect a negative association between individuals' mismatch dummy D_{it} and their $wage_{it}$, i.e. $\beta < 0$.

4.2 Potential sources of bias

OLS estimations derived from the equation shown above may suffer from three sources of bias: (i) heterogeneous horizontal mismatches, (ii) heterogeneity in unobserved person fixed effects, e.g. ability, and (iii) optimizing behaviour in switching jobs.

[8]For the sake of simplicity, I will refer to mismatch as a binary measurement in this Section. However, most estimates presented in Section 5 use the occupational distance as the main independent variable; Section 3.2 comprises the argumentation behind this.

Firstly, the degree of human capital loss between someone's learned and this person's current occupation may vary for two reasons: on the one hand, the loss of human capital generally increases with the occupation specificity of the mismatched person's human capital (Nordin *et al.*, 2010; Zhu, 2014). For instance, a person with a degree in medicine, which is considered to provide very specific occupational skills, can on average transfer less human capital when switching jobs than a person with a degree in business administration. On the other hand, the loss of human capital increases with the occupational distance between the learned and the current occupation of the mismatched person. For instance, an engineer who works as a technician loses much less of his human capital than if he worked as an office clerk. It seems therefore likely that people with more general skills are overrepresented in the mismatched population and that they chose occupations which are close to their learned occupation in terms of required skills. The continuous mismatch measurement introduced in Section 3.2 accounts for this potential source of bias.

Secondly, unobserved personal characteristics ϕ_i likely affect mobility in the labour market. The most prominent example in the literature is ability. Gibbons and Katz (1991) show how individuals adversely select into job changes when outside employers cannot observe their ability. The same mechanism might lead to adverse selection of less able workers into mismatch (Boudarbat and Chernoff, 2012; Kucel and Vilalta-Bufi, 2012). However, this could also be reversed: high ability workers might receive outside offers from firms regardless of their formal qualifications. Either way, an endogeneity bias potentially arises from individuals' unobserved ability. Formally, this biases β in the above shown equation upward if $cov(D_{it}, \phi_i > 0)$ and downward if $cov(D_{it}, \phi_i < 0)$.[9] Note that an upward (downward) bias corresponds to underestimating (overestimating) the negative wage effect since I presume $\beta < 0$. The mismatch literature usually deals with this second source of bias by applying fixed-effect estimations.

Thirdly, wage offers arguably strongly affect individuals' job search behaviour and labour market mobility (Mortensen, 1986; Rogerson *et al.*, 2005). Thus, simultaneous changes in the dependent variable, wage, and the independent variable of interest, the mismatch indicator, give rise to endogeneity concerns. Accordingly, a majority of the job- or employer-switchers in my sample realize wage gains (Figure A.4). Although, people becoming mismatched probably represent a non-random subpopulation of all job switchers, it seems likely that a share of the mismatched persons become mismatched exactly because they can coincidently realize a wage gain. As a consequence, the concept of "mismatch", with its negative connotation, may be misleading. Presumably, people do not hesitate to accept a job offer at a higher wage, despite the fact that the offered job does not match their formal

[9]Note: this holds only for $\beta < 0$, e.g. a mismatch wage penalty, and $\phi_i > 0$, e.g. ability.

qualifications. Reassuringly, Robst (2007a) finds that employees selecting into mismatch due to payment and promotion opportunities reasons earn substantially more than their matched counterparts. This leads to an underestimation of mismatch wage penalties in the model shown above compared to a scenario where people were randomly assigned to mismatches. Section 4.3 elaborates more on this issue and Section 4.4 proposes an IV strategy to deal with it.

4.3 Fixed-effect estimations

Given the panel structure of the SHP, fixed-effect estimations are one obvious and promising strategy for addressing the second source of bias described above. Fixed-effect estimations allow it to keep unobservable personal characteristics (e.g. ability) fixed when analysing wage effects of mismatched individuals. Exploiting the same dataset as in the present paper and applying fixed-effect estimations, Schweri *et al.* (2019) neither find wage penalties for males considering themselves as mismatched nor males being objectively mismatched. Bender and Heywood (2009) apply fixed-effect estimations to a panel dataset of US doctoral students and reveal a small wage penalty for males but no wage penalty for females.

[Table 4 around here]

However, I argue that wage effects thus identified are most likely average effects, which aggregate different patterns leading to mismatch (or match) situations together with their distinctive wage implications. I claim that this appears because fixed-effect estimations fail to account for the likely dependency between individuals' switches into (or out of) mismatches and their wage expectations. This endogeneity concern corresponds to the third source of bias described above. To understand this endogeneity concern in the context of horizontal mismatches, I describe, in what follows, the four possible interactions between switches into or out of a mismatch situation and individuals' wages (see also table 4). Moreover, I set out the implications of these four interaction cases for an identification within a fixed-effect setting:

- A person works in her/his learned occupation. Then the person accepts a position in an occupation different from any of the person's learned occupations offering a higher wage. Thus, I refer to this case as becoming "voluntarily mismatched".[10] Because I observe a wage increase and meanwhile the mismatch-dummy D_i switches from 0 to 1, the estimated wage effect of becoming

[10]Note: I hereby define the terms "voluntary" and "involuntary" in a purely monetary way. A switch going hand in hand with a wage increase is considered voluntary and a switch going hand in hand with a wage decrease is considered involuntary, respectively. Obviously, this omits other potential reasons for an occupational switch, e.g. any intrinsic motivation.

mismatched yield by fixed-effect estimations is positive. In my sample I observe 122 such cases accounting for 36.6% of all switches from match to mismatch or vice versa.[11]

- A person works in her/his learned occupation. Then the person loses her/his position and accepts a position in an occupation different from any of the person's learned occupations offering a lower wage. Thus, I refer to this case as becoming "involuntarily mismatched". Because I observe a wage decrease and meanwhile the mismatch-dummy D_i switches from 0 to 1, the estimated wage effect of becoming mismatched yield by fixed-effect estimations is negative. I observe 76 such cases in my sample, accounting for 22.8% of all switches from match to mismatch or vice versa.

- A person works in an occupation different from any of her/his learned occupations. Then the person accepts a position in any of the person's learned occupations offering a higher wage. Thus, I refer to this case as becoming "voluntarily matched". Because I observe a wage increase and meanwhile the mismatch-dummy D_i switches from 1 to 0, the estimated wage effect of becoming mismatched yielded by fixed-effect estimations is negative. I observe 83 such cases in my sample, accounting for 24.9% of all switches from match to mismatch or vice versa.

- A person works in an occupation different from any of her/his learned occupations. Then the person loses her/his position and accepts a position in any of the person's learned occupations offering a lower wage. Thus, I refer to this case as becoming "involuntarily matched". Because I observe a wage decrease and meanwhile the mismatch-dummy D_i switches from 1 to 0, the estimated wage effect of becoming mismatched yielded by fixed-effect estimations is positive. I observe 56 such cases in my sample, accounting for 15.6% of all switches from match to mismatch or vice versa.

In a fixed-effect setting, cases 2 and 3 reveal a mismatch wage penalty, while cases 1 and 4 reveal a wage increase for "being mismatched". Consequently, any overall effect provided by fixed-effect estimations merely represents an effect *on average* that is too small for one subpopulation and wrongly identified for another subpopulation. Conclusions derived from these fixed-effect estimations are therefore potentially misleading. If, for example, the effect of a mismatch wage penalty is mainly driven by graduates who find their first position in their learned occupation (case 3), one cannot derive any – or one may derive a false – conclusion for individuals who are involuntarily mismatched due to a layoff (case 2). Moreover, fixed-effect estimation are based on individuals switching from match to

[11] It is possible that in some cases individuals underwent unemployment spells while switching from match to mismatch or vice versa, respectively. In this case, the switch from the occupation before to the occupation after the unemployment spell is relevant. The unemployment spell is simply omitted because my sample only consists of employed individuals. However, table 10 indicates that the coefficients yielded by my wage estimations are insensitive to the inclusion of individuals undergoing an unemployment spell during the sample period.

mismatch or vice versa during the sample period. In total, I merely observe 333 (198 to mismatch and 135 to match, respectively) such switches stemming from 248 individuals. Contrarily, individuals being mismatched (n=525) or matched (n=457) throughout the entire sample period do not contribute to any effect yielded by fixed-effect estimations. This is especially worrying if the subpopulation of individuals being mismatched or matched throughout the entire sample period differs systematically from individuals switching within the sample period.

4.4 IV-approach

This Section introduces an instrumental variable approach to address the sources of bias described in Section 4.2 and the remaining shortcomings of fixed-effect estimations described in Section 4.3. The first part of the section discusses the choice of the instrument and its hypothesised first-stage relation to the endogenous mismatch variable. In addition to this first-stage relation, an instrument needs to satisfy the independence assumption and the exclusion restriction to be valid. These two requirements are not formally testable and thus demand a critical examination (Angrist and Pischke, 2014; Imbens, 2014). The remaining parts of this section provide this.

First stage

Leaning on the task-based approach, Section 2 highlights how technological change differently affects demand for three task types (complementary, substitutable, and unaffected) in the labour market, and therefore also for occupations bundling these tasks (Figure 1). The same Section 2 pointed out how task shifting technological change potentially increases or decreases horizontal mismatches between demanded tasks and supplied skills in the labour market. Based on this general pattern, I put forth two specific mechanisms that presumably underpin an association between the task shares of individuals' learned occupations and their mismatch probability.

Firstly, *inter-occupation* employment shifts lower the number of positions in occupations bundling substitutable tasks, while positions in occupations bundling complementary tasks become widely available. On the one hand, these inter-occupation shifts result in an oversupply of individuals with learned substitutable occupations and thus trigger mismatches among them. On the other hand, numbers of positions in occupations bundling complementary or unaffected tasks increase or remain stable. This leads to low mismatch numbers among individuals who learned these occupations.

Secondly, complementary tasks become more demanded within occupations (*intra-occupation*) at the expense of substitutable tasks. Consequently, returns to complementary tasks rise, while returns to substitutable tasks decline across occupations.[12] This enhances varying occupational mobility patterns depending on the task composition of individuals' learned occupations. On the one hand, the increasing demand for mostly complementary skills across various occupations provides well-paid open positions for individuals disposing over these complementary skills (individuals with complementary learned occupations) although they lack the formal qualifications for these occupations. This might *pull* individuals into mismatches which are, however, perceived as voluntary.[13] On the other hand, the demand for skills executing substitutable tasks deceases even within occupations bundling these tasks to a large extent. This lowers the demand for individuals with mostly substitutable skills generally *and* within their learned occupations. Thus, intra-occupational task shifts might *push* these individuals out of their learned occupations and lead to mismatches that are perceived as involuntary. Neither a *pull-* nor a *push-mechanism* concerns individuals primarily in unaffected learned occupations. Demand for their skills outside their learned occupations and thus the number of outside options pulling them out of their learned occupation remains stable. Meanwhile, the task composition of their learned occupations does not shift towards more complementary tasks. This limits the attractiveness of their learned occupations for individuals with a more complementary skill bundle and therefore also their potential of being pushed out of their learned occupation.

Considering the continuous mismatch measurement introduced in Section 3.2, both of these effects on the extensive margin – being mismatched – reinforce themselves on the intensive margin which accounts for the magnitude of a perceived mismatch in terms of occupational distance. Individuals who learned complementary occupations are, if mismatched, likely to find a position in a close occupation for which demand also increased due to a similar occupational task composition. In contrast, lower demand for occupations bundling substitutable tasks might force individuals who learned these occupations to move to rather different occupations in case of being mismatched.

Overall, I primarily expect task shifting technological change to enhance mismatches among individuals who learned occupations bundling substitutable tasks. Second, task shifting technological change triggers two opposing effects for individuals who learned rather complementary occupations, and it remains a priori ambiguous which effect dominates. Third and finally, as per definition, technology has little impact on unaffected tasks, I assume individuals who learned occupations bundling these tasks are seldom prone to mismatches. These hypothesised associations between the task composition of individuals' learned occupation and their mismatch incidence represent the first stage of my IV setting. Section 5.1 applies OLS estimations to evaluate them.

[12]Spitz-Oener (2006) and Dengler and Matthes (2015) described these intra-occupation task shifts among German occupations.

[13]Early works underpinning how occupational mobility does not necessarily lead to wage decreases, even though movers are expected to lose some of their specific human capital include Johnson (1978), Topel and Ward (1992), and Neal (1999).

Independence assumption

The independence assumption requires the instrument to be randomly or as good as randomly assigned (Angrist and Pischke, 2008). The first-best solution to meet this requirement is by design. Prominent examples of such instruments are draft lotteries (e.g. Angrist, 1990), giving birth to twins (Angrist *et al.*, 2010; Rosenzweig and Wolpin, 1980), or random variation in newborns' gender composition (Angrist and Evans, 1996). Contrarily, the task share of someone's learned occupation is obviously not randomly assigned. Substitutable tasks bundle – for example – often in blue-collar occupations, which are accessible without a university degree. Hence, the task share of someone's learned occupation correlates with education, and moreover affects the dependent variable wage.

Thus, I need to relax the random assignment assumption and require it "to hold only within subpopulations defined by covariates" (Imbens, 2014, p.27).[14] Optimally, these covariates include all factors that affected an individual's occupational choice and are thus determined prior to the instrument (Deuchert and Huber, 2017). One such factor is a person's gender, assuming males chose more manual occupations *ceteris paribus*. However, this control is redundant due to the sample restrictions to males only. Another factor determining someone's occupational choice is school performance. Most occupations bundle people of similar school performances, and many occupations require a certain level of education. Thus, I would like to control for a personÄôs school performance prior to any occupational choice, e.g. at the end of compulsory school. Unfortunately, the Swiss Household Panel does not contain this information. The strategy to mitigate the issue nevertheless is twofold.

In all estimations, I control for different educational categories (VET, Tertiary-B, and Tertiary-A). These educational attainment categories aim to approximate an individual's school performance prior to her/his occupational choice. I argue that the task share of an individual's chosen occupation is as good as random once I control for educational attainment.

In Section5.3, I present IV-estimations within educational subgroups. The motivation for this is similar to that above: The task share of someone's learned occupation is plausibly closer to random within youngsters opting for VET (e.g. becoming a commercial clerk or an electrician) than between a youngster opting for VET and a youngster applying for university. Moreover, these subsample estimations permit to identify varying mismatch wage penalties across different educational cohorts.

Exclusion restriction

The exclusion restriction requires that the instrument affects the outcome only through the endogenous variable (Angrist and Pischke, 2008). In a violation of this restriction, it seems likely that the task

[14] Baiocchi *et al.* (2010) use matching methods for the same purpose.

share of individuals' learned occupations directly affects their wages, e.g. through the type of skills they acquired when learning their occupation. Concretely, I assume the channel through which the task content of individuals' learned occupations affects their current wages works through the task content of their current occupations.[15] This enables clipping this direct link by controlling for the share of task j of individuals' current occupations *cocc* at time t, $T_{it}^{j,cocc}$; whereby the share of task type j of individuals' learned occupations *locc* at time t, $T_{it}^{j,locc}$, represents the instrument. Deuchert and Huber (2017), underpinning theoretically how the exclusion restriction can be sustained by controlling for any direct effects.

Taking these requirements into account and replacing the mismatch dummy D_{it} with the preferred continuous mismatch measurement $OccDist_{it}$, the equation shown above transforms into the two following equations:

$$log(Wage_{it}^{cocc}) = \beta_0 + \beta_1 \widehat{OccDist}_{it} + \beta_2 x_{it} + \beta_3 z_{f[it]} + \beta_4 T_{it}^{j,cocc} + \epsilon_{it},$$

where $\widehat{OccDist}_i$ is instrumented as follows:

$$OccDist_{it} = \alpha_0 + \alpha_1 T_{it}^{j,locc} + \alpha_2 x_{it} + \alpha_3 z_{f[it]} + \alpha_4 T_{it}^{j,cocc} + \upsilon_{it}$$

$Wage_{it,cocc}$ is individual i's wage in current occupation *cocc* at time t. As set out above, individual characteristics x_{it} crucially include educational dummies (VET, VET high school, VET high school with baccalaureate, technical or vocational school, Tertiary-B track, university of teacher education, universities of applied science, universities, and post-graduate degrees). Adding the share $T_{it}^{j,cocc}$ of task j of individual i's current occupation *cocc* at time t sustains the exclusion restriction. The occupational distance $OccDist_{it}$ is now instrumented with the respective share of task j of an individual i's learned occupation *locc* at time t,[16] $T_{it}^{j,locc}$.

[15]Note that I already set out above why controlling for – among other factors – educational attainment is necessary in the present IV setting. Though I argued this is the case due to the non-random assignment of the instrument, one could also argue education is another channel over which individuals' learned occupations affect their wages directly. In this sense, controlling for educational attainment also helps clip any direct link between the instrument and the outcome variable and thus satisfy the exclusion restriction.

[16]Note that also individuals' learned occupations are potentially time-variant due to new formal qualifications acquired during the sample period.

5 Results

5.1 First stage results

Table 5 exploits the association between the task shares of individuals' learned occupations and their mismatch incidence in three ways. Firstly, columns (1) - (3) regress the mismatch dummy D_{it} on the task shares of individuals' learned occupations (extensive margin). Secondly, columns (4) - (6) restrict the sample to mismatched persons and yield the correlation between the task composition of their learned occupations and the strength of their mismatch in terms of occupational distance $OccDist_{it}$ (intensive margin). Thirdly, columns (7) - (9) display the first stage estimates by regressing the preferred mismatch measurement $OccDist_{it}$ on the task shares of individuals' learned occupations. I discuss these first stage relations together with the three hypotheses concerning their direction put forth in Section 4.4.

According to column (1) the association between the complementary task share of individuals' learned occupations and their mismatch probability is rather weak and statistically only significant on the 10%-level. This seems to support the ambiguous relation between the complementary task share of individuals' learned occupations and their mismatch probability hypothesised in Section 4.4. On the one hand, individuals with complementary learned occupations are able to avoid mismatches due to broadly available positions within their learned occupation. On the other hand, these individuals profit from an increased demand for their skills in other occupations, which might allow them to realize a wage gain while becoming mismatched. Contrarily and in line with the hypothesis put forth in Section 4.4, the substitutable task share of individuals' learned occupations and their mismatch probability correlates positively (column 2). According to the point estimator in column (2), a one standard deviation (0.26) higher substitutable task share is associated with a higher mismatch probability of 15 percentage points. Presumably, the scarcity of positions in occupations bundling substitutable tasks augments the mismatch probability of individuals who learned these occupations. The negative coefficient in column (3) suggests the opposite for individuals who learned rather unaffected occupations.

[Table 5 around here]

In columns (4) - (6), I regress individuals' occupational distance $OccDist_{it}$ on the three types of task shares of someone's learned occupations while restricting the sample to mismatched individuals, i.e. $OccDist_{it} > 0$. This allows me to interpret the resulting estimators as the first stage association on the intensive margin. According to column (5), individuals with substitutable learned occupations struggle to find close occupations in case of a mismatch. This seems plausible because these close occupations likely bundle mostly substitutable tasks as well and therefore face the same decline in demand. Contrarily, columns (4) and (6) suggest that mismatched individuals with complementary and – to an ever greater extend – unaffected learned occupations tend to end up in close occupations in terms of $OccDist_{it}$. This seems consistent with the hypothesis that positions in occupations bundling rather complementary or unaffected tasks become widely available or – at least – remain stable. However, the lower coefficient in column (4) compared to column (6) somewhat contradicts this argument. One explanation could be that individuals with complementary learned occupations disproportionally dispose over skills that are demanded throughout various occupational fields. Therefore, these individuals get – compared to individuals with unaffected learned occupations – attractive job offers in occupations that are relatively unrelated to their learned occupations.

Accounting for the association between the task share of individuals' learned occupations and their mismatch probability on both the extensive margin and the intensive margin simultaneously yields the preferred first stage estimates in columns (7) - (9). Overall, the displayed coefficient in column (8) indicates high occupational distances for individuals with learned occupations bundling rather substitutable tasks, while individuals with learned occupations bundling tasks unaffected by new technology display smaller occupational distances according to column (9). To be precise, an additional standard deviation in the share of substitutable (unaffected) tasks in individuals' learned occupation increases (decreases) their occupational distance by 29.3 (23.4) percentage points. In contrast, the correlation between the complementary task share of individuals' learned occupation and their occupational distance is about five times smaller and statistically less significant (column 7).

Considering the general rule that F-statistics above 20 indicate sufficient explanatory power on the first stage (Bound *et al.*, 1995), only the share of substitutable and the share of unaffected tasks are valid instruments, while the share of complementary tasks has insufficient explanatory power for individuals' mismatch probability. In forthcoming analysis, I will therefore employ the share of substitutable and unaffected tasks as instruments, and moreover, include them simultaneously in most estimations.

5.2 Main results

Table 6 presents the main results relying on the continuous mismatch measurement (see Section 3.2) as the dependent variable.[17] The table displays OLS, fixed-effect, and IV (first-stage and 2SLS) estimations as described in Section 4.

[17]Table A.1 contains an extended output and shows the coefficients of various control variables.

[Table 6 around here]

The OLS estimator in column (1) of table 6 reveals a positive average wage difference of 0.7% between a matched and an average (in terms of occupational distance) mismatched person, all else being equal. The fixed-effect estimator in column (2) accounts for unobserved heterogeneity among individuals selecting into mismatch and is slightly negative but close to zero as well. This suggests that no wage penalty stems from becoming horizontally mismatched. However, as highlighted in Section 4, I argue this fixed-effect estimator merely yields an average effect by mixing different underlying mechanisms pointing in distinct directions.

Thus, I draw attention to the IV estimation results in columns (3) - (8) of table 6. Column (4) utilizes the share of substitutable tasks as an instrument and yields a mismatch wage penalty of 11.9% for a person in an average mismatch in terms of occupational distance.[18] This estimate is statistically significant at the one percent level and economically relevant. With an annual gross wage of roughly 117,000 (median: 105,000) this amounts to 13,900 (12,500) Swiss francs wage penalty per year.

Contrarily, column (6) – using the share of unaffected tasks as an instrument – yields a smaller mismatch wage penalty (-6.2%) that is statistically insignificant. This result arises due to the relatively small and imprecise reduced form estimate exploiting the unaffected task share displayed in column (3) of table A.2.

How can these different mismatch wage penalties shown in table 6 be explained?[19] In the spirit of Imbens (2014) and Angrist and Pischke (2014), I claim the negative effect yielded in column (4) and the small and imprecisely estimated effect yielded in column (6) represent local average treatment effects (LATE) for different subgroups – or *compliers* as they call them. Compliers suffering from the mismatch wage penalty yielded in column (4) are mismatched individuals with highly substitutable learned occupations, which would not be mismatched had they learned less substitutable occupations. Task shifting technological change increased their mismatch probability and their occupational distance in case of a mismatch by shortening available positions within their learned occupations *and* within close occupations. Moreover, a general shift away from substitutable tasks limits their returns to skills needed to execute these tasks across occupations. Therefore, individuals with mostly substitutable learned occupations (compliers in column 4 of table 6) receive relatively poor outside options and thus suffer from a mismatch wage penalty.

Conversely, the LATE yielded in column (6) of table 6 pertains for individuals with learned occu-

[18] Note that the median of the occupational distance measurement for the mismatched individuals is 0.96 and thus very close to the mean of one. In conclusion, the effective mismatch penalty exceeds the estimated 11.9% for roughly half of all mismatched individuals and falls behind this 11.9% for the other half of all mismatched individuals, respectively.

[19] From an econometric point of view, this is straightforward: The reduced form estimates of table A.2 display a negative and statistically significant association between $T_{it}^{locc,j}$ and $wage_{it}$ for $j = substitutable$ but not for $j = unaffected$.

pations bundling few unaffected tasks.[20] However, it remains ambiguous how returns for *other than unaffected tasks* in the general labour market and thus outside options for these compliers evolved. Hence, having few skills to execute unaffected tasks and being mismatched is not sufficient to suffer from a mismatch wage penalty. Moreover, these compliers arguably represent a mixture of individuals with complementary and substitutable learned occupations, respectively. In Section 2, I argued that the former likely select into mismatches due to valuable outside options while the latter tend to be mismatched involuntarily. This further contributes to the insignificant reduced form association between the share of unaffected tasks of individuals' learned occupations and their wages (column 3 of table A.2), and thus to the statistically insignificant mismatch wage effect for this subgroup in column (6) of table 6. However, one should notice that the 95% confidence intervals of the point estimators in columns (4) and (6) overlay. Thus, one cannot reject the null-hypothesis that the two estimated effects are statistically not different.

In column (8), I exploit the share of substitutable and the share of unaffected tasks simultaneously as instruments. The thereby revealed mismatch wage penalty amounts to roughly 10%. Again, on the 95%-level this estimator is not significantly different from the point estimators in columns (4) and (6), respectively. Column (7) reveals the corresponding first-stage and points to the same conclusion as columns (3) and (5): having learned an complementary occupation is positively correlated with occupational distance, while having learned an unaffected occupations is associated with a low occupational distance between learned and current occupation.

Table 7 employs the "classical" binary mismatch variable. Consistent with on average higher wages among mismatched individuals yielded in table 1, the OLS-estimator displays a positive correlation between the mismatch dummy and wages (column 1, table 7). However, this positive association vanishes when applying fixed-effect estimations and thus accounting for unobservable personal characteristics in column 2 of table 7.

[Table 7 around here]

Turning to the IV estimations in columns (3) to (8), the much higher coefficient using the binary mismatch variable in table 7 compared to the same specifications in table 6 are striking. It thus seems questionable how credible a mismatch wage penalty of 24% is (column 4, table 7). Since the underlying reduced form estimations in model (4) of table 7 does not differ from model (4) of table 6 – in both cases the substitutable task share of an individual's learned occupation is regressed on her/his wage

[20]They comply with "being mismatched" due to having learned occupations bundling few unaffected tasks, whereas they would not "be mismatched" had they learned more unaffected tasks.

– this difference is entirely driven by the underlying first-stage estimations.[21] Table 5 displays these diverging first-stage estimates for the binary (D_{it}, column 2, table 5) and the continuous ($OccDist_{it}$, column 8, table 5) mismatch measurement, respectively. Thereby, one should notice the much lower R^2 in column (2) of table 5 compared to column (8) of table 5. Apparently, the substitutable task share of an individual's learned occupation contains more explanatory power for mismatches measured continuously than captured by a binary variable. Again, I conclude that the use of the continuous mismatch measurement is superior to the mismatch dummy.

5.3 Subsample results

Education cohorts

Recently, Hanushek *et al.*'s (2017) argued that vocational education's advantages in smoothing the school-work transition at the beginning of individuals' careers turns into a disadvantage in both employment and wages at later career stages. One mechanism put forth by Hanushek *et al.* (2017) to explain this pattern is the higher specificity of human capital acquired during a vocational education compared to rather general human capital acquired at a high school. On the one hand, individuals with a vocational degree easily find a position right after graduation but face difficulties adjusting their specific human capital to changing demands in the labour market occurring during their career, e.g. due to technological change. Individuals with general human capital, on the other hand, often face difficulties bringing their general skills in a specific position right after graduation, but they adopt more easily to a changing labour market and thus their employment and wage perspectives shape up well over their lifecycle.[22] Horizontal skill mismatches among individuals with a vocational degree might be one channel through which Hanushek *et al.*'s (2017) arguments materialize.

[Table 8 around here]

Table 8 tests this claim by estimating mismatch wage penalties among education cohorts (VET, Tertiary-B, and Tertiary-A) subsamples. All OLS and fixed-effect estimations show close-to-zero and statistically insignificant effects as in the fullsample estimations in table 6. IV estimations in columns (3), (6), and (9) rely on the share of substitutable task share as an instrument which yielded a statistically significant mismatch wage penalty in the fullsample (column 4 of table 6).

Overall, the findings presented in table 8 suggest that horizontal mismatches triggered by task shifting technological change do not represent a channel through which Hanushek *et al.*'s (2017)

[21] The IV estimator equals the ratio of the reduced form to the first-stage estimation.

[22] Partly supporting these hypotheses, Korber and Oesch (2019) find substantially lower earnings for Swiss individuals with a vocational degree once they enter their thirties. However, they do not find diverging employment chances across education cohorts over the lifecycle.

argument materializes. Although, the mismatch wage penalty for individuals with a VET degree is somewhat smaller compared to their counterparts with a tertiary degree, these differences are statistically not significant. Furthermore, one should notice the relative weak first-stage association among individuals with a tertiary-A degree, which leads to the very imprecise 2SLS-estimate in column (9).

Age cohorts

Table 9 presents subsample estimations for individuals who are younger than forty-six and individuals who are forty-six or older, respectively. Simple conditional comparisons of matched and mismatched individuals in columns (1) and (4) reveal that mismatched individuals only earn less than their matched counterparts at later stages of their work careers. Interestingly, fixed-effect estimations controlling for heterogeneity in unobservable personal characteristics reveal the opposite (columns 2 and 5). One explanation for this pattern might be that individuals' increasingly acquired informal human capital dominates at later career stages over formally acquired degrees and thus leads to the diminishing of a mismatch wage penalty at later stages of someone's career. Concretely, wage negotiations between firms and young job seekers are mostly based on formal degrees; what else can firms observe? As a consequence, young people suffer from a wage penalty if they cannot find a position matching their formal degree. At later stages of individuals' careers, firms (and job seekers) are more and more able to base their wage offers on informally accumulated human capital, which becomes increasingly visible, e.g. job references or previous occupationally relevant performance. Therefore, firms are willing to pay relatively high wages irrespective of the formal qualification a job applicant has or has not.

[Table 9 around here]

As hypothesised in section 2, the instrumental variable estimates are somewhat stronger among the older cohort. However, this difference between the age cohorts of roughly one quarter is statistically insignificant. It seems that task shifting technological change triggering mismatches is a threat for individuals at various stages of their career.

Unemployment spells

[Table 10 around here]

Task shifting technological change arguably not only enhances horizontal mismatches but also unemployment. However, observations during an unemployment spell drop out of my sample because I am neither able to define the mismatch status of unemployed individuals nor their current wage.

Potentially this leads to an underestimation of the overall financial losses (assuming unemployment is financially more harmful than being mismatched) suffered by individuals who lose a position in their previously learned occupation and become mismatched *or* unemployed. Table 10 tackles this concern by applying the main estimations presented in table 6 to a subsample of individuals' who were always employed when being observed. The results yielded in table 10 are almost identical to those yielded in table 6 and thus mitigate concerns that previously shown results are biased due to unemployment spells.

6 Conclusion

This paper investigates whether horizontally mismatched individuals suffer from a wage penalty. The answer – on average and revealed by OLS estimations – is no. Individuals who work in an occupation for which they have no formal degree earn – conditionally on observables – even more than similar individuals. Turning to fixed-effect estimations and thus accounting for unobservable covariates, e.g. ability, this positive association vanishes.

In the present paper, I argue however that this is not the end of the story. Descriptive evidence on individuals' wage evolution when becoming matched or mismatched suggests that fixed-effect estimations aggregate heterogeneous occupational mobility patterns and thus merely yield a mismatch wage effect on average. Presumably, some individuals select into mismatches and coincidently realize a higher wage, while others are negatively affected by a mismatch incidence and suffer from a wage penalty.

To cope with this heterogeneity and to isolate the – from a policy perspective – most relevant mismatch incidences, I propose an IV approach. In times of task shifting technological change, I surmise on the one hand that individuals' mismatch probability is positively correlated with the substitutability of their learned occupations' task bundle. On the other hand, individuals who learned occupations bundling few affected tasks are more likely to stay in their learned occupation. Based on this pattern, I regard the task composition of individuals' learned occupation – conditional on their educational attainment and the task composition of their current occupation – as a valid instrument for the endogenous mismatch variable.

Applying this IV approach to a sample of roughly 10,500 person-year observations, I estimate a negative wage effect of roughly 12% for mismatched Swiss males. However, this a mismatch wage penalty is only revealed when exploiting the share of substitutable tasks across individuals' learned occupations as an instrument. This seems plausible: the estimated 12% mismatch wage penalty refers to a LATE for the subgroup of *compliers* which are – in this setting – mismatched individuals with learned occupations displaying high shares of substitutable tasks who would not be mismatched had they learned less substitutable occupations.

In conclusion, mismatches represent a labour market phenomenon with different aspects. Many individuals “accept” mismatches to increase their salaries. Based on classical economic theory, in which a wage increase amplifies a better employee-employer match in terms of human capital allocation, the term *mis*match is therefore often misguiding. However, the analysis in this paper shows that some mismatches are associated with wage losses. From a policy perspective, these mismatches might be the most relevant because they are not only monetarily harmful to affected individuals but, due to a suboptimal allocation of human capital investments, also to the economy as a whole. To isolate these harmful mismatches, one needs to disentangle diverging sources and mechanisms contributing to the phenomena “mismatch”. This in turn requires accurate estimation strategies. The main contribution of this paper is to provide one such estimation strategy and hopefully to guide the path for more to come.

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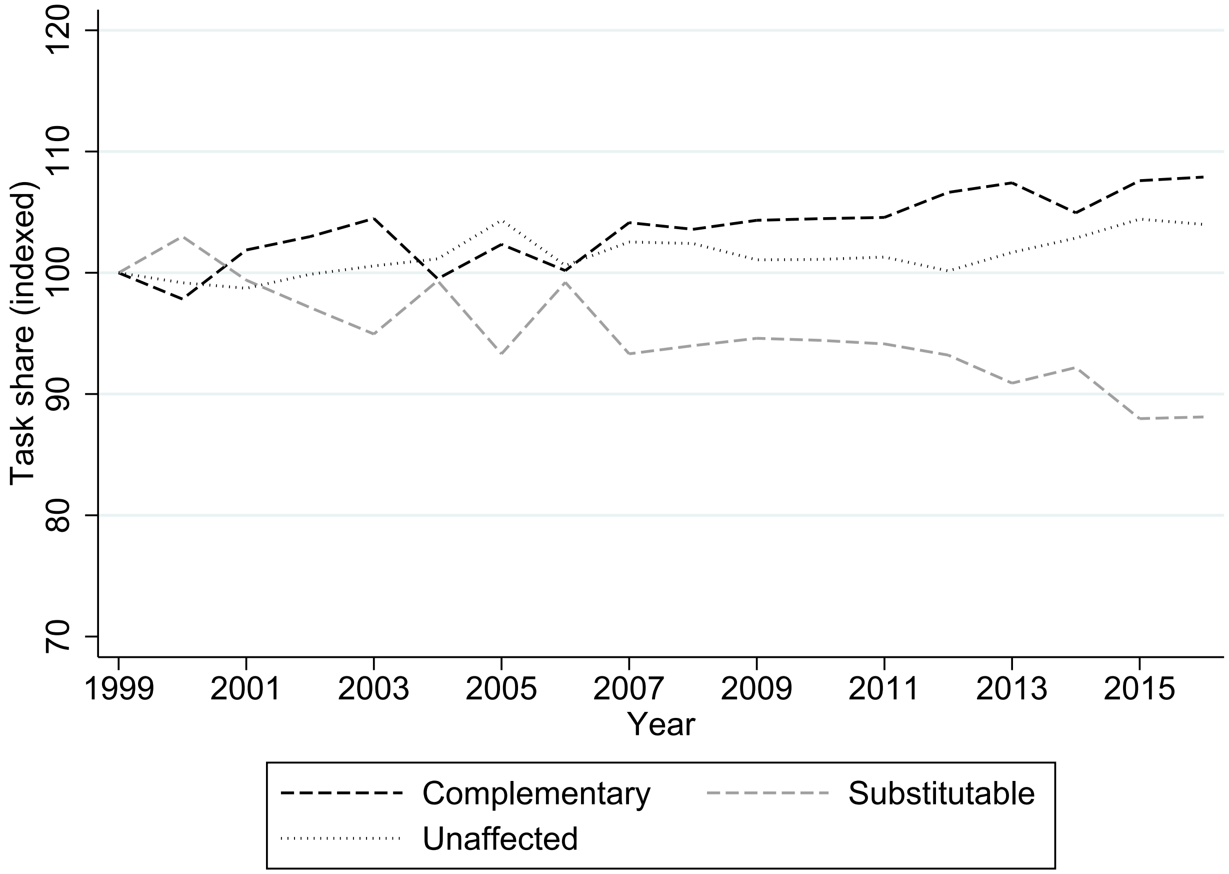
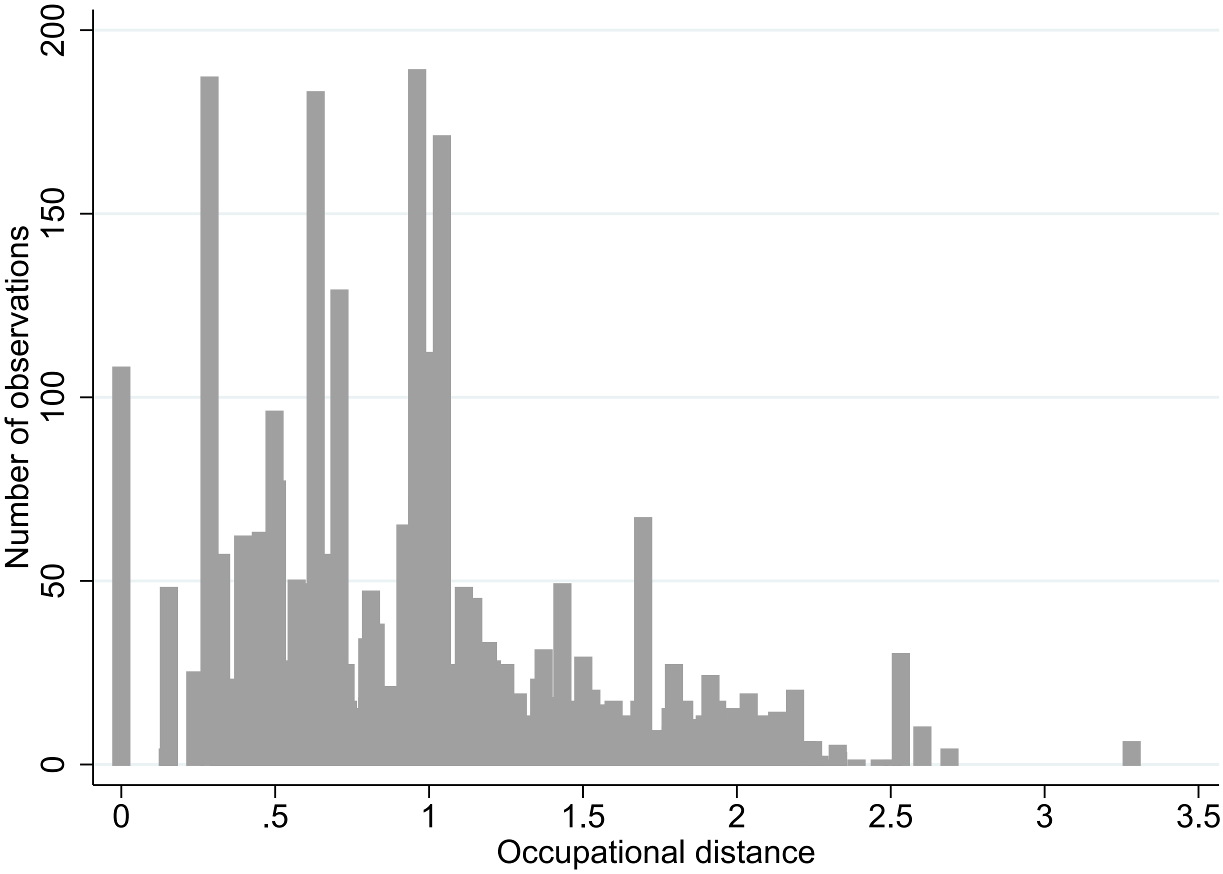
7 Figures

Figure 1: Task shares in Switzerland 1999 - 2016



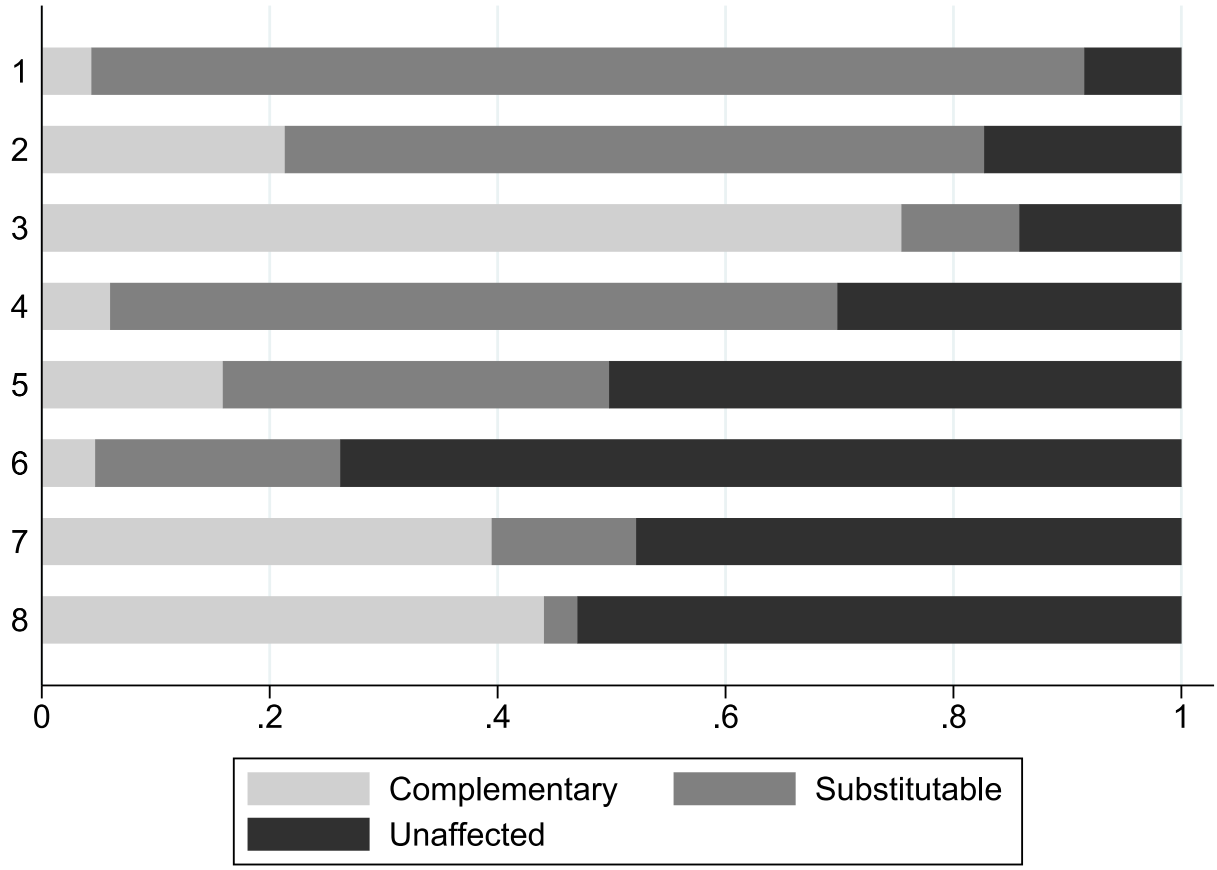
Sources: SHP 1999 - 2016, SJMM 1999 - 2016, own calculations.

Figure 2: Distribution of the continuous mismatch measurement



Notes: Only person-year observations included if individual is mismatched (n=5,483). Person-year observation of matched individuals excluded (n=4,988). Sources: BIBB/BAuA Qualification and Career Surveys 2006/2012, SHP 1999 - 2016, own calculations.

Figure 3: Task shares per 1-digit occupation



Notes: Task shares on level of SSCO 1-digit occupations. Occupations are: 1 Agricultural and forestry professions, livestock breeding professions, 2 Production occupations in industry and trade (excluding construction), 3 Technical and IT professions, 4 Professions in the building and construction industry and mining, 5 Trade and traffic professions, 6 Occupations in the hospitality industry and professions for the provision of personal services, 7 Professions in management and administration, banking, insurance and law, 8 Health, teaching and cultural professions, scientists. Sources: SHP and SJMM 1999 - 2016, own calculations.

8 Tables

Table 1: Descriptive statistics

	Full sample	Matched	Mismatched	Difference
Individual characteristics				
Age	45.3	44.4	46.0	-1.63***
% Children	0.48	0.52	0.45	0.06**
% Married	0.74	0.75	0.73	0.03
% Foreign	0.09	0.09	0.09	0.00
% Director	0.14	0.13	0.15	-0.02
% Supervisor	0.69	0.70	0.69	0.01
% Further Educ.	0.45	0.47	0.43	0.04**
Employment in %	96.5	96.4	96.6	-0.22
% VET	0.38	0.39	0.38	0.01
% Tertiary-B	0.35	0.32	0.38	-0.06**
% Tertiary-A	0.26	0.29	0.24	0.06**
Firm informations				
% <10 Emp.	0.12	0.12	0.12	0.01
% 10 - 49 Emp.	0.21	0.22	0.19	0.03*
% 50 - 99 Emp.	0.10	0.10	0.10	-0.00
% 100+ Emp.	0.48	0.46	0.49	-0.03
Industrial sector	0.27	0.28	0.26	0.01
Service sector	0.66	0.64	0.67	-0.03
Wage and mismatch				
Log monthly wage	8.97	8.94	8.99	-0.05**
Mismatch dummy	0.52	0.00	1.00	-1.00***
Occ. distance	0.53	0.00	1.00	-1.00***
Task shares learned occupation				
Complementary	0.37	0.38	0.36	-0.01
Substitutable	0.42	0.40	0.44	-0.04*
Unaffected	0.21	0.22	0.20	0.02
Task shares current occupation				
Complementary	0.44	0.40	0.47	-0.07***
Substitutable	0.30	0.36	0.25	0.10***
Unaffected	0.26	0.24	0.27	-0.03**
N(person-year)	10,471	4,988	5,483	-
N(person)[a]	1,224	457	525	-

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Most variables contain some missings, which are coded as such but not displayed in the table, and thus not all percentage informations sum up to one. [a]Person observations are considered matched (mismatched) if a person is matched (mismatched) in every year she/he is observed. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

Table 2: Task items in BIBB/BAuA 2006/2012

	SHP sample statistics			
Items as in BIBB/BAuA 2006/2012	Mean	Standard deviation	Min.	Max.
Manufacture, production of goods and merchandise	0.313	0.255	0.015	0.875
Measuring, testing, quality control	0.633	0.170	0.264	0.909
Monitoring, control of machines, plants, processes	0.411	0.221	0.085	0.889
Repair, overhaul	0.358	0.180	0.046	0.826
Retail, procurement, selling	0.311	0.136	0.090	0.757
Transport, storage, dispatch	0.374	0.140	0.136	0.861
Advertising, marketing, public relations	0.260	0.148	0.057	0.772
Organizing, planning and preparing work processes	0.548	0.109	0.246	0.826
Development, research, construction	0.287	0.136	0.050	0.766
Training, teaching, educating	0.424	0.189	0.100	0.986
Collecting information, researching, documenting	0.657	0.183	0.219	0.933
Advising and informing	0.102	0.134	0.013	0.687
Hosting, accommodating, preparing food	0.186	0.200	0.017	0.927
Nursing, caring, healing	0.295	0.136	0.013	0.735
Securing, protecting, guarding, monitoring	0.743	0.196	0.183	0.999
Cleaning, waste disposal, recycling	0.380	0.191	0.045	0.819
N(Occupations)	86			

Notes: Task items values refer to 0=never, 0.5=seldom, and 1=often and are aggregated at the 3-digit level of 144 German occupations. These values are then converted to the 86 SSCO 3-digit occupations observed in the SHP. Sources: SHP 1999 - 2016, BIBB/BAuA 2006/2012, own calculations.

Table 3: Task items in the SJMM and their categorization

Items	Mean[a]	Standard deviation	Min.	Max.	Experts' task categorization[a]
Cultivation, breeding, wining/dismantling	0.043	0.170	0	0.867	2 / 2 / 2
Handicraft/machine production	0.127	0.219	0	1	2 / 2 / 2
Install, assemble, build	0.050	0.135	0	0.769	2 / 2 / 2
Setup, programming, control, operation	0.081	0.164	0	0.730	3 / 2 / 2
Repair, maintain, restore	0.030	0.088	0	0.725	3 / 2 / 2
Warehousing, shipping, transport	0.045	0.152	0	0.930	3 / 2 / 2
Buy/sell, collect (cash), advise customers	0.091	0.184	0	0.883	3 / 2 / 3
Writing, correspondence, edit forms	0.037	0.086	0	0.538	1 / 3 / 3
Calculate, keep accounts	0.012	0.044	0	0.332	2 / 3 / 2
EDP activities, programming	0.014	0.074	0	0.652	1 / 1 / 1
Serve, host	0.015	0.064	0	0.533	3 / 3 / 3
Ironing, cleaning, waste disposal	0.025	0.110	0	0.779	3 / 3 / 3
Secure, guard	0.012	0.079	0	0.724	3 / 2 / 3
Analyse/research, review	0.073	0.158	0	1	1 / 1 / 1
Plan, construct, design/draw	0.045	0.139	0	0.936	1 / 1 / 1
Instruct and hire employees	0.010	0.033	0	0.254	3 / 3 / 3
Dispose, organize, lead/lead	0.079	0.093	0	0.551	3 / 1 / 1
Educate/teach/train, advise	0.095	0.248	0	1	3 / 1 / 3
Jurisdiction, administration of justice	0.009	0.083	0	0.775	3 / 1 / 3
Care/supply, medical/cosmetic	0.073	0.198	0	0.900	3 / 1 / 3
Publish, work artistically	0.036	0.142	0	0.975	3 / 3 / 1
N(Occupations)	87				

Notes: [a]Occupational average of task item as listed in SJMM 1999 - 2016 at the 3-digit level of 87 Swiss occupations observed in the SJMM. [b]Task assignment of three independent experts; 1=complementary task, 2=substitutable task, 3=unaffected task. Source: SJMM 1999 - 2016, own calculations.

Table 4: Four mismatch cases

Share of task j in learned occ. $T_{it}^{j,locc}$	Case 1 *Voluntary mismatch*	Case 2 *Involuntary mismatch*	Case 3 *Voluntary match*	Case 4 *Involuntary match*
$j = complementary$	0.386	0.322	0.408	0.360
	(0.302)	(0.290)	(0.288)	(0.274)
$j = substitutable$	0.413	0.486	0.375	0.447
	(0.336)	(0.336)	(0.314)	(0.320)
$j = unaffected$	0.201	0.192	0.217	0.193
	(0.237)	(0.220)	(0.222)	(0.214)
$OccDist_i$ in t	0.989	1.044	–	–
	(0.414)	(0.526)		
$OccDist_i$ in $t-1$	–	–	0.763	0.771
			(0.441)	(0.391)
Number of cases	122	76	83	52
Share of all cases	0.366	0.228	0.249	0.156
$D_{i,t} - D_{i,t-1}$	+1	+1	−1	−1
$Wage_{i,t} - Wage_{i,t-1}$	> 0	< 0	> 0	< 0
$E[Wage_{i,t} \| D_{i,t} = 1]$ $-E[Wage_{i,t-1} \| D_{i,t-1} = 0]$	+	−	−	+

Notes: The four cases are described in Section 4. Sample consists of working male population between the age of 20 and 65. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, own calculations.

Table 5: First-stage estimates

	D^a_{it}			$OccDist_{it}$ if $D_{it}=1$			$OccDist_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$T^{j,locc}_{it}$, $j = comp.$	-0.121*			-0.225***			-0.225**		
	(0.073)			(0.068)			(0.100)		
$T^{j,locc}_{it}$, $j = subs.$		0.553***			0.661***			1.113***	
		(0.074)			(0.103)			(0.126)	
$T^{j,locc}_{it}$, $j = unaff.$			-0.574***			-0.572***			-1.203***
			(0.098)			(0.127)			(0.161)
Constant	0.112	0.239	0.098	0.581**	0.263	0.339	-0.032	-0.003	-0.146
	(0.212)	(0.206)	(0.209)	(0.290)	(0.305)	(0.267)	(0.266)	(0.244)	(0.245)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$T^{j,cocc}_{it}$	$j = comp.$	$j = subs.$	$j = unaff.$	$j = comp.$	$j = subs.$	$j = unaff.$	$j = comp.$	$j = subs.$	$j = unaff.$
R-squared	0.083	0.159	0.113	0.165	0.229	0.282	0.080	0.238	0.204
Observations	10471	10471	10471	5483	5483	5483	10471	10471	10471
F-stat	2.73	55.94	34.56	10.98	41.23	20.18	5.10	78.49	55.99

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Sample consists of working male population between the age of 20 and 65. Mean task shares are averaged over all learned occupations. [a]Minimum sum of absolute differences between 16 task items in any learned occupation and 16 task items of the current occupation: $(|TaskItem_{1,locc} - TaskItem_{1,cocc}| + ... + |TaskItem_{16,locc} - TaskItem_{16,cocc}|)$. $T^{j,cocc}_{it}$ Refers to the task share of an individuals current occupation of the same task category as the one(s) that is (are) the independent variable(s) in the respective model. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

Table 6: Main results – continuous mismatch

	$Wage_i$							
			IV		IV		IV	
	OLS	FE	First-stage	2SLS	First-stage	2SLS	First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$OccDist^a_{it}$	0.007	-0.007		-0.119***		-0.062		-0.098***
	(0.011)	(0.012)		(0.033)		(0.043)		(0.029)
$T^{j,locc}_{it}$ $j = subs.$			1.113***				0.957***	
			(0.126)				(0.107)	
$T^{j,locc}_{it}$ $j = unaff.$					-1.203***		-0.874***	
					(0.161)		(0.149)	
Constant	8.983***	8.643***	-0.003	9.151***	-0.146	8.912***	-0.141	9.108***
	(0.104)	(0.116)	(0.244)	(0.108)	(0.245)	(0.106)	(0.234)	(0.105)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$T^{j,cocc}_{it}$	No	No	$j = subs.$	$j = subs.$	$j = unaff.$	$j = unaff.$	$j^1 = subs.$	$j^1 = subs.$
							$j^2 = unaff.$	$j^2 = unaff.$
Instrument, $T^{j,locc}_{it}$	–	–	–	$j = subs.$	–	$j = unaff.$	–	$j^1 = subs.$
								$j^2 = unaff.$
R-squared	0.562	0.435	0.238	0.562	0.204	0.554	0.314	0.571
Observations	10471	10471	10471	10471	10471	10471	10471	10471
F-stat(First Stage)			78.49		55.99		52.24	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the monthly log real wage. Sample consists of working male population between the age of 20 and 65. Task shares are averaged over all learned occupations. [a]Minimum sum of absolute differences between 16 task items in any learned occupation and 16 task items of the current occupation: $(|TaskItem_{1,locc} - TaskItem_{1,cocc}| + ... + |TaskItem_{16,locc} - TaskItem_{16,cocc}|)$. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

Table 7: Main results – mismatch dummy

	$Wage_i$							
			IV		IV		IV	
	OLS	FE	First-stage	2SLS	First-stage	2SLS	First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_{it}^{a}	0.033**	-0.005		-0.240***		-0.130		-0.205***
	(0.013)	(0.014)		(0.070)		(0.094)		(0.063)
$T_{it}^{j,locc}$ $j = subs.$			0.553***				0.477***	
			(0.074)				(0.073)	
$T_{it}^{j,locc}$ $j = unaff.$					-0.574***		-0.403***	
					(0.098)		(0.102)	
Constant	8.980***	8.645***	0.239	9.209***	0.098	8.934***	0.210	9.166***
	(0.104)	(0.116)	(0.206)	(0.120)	(0.209)	(0.109)	(0.206)	(0.115)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$T_{it}^{j,cocc}$	No	No	$j = subs.$	$j = subs.$	$j = unaff.$	$j = unaff.$	$j^1 = subs.$	$j^1 = subs.$
							$j^2 = unaff.$	$j^2 = unaff.$
Instrument, $T_{it}^{j,locc}$	–	–	–	$j = subs.$	–	$j = unaff.$	–	$j^1 = subs.$
								$j^2 = unaff.$
R-squared	0.563	0.435	0.159	0.496	0.113	0.526	0.178	0.520
Observations	10471	10471	10471	10471	10471	10471	10471	10471
F-stat(First Stage)			55.94		34.56		37.29	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the monthly log real wage. Sample consists of working male population between the age of 20 and 65. Task shares are averaged over all learned occupations. [a]Mismatch dummy equals one if none of an individual's learned occupation matches her/his current on the 3-digit level of the SSCO 2000 and zero otherwise. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, own calculations.

Table 8: Subsample results – education cohorts

	$Wage_i$								
	VET			Tertiary-B			Tertiary-A		
	OLS	FE	IV	OLS	FE	IV	OLS	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$OccDist^a_{it}$	0.009	-0.007	-0.083*	-0.005	-0.000	-0.150***	-0.002	-0.013	-0.156
	(0.015)	(0.015)	(0.045)	(0.017)	(0.016)	(0.045)	(0.031)	(0.033)	(0.125)
Constant	8.967***	8.795***	9.199***	9.326***	8.762***	9.413***	8.996***	8.639***	9.015***
	(0.138)	(0.144)	(0.140)	(0.225)	(0.204)	(0.221)	(0.245)	(0.248)	(0.249)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$T^{j,cocc}_{it}$	No	No	$j = subs.$	No	No	$j = subs.$	No	No	$j = subs.$
Instrument, $T^{j,locc}_{it}$	–	–	$j = subs.$	–	–	$j = subs.$	–	–	$j = subs.$
R-squared	0.486	0.366	0.518	0.411	0.441	0.408	0.508	0.462	0.471
Observations	4012	4012	4012	3701	3701	3701	2758	2758	2758
F-stat(First Stage)			32.51			49.39			8.146

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the log real gross income per year. Sample consists of working male population between the age of 25 and 65. [a]Minimum sum of absolute differences between 16 task items in any learned occupation and 16 task items of the current occupation: $(|TaskItem_{1,locc} - TaskItem_{1,cocc}| + ... + |TaskItem_{16,locc} - TaskItem_{16,cocc}|)$. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

Table 9: Subsample results – age cohorts

	$Wage_i$					
	Age 25-45			Age 46-65		
	OLS (1)	FE (2)	IV (3)	OLS (4)	FE (5)	IV (6)
$OccDist_{it}^{a}$	0.009	-0.030**	-0.111***	-0.043***	0.016	-0.140***
	(0.013)	(0.013)	(0.034)	(0.014)	(0.024)	(0.050)
Constant	8.541***	8.258***	8.608***	8.622***	9.089***	8.817***
	(0.153)	(0.178)	(0.157)	(0.580)	(0.435)	(0.623)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes
Educational dummies	Yes	Yes	Yes	Yes	Yes	Yes
$T_{it}^{j,cocc}$	No	No	$j = subs.$	No	No	$j = subs.$
Instrument, $T_{it}^{j,locc}$	–	–	$j = subs.$	–	–	$j = subs.$
R-squared	0.596	0.545	0.587	0.514	0.145	0.481
Observations	5203	5203	5203	5268	5268	5268
F-stat			77.26			35.21

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the monthly log real wage. Sample consists of working male population between the age of 25 and 65. [a]Minimum sum of absolute differences between 16 task items in any learned occupation and 16 task items of the current occupation: $(|TaskItem_{1,locc} - TaskItem_{1,cocc}| + ... + |TaskItem_{16,locc} - TaskItem_{16,cocc}|)$. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

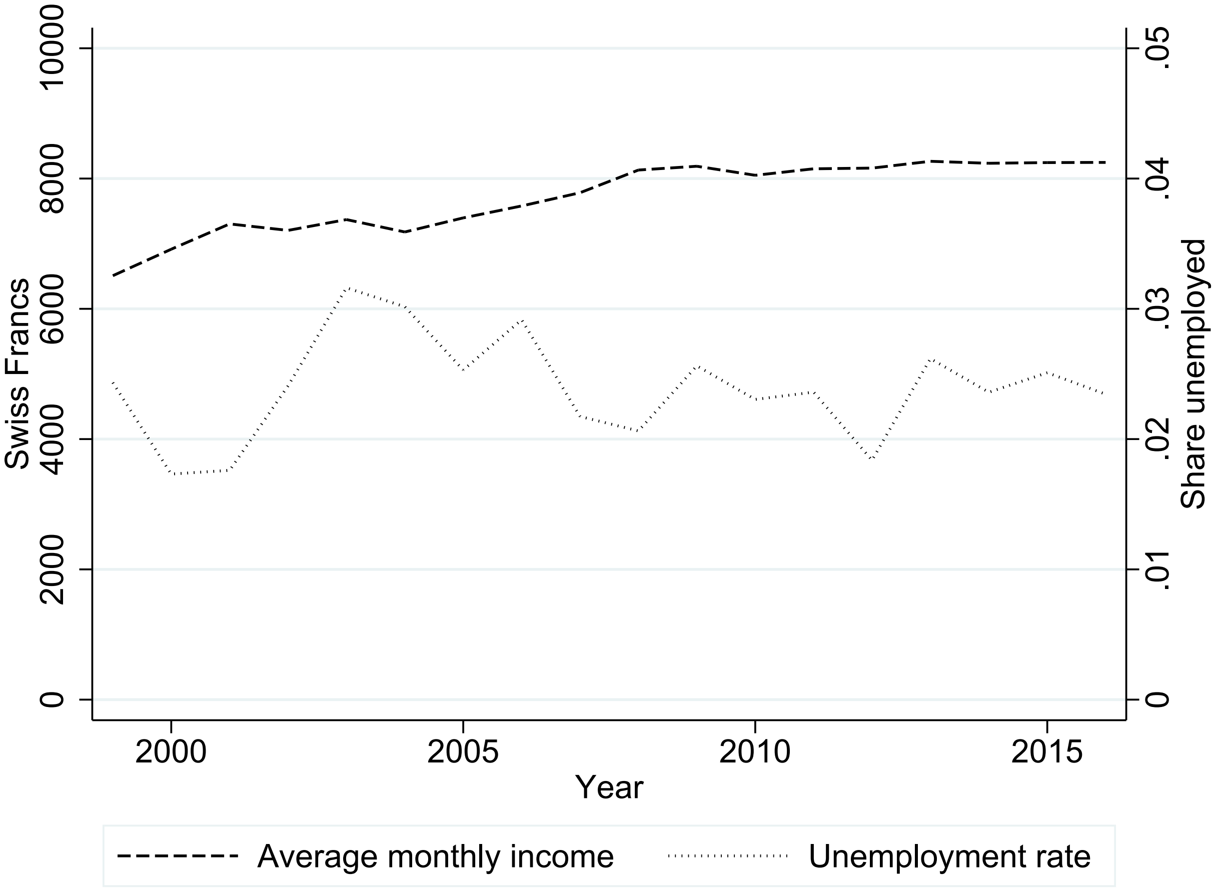
Table 10: Subsample results – exclude individuals with unemployment spell(s)

	$Wage_i$							
			IV		IV		IV	
	OLS	FE	First-stage	2SLS	First-stage	2SLS	First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$OccDist_{it}^{a}$	0.012	0.004		-0.119***		-0.056		-0.097***
	(0.011)	(0.012)		(0.033)		(0.043)		(0.029)
$T_{it}^{j,locc}$ $j = subs.$			1.113***				0.957***	
			(0.126)				(0.107)	
$T_{it}^{j,locc}$ $j = unaff.$					-1.203***		-0.874***	
					(0.161)		(0.149)	
Constant	9.011***	8.651***	-0.003	9.180***	-0.146	8.941***	-0.141	9.134***
	(0.107)	(0.120)	(0.244)	(0.109)	(0.245)	(0.108)	(0.234)	(0.106)
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$T_{it}^{j,cocc}$	No	No	$j = subs.$	$j = subs.$	$j = unaff.$	$j = unaff.$	$j^1 = subs.$	$j^1 = subs.$
							$j^2 = unaff.$	$j^2 = unaff.$
Instrument, $T_{it}^{j,locc}$	–	–	–	$j = subs.$	–	$j = unaff.$	–	$j^1 = subs.$
								$j^2 = unaff.$
R-squared	0.564	0.452	0.238	0.564	0.204	0.557	0.314	0.574
Observations	9923	9923	10471	9923	10471	9923	10471	9923
F-stat(First Stage)			75.43		53.61		49.75	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the monthly log real wage. Sample consists of working male population between the age of 20 and 65. Task shares are averaged over all learned occupations. [a]Minimum sum of absolute differences between 16 task items in any learned occupation and 16 task items of the current occupation: $(|TaskItem_{1,locc} - TaskItem_{1,cocc}| + ... + |TaskItem_{16,locc} - TaskItem_{16,cocc}|)$. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

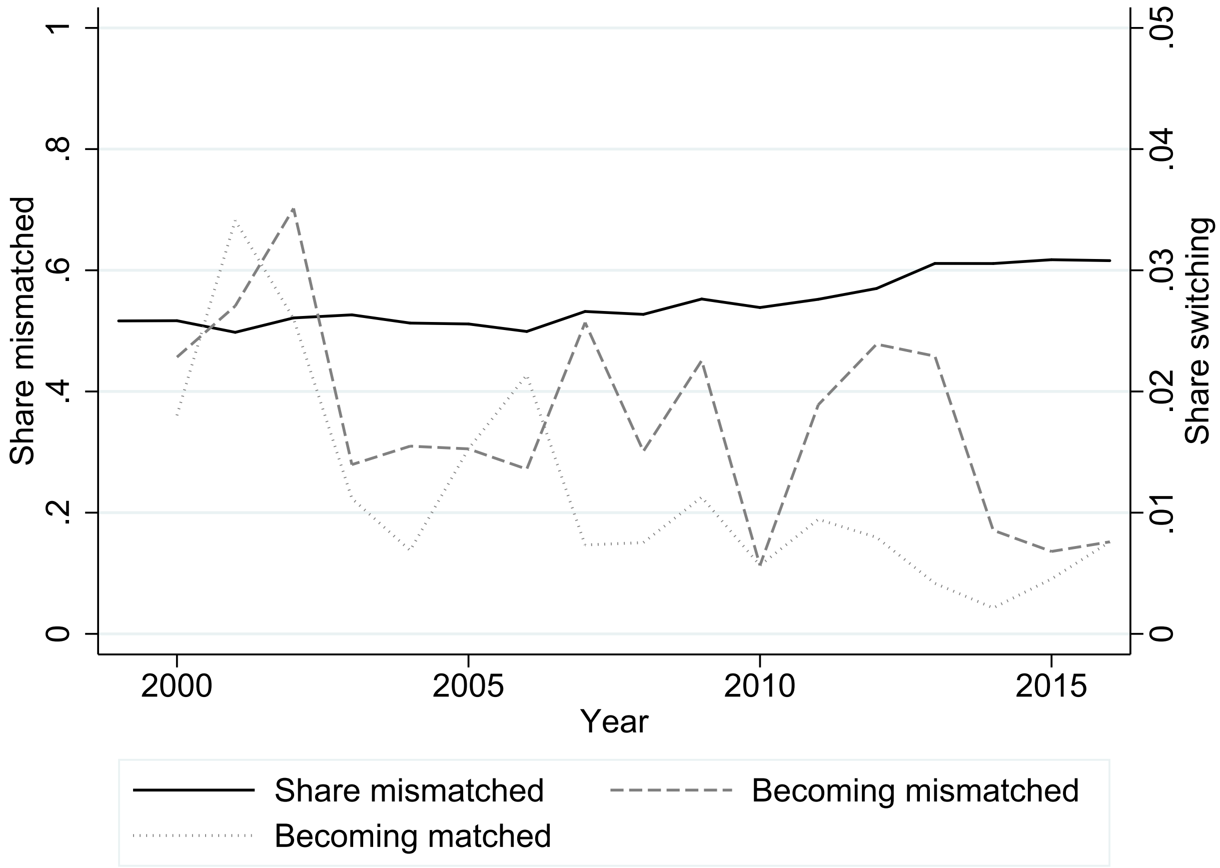
A Additional Tables and Figures

Figure A.1: Income and unemployment in Switzerland 1999-2016



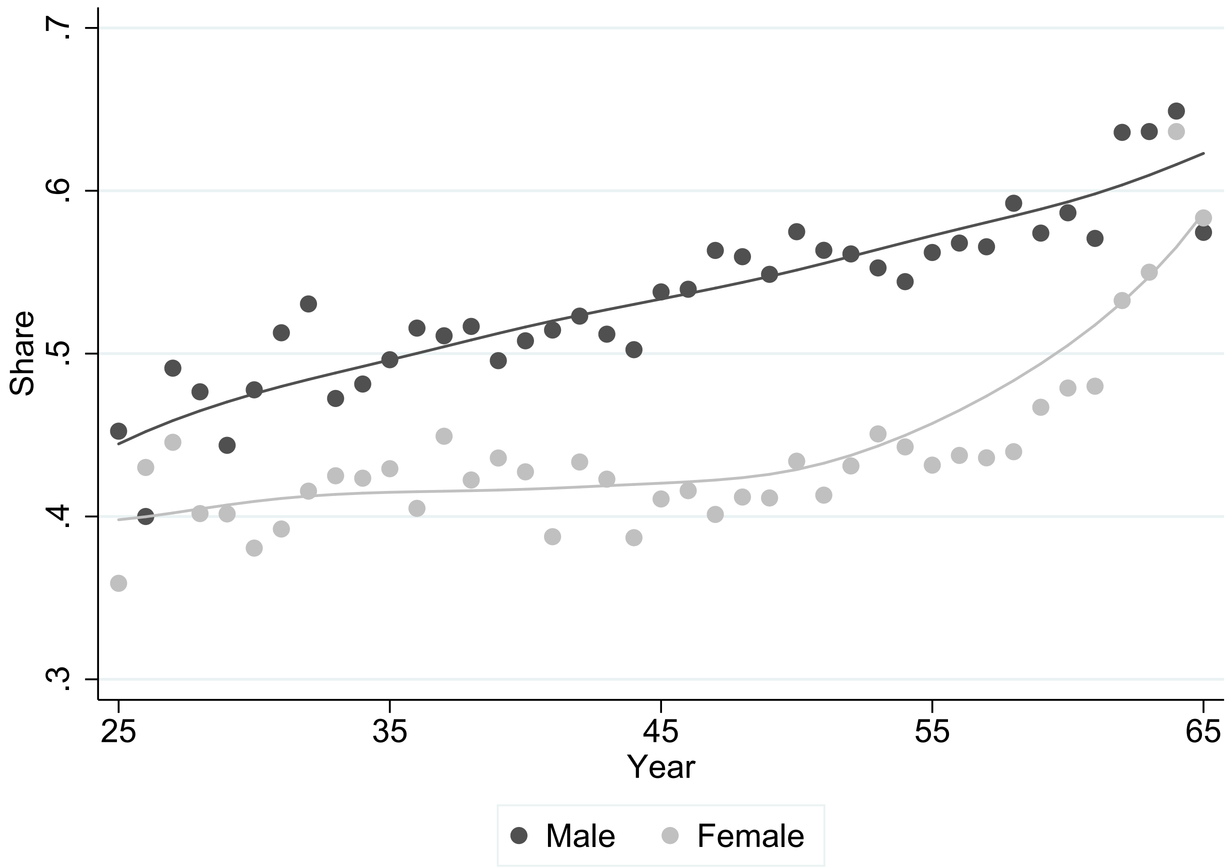
Source: SHP 1999 - 2016, own calculations.

Figure A.2: Mismatch level and switches 1999-2016



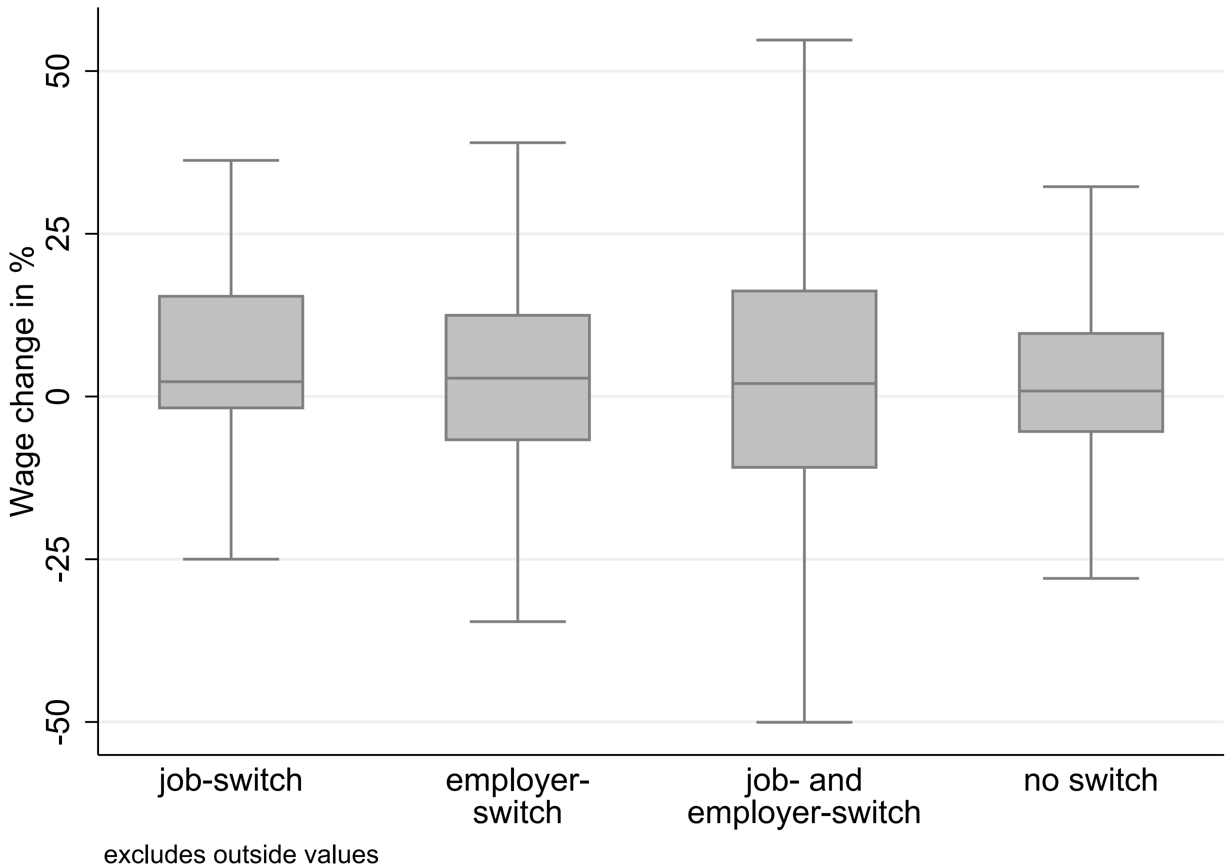
Source: SHP 1999 - 2016, own calculations.

Figure A.3: Male and female share of mismatched individuals by age



Source: SHP 1999 - 2016, own calculations.

Figure A.4: Job- and employer-switches and wage changes



Source: SHP 1999 - 2016, own calculations.

Table A.1: Main results – extended output

	$Wage_i$							
	IV		IV		IV		IV	
	First stage (1)	2SLS (2)	First stage (3)	2SLS (4)	First stage (5)	2SLS (6)	First stage (7)	2SLS (8)
$T_{it}^{j,locc}$, $j = comp.$	-0.225**							
	(0.100)							
$T_{it}^{j,cocc}$, $j = comp.$	0.182**	0.169***						
	(0.091)	(0.039)						
$T_{it}^{j,locc}$, $j = subs.$			1.113***				0.957***	
			(0.126)				(0.107)	
$T_{it}^{j,cocc}$, $j = subs.$			-1.361***	-0.399***			-1.138***	-0.365***
			(0.118)	(0.041)			(0.111)	(0.038)
$T_{it}^{j,locc}$, $j = unaff.$					-1.203***		-0.874***	
					(0.161)		(0.149)	
$T_{it}^{j,cocc}$, $j = unaff.$					1.323***	0.132***	1.073***	0.083**
					(0.133)	(0.045)	(0.124)	(0.039)
$OccDist_{it}^{a}$		-0.315		-0.119***		-0.062		-0.098***
		(0.207)		(0.033)		(0.043)		(0.029)
Age	0.033***	0.049***	0.027***	0.040***	0.030***	0.041***	0.026***	0.040***
	(0.011)	(0.009)	(0.010)	(0.004)	(0.010)	(0.004)	(0.010)	(0.004)
Age^2	-0.000**	-0.000***	-0.000**	-0.000***	-0.000**	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Foreign	0.062	-0.032	0.094	-0.043*	0.050	-0.040*	0.088	-0.043*
	(0.065)	(0.034)	(0.060)	(0.025)	(0.062)	(0.024)	(0.058)	(0.024)
Children	0.000	0.044***	-0.002	0.047***	-0.005	0.040***	-0.007	0.046***
	(0.037)	(0.017)	(0.034)	(0.013)	(0.035)	(0.013)	(0.033)	(0.013)
Married	-0.075	0.034	-0.076*	0.051***	-0.070	0.052***	-0.073*	0.053***
	(0.047)	(0.027)	(0.045)	(0.017)	(0.045)	(0.016)	(0.044)	(0.017)
Further Educ.	-0.045**	0.019	-0.055***	0.022**	-0.041**	0.033***	-0.051***	0.023**
	(0.022)	(0.014)	(0.020)	(0.009)	(0.021)	(0.009)	(0.019)	(0.009)
Employment in %	-0.001	0.009***	-0.000	0.010***	-0.001	0.009***	-0.000	0.010***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Tertiary-B[b]	-0.023	0.147***	-0.060	0.129***	-0.059	0.182***	-0.067*	0.134***
	(0.045)	(0.025)	(0.041)	(0.017)	(0.041)	(0.016)	(0.039)	(0.016)
Tertiary-A	-0.189***	0.222***	-0.155***	0.229***	-0.203***	0.337***	-0.138***	0.242***
	(0.052)	(0.051)	(0.053)	(0.025)	(0.046)	(0.022)	(0.051)	(0.024)
Constant	-0.032	8.919***	-0.003	9.151***	-0.146	8.912***	-0.141	9.108***
	(0.266)	(0.138)	(0.244)	(0.108)	(0.245)	(0.106)	(0.234)	(0.105)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0873	0.474	0.213	0.566	0.183	0.551	0.314	0.571
Observations	10471	10471	10471	10471	10471	10471	10471	10471
F-stat	8.112		62.25		50.41		52.24	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the log real gross income per year. Sample consists of working male population between the age of 20 and 65. $T_{it}^{j,locc}$Refers to the respective average share of task j of individual ii's learned occupations. $T_{it}^{j,cocc}$Refers to the respective task share of task j of individual ii's current occupation. [a]Minimum sum of absolute differences between 16 task items in any learned occupation and 16 task items of the current occupation: $(|TaskItem_{1,locc} - TaskItem_{1,cocc}| +$ $... + |TaskItem_{16,locc} - TaskItem_{16,cocc}|)$. [b]To simplify the presentation of education cohort differences I only include three broad educational dummies (VET, tertiary-B and tertiary-A) in the presented extended output, whereas I include eight educational dummies in all other estimations. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, and BIBB/BAuA 2006/2012, own calculations.

Table A.2: Reduced form estimates

	$Wage_i$			
	(1)	(2)	(3)	(4)
$T_{it}^{j,locc}$, $j = comp.$	0.071**			
	(0.035)			
$T_{it}^{j,locc}$, $j = subs.$		-0.132***		-0.121***
		(0.037)		(0.038)
$T_{it}^{j,locc}$, $j = unaff.$			0.075	0.047
			(0.052)	(0.051)
Constant	8.929***	9.152***	8.921***	9.136***
	(0.105)	(0.104)	(0.104)	(0.105)
Personal controls	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes
Educational dummies	Yes	Yes	Yes	Yes
$T_{it}^{j,cocc}$	$j = comp.$	$j = subs.$	$j = unaff.$	$j^1 = subs.$ $j^2 = unaff.$
R-squared	0.569	0.585	0.563	0.585
Observations	10471	10471	10471	10471

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses clustered at individual level. Dependent variable is the monthly log real wage. Sample consists of working male population between the age of 20 and 65. Task shares are averaged over all learned occupations. Sources: SHP 1999 - 2016, SJMM 1999 - 2016, own calculations.