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Routine job dynamics in the Swiss labor market

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Abstract

I investigate the role of labor market flows in the decline of routine employment in Switzerland between 1992 and 2018 using rich individual-level panel data from the Swiss Labour Force Survey. Existing research on the labor market effects of digital transformation has identified jobs with a high content of routine tasks as particularly prone to automation. My analysis shows that the decline in routine employment was almost entirely driven by decreasing inflow rates from non-participation and non-routine occupations as opposed to increasing outflow rates from routine jobs. Performing Oaxaca-Blinder-type nonparametric decompositions, I find that these inflow rate decreases can primarily be accounted for by changed propensities to transition into routine occupations, whereas demographic changes play a minor role. The propensity to transition from non-routine into routine employment has decreased for all distinguished demographic groups, while the propensity to enter the labor market into routine cognitive employment has particularly decreased for middle-aged individuals and those with low or medium education. My findings suggest that the Swiss labor market is evolving differently than the US labor market in the wake of the digital transformation.

Keywords: Routine jobs, Digitalization, Upgrading, Job polarization, Routine-biased technical change

JEL: E24, J21, O33

1 Introduction

In recent decades, tremendous advances in digital technology have significantly affected labor markets of developed economies. In particular, digital technologies have heterogeneous effects on workers' labor market opportunities depending on their skill level and the importance of routine tasks in their occupations (Autor et al., 2003; Katz & Murphy, 1992). In turn, these heterogeneous labor market effects have been identified as main drivers of job polarization in the USA and other developed countries, characterized by a declining employment share of middle-wage occupations and increased shares at the lower and upper end of the wage distributions (Acemoglu & Autor, 2011; Goos et al., 2009). While recent studies found a decline in routine employment in Switzerland on an aggregate level (Kurer, 2019; Kurer & Palier, 2019), little is known about individual-level dynamics on how the Swiss labor force has adapted to digitalization.

In regard to labor market effects of digital technology, two main mechanisms have been at the center of scientific debate: The first mechanism, skill-biased technological change, states that the benefits of digital technology for workers in terms of employment prospects and wages increase with their skill level (Katz & Murphy, 1992). The second mechanism, routine-biased technological change, argues that digital technology tends to substitute workers in routine-intensive jobs while complementing those in non-routine occupations (Autor et al., 2003). Whereas the first narrative projects a general labor market "upgrading" due to digitalization, the second predicts a "de-routinization" accompanied by a "job polarization" of the labor market, as routine jobs tend to be located in the middle of the wage distribution and non-routine occupations at the upper and lower tails. While the literature focusing on the US labor market found convincing evidence supporting recent job polarization trends (e.g.,

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Acemoglu & Restrepo, 2022; Autor et al., 2008; Goos & Manning, 2007; Goos et al., 2009), studies for Europe show considerable cross-country variation between general upgrading and polarization (see, e.g., Fernández-Macías, 2012; Kurer & Palier, 2019; Oesch & Piccitto, 2019; Oesch & Rodríguez Menés, 2011).

Only few studies investigate individual-level dynamics driving these observed aggregate trends. Using German administrative panel data, Bachmann et al. (2019) show that employment prospects of individuals in jobs with higher routine task content are generally worse and have worsened in the past four decades. For the USA, Cortes et al. (2020) analyze changes in individual-level transitions into and out of routine employment over time and find that individuals decreasingly (re-)enter routine employment from unemployment and non-participation driven by declined propensities to do so, rather than by changes in demographic composition of the labor force. For Switzerland, Kurer (2019) finds that a substantial share of routine workers transitioned into retirement in recent decades. While he suspects young labor market entrants are insufficiently replacing them and thus "natural turnover" at play, individual-level dynamics and how they are driving the changes in Swiss routine employment have remained unexplored: Are changes in inflows or outflows, e.g., into unemployment, responsible for its recent decline? Can it be accounted for by changes in the demographic composition of the labor force? Have typical routine workers increasingly renounced routine occupations because they prefer alternative employment options, or do they have an increasingly difficult time finding such a job? And are specific demographic groups particularly affected by this occupational change?

This paper investigates these questions and provides three main contributions. First, drawing from a representative Swiss panel data set, I analyze transition rates into and out of employment in routine occupations between 1992 and 2018. I classify survey respondents in accordance with their labor market status (employed, unemployed, non-participation), and following recent literature (e.g., Acemoglu & Autor, 2011; Cortes et al., 2017; Jaimovich & Siu, 2020), I split the group of employed workers into four occupational groups (routine manual, routine cognitive, non-routine manual, non-routine cognitive) in order to track their transitions over time. I show that decreasing inflow rates from non-routine employment and non-participation into routine jobs are accounting for their decline, and not increasing job loss or retirement rates of routine workers. Accordingly, Swiss de-routinization is not happening by natural turnover. Second, closely following the approach of Cortes et al. (2020), I perform Oaxaca-Blinder decompositions (Blinder, 1973; Oaxaca, 1973) of the changes in these key inflow rates and show that they are mostly driven by declined transition propensities conditional on demographic characteristics, rather than changes in the demographic composition of the Swiss labor force. This indicates that individuals who—given their sex, education level, age, etc., previously tended to take on routine jobs have less and less done so, e.g., because of worsened job opportunities in these occupations. Third, I demonstrate that propensities to transition from non-routine into routine employment decreased independently of workers' demographic characteristics, but most for individuals with lower education. The decline in propensities to enter the labor market into routine cognitive jobs is mainly driven by individuals with low or medium education and middle-aged persons. Contrary to the assumption of Kurer (2019), young labor market entrants do not play a prominent role in the decline of Swiss routine employment.

Understanding these individual-level dynamics is important for three reasons. First, characterizing the process of declining routine employment on an individual-level helps to formalize and evaluate theories on how digitalization is affecting different labor markets, with Switzerland representing a coordinated but still rather flexible and high-skilled variant that builds on a employment-centered dual education system. If the declining share of routine employment were mainly due to demographic changes, such as the aging of the Swiss population or the increasing participation of women, one could argue that it is a natural consequence of demographic or societal change. If, on the other hand, the changes are mainly due to changes in propensities to work in routine jobs, this would suggest that it might be attributable to occupational change driven by digitalization. Second, and particularly relevant for policy makers, the understanding of these individual-level dynamics facilitates to identify and comprehend economic, societal and political implications of de-routinization in Switzerland. Whether de-routinization is happening rather gradually by declining inflows into routine employment or through large-scale layoffs of routine workers will likely impact the economic and social status as well as political preferences of affected individuals.[1] Third, and related to the previous point, it reveals occupational and demographic groups that may not benefit or even experience disadvantages from occupational change induced by digitalization and might therefore be suitable targets of policy aiming

[1] See, e.g., Kurer and Palier (2019) discussing mechanisms linking job polarization and political behavior. For the USA, Frey et al. (2018) even argue that the adoption of automation technology might have swung the 2016 US elections in favor of Donald Trump.

at diminishing adverse labor market effects of digital transformation.

The remainder if this paper is structured as follows. Section 2 provides a short review of the literature on labor market effects of digital technology and how it might affect supply and demand for routine employment in Switzerland. In Sect. 3, I introduce the panel data set used, the Swiss Labour Force Survey, in more detail and elaborate how it allows the observation of flows between different labor market states in Switzerland from 1992 to 2018. Section 4 follows with the identification of changes in transition rates that are driving the decline in routine employment. In Sect. 5, I perform Oaxaca-Blinder decompositions of the changes in these key transition rates. In Sect. 6, I discuss my findings and compare them with the results of Cortes et al. (2020) for the USA. Section 7 concludes.

2 Digital technology and the labor market

Technological change is theoretically considered and has empirically been determined as main driver of long-term economic growth (e.g., Kogan et al., 2017; Romer, 1990). At the same time, most new technologies are introduced in order to save human labor. The steam engine constitutes the best-known example of a technological advancement that during the eighteenth and nineteenth centuries transformed first the British and subsequently many more agrarian and handicraft economies into those dominated by steam powered machinery. While it made countless job profiles obsolete, it required for masses of workers operating the machines and increased overall employment.

More recently, the tremendous improvement of digital storage capability and the emergence of internet communication allowed the increased computerization and automation of our economies in general and the labor market in particular. There is an ongoing lively public and scientific debate on the effects of computer technology on the labor market. While advances in technology historically have always been displacing certain types of work and creating others, the net employment effect has generally been positive (Kogan et al., 2017; Vivarelli, 2014). However, concerns in society that this time might be different and computers, artificial intelligence, robots and alike might net diminish human labor are widespread, some even warning against a "jobless future" (Ford, 2015; Rifkin, 2014).

While such doom and gloom perspectives have generally not been backed by economics, the way technological change is affecting the structure of employment has been in focus since the beginning of classic economics. The broad introduction of computers into the workplaces of developed economies from the 1960s on has been linked to an increased labor demand for skilled workers at the cost of unskilled ones, commonly known as skill-biased technological change [SBTC, Katz and Murphy (1992)]. The assessment that workers' benefits from technology increase with their skill level has since been supported by various studies determining similar labor market dynamics induced by SBTC in virtually all developed economies in the late twentieth century, predicting a general "upgrading" of the labor force (e.g., Autor & Katz, 1999; Berman et al., 1998; Goldin & Katz, 2010).

Even more recently however, scholars observed changes in the wage structure that did not fit into the narrative of SBTC: The USA and other developed countries experienced a declining share of occupations in the middle of the wage distribution, while those at the lower and upper tail increased (e.g., Autor et al., 2008; Goos & Manning, 2007; Goos et al., 2009). This job polarization has been connected with a de-routinization of the labor force, a declining share of employment in occupations with a high content of routine tasks, i.e., that are performed by following well-defined sets of procedures (Goos et al., 2014; Jaimovich & Siu, 2020). In turn, this decline of routine-intensive occupations has been attributed to the fact that new technologies are particularly effective at executing such types of tasks: Autor et al. (2003) ascertained that computer technology tends to substitute workers in routine jobs while complementing those in non-routine occupations, also known as routine-biased technological change (RBTC). As a result, the increasing demand for non-routine workers drives the share of both generally low-paid non-routine manual employment as well as particularly well-paid non-routine cognitive employment, leading to the observed polarization.

While the recent literature focusing on the USA found convincing evidence supporting job polarization trends in the past decades, studies for Europe show considerable cross-country variation: Fernández-Macías (2012) found a plurality of patterns depending on the institutional setups of the labor markets, ranging from job polarization in Continental Europe, upgrading in Scandinavia and a relative expansion of middling jobs in Southern Europe. Similarly, Oesch and Rodríguez Menés (2011) found a U-shaped pattern of upgrading consistent with the RBTC hypothesis for Britain, Germany, Spain and Switzerland, with cross-country differences in the lower tail of the wage distribution, suggesting that wage-setting institutions channel technological change into more or less polarized patterns of upgrading: Powerful unions, high minimum wages, heavy pay-roll taxes and generous unemployment benefits suppress the creation of low wage jobs. For the period between 1992 and 2015, Oesch and Piccitto (2019) observed occupational upgrading for Germany, Spain and Sweden, and polarization dynamics in the UK. Furthermore, Kurer and Palier (2019) find that while magnitudes vary, the share of routine employment has declined in all 29 European economies they examined and the shares of non-routine cognitive and non-routine manual jobs increased in most of these countries.

Empirical assessment on how Switzerland's labor force, typically exhibiting low unemployment, high wages and relatively low income inequality, is adapting to digital transformation is still inconclusive. Switzerland is considered a coordinated market economy, however its labor market legislation is, compared to other coordinated market economies such as Germany or France, rather liberal (Emmenegger, 2010; Hall & Soskice, 2001). Additionally, the dual Swiss education system prepares future workers rather selectively for the labor market and offers a wide range of educational and career paths for people with both academic and vocational training (Schoon & Bynner, 2019). The two most recent studies on occupational change in Switzerland come to somewhat ambiguous trend classifications. Murphy and Oesch (2017) focus on employment changes across the income distribution in Switzerland. While the three quintiles with highest income experienced consistent absolute growth between 1970 and 2010, the trends for the lower quintiles point to job polarization in the 1980s but distinct upgrading in the 1990s and to a smaller degree in the 2000s. Kurer (2019), on the other hand, focuses on changes in the relative labor shares of occupational groups, distinguished by their job's routine, manual and cognitive content. His data for 1999 to 2016 show indeed a shrinking share of routine workers while non-routine cognitive employment gained and non-routine employment remained rather stable.

What dynamics might be driving the relative decline in routine employment in Switzerland, and how are they related to digital transformation? Demand-side, companies might find digital technology a suitable substitute for human labor, particularly for executing routine tasks. Such an increase in digital technology would increase the routine factor input as a whole and lead to diminishing returns and/or a decreasing demand for workers in jobs with a high share of routine tasks (Cortes et al., 2017). As a result, routine occupation loses attractiveness in terms of wages and job opportunities, reducing propensities of workers to enter or stay in such employment. In regard to labor supply, Kurer et al. (2019) observes a significant share of workers exiting routine jobs into retirement and suspects that they are not sufficiently replaced by other labor market participants or entrants. However, it is unclear whether there might be a lack of candidates with suitable characteristics to replace the retirees or whether the propensities of suitable candidates to work in routine jobs might have decreased: They might prefer other kinds of employment, or companies abstain from refilling vacant routine job positions in the first place.

Digital technology not only increases productivity of high-skilled workers (Katz & Murphy, 1992) but also of non-routine cognitive occupations (Autor et al., 2003), in which such workers are disproportionately well represented (Acemoglu & Autor, 2011), both resulting in a rising demand for and wage compensation of high-skilled workers. Workers are likely to react by investing more in education and skill acquisition resulting in more individuals qualifying for occupations that are generally more attractive compared to routine jobs in terms of wages and job opportunities. Moreover, providers of education might react by increasing their education capacities as a result and adjust their curricula to the changed demands for skills. In fact, the Swiss education system has introduced major new educational pathways in the late 1990s, particularly allowing vocational training graduates improved possibilities to acquire higher education (Bonassi & Wolter, 2002). In sum, such a general upskilling of the labor force would increase the supply of potential non-routine cognitive workers while reducing the supply of potential routine workers.

3 Data

In order to disentangle what is driving the decline of routine employment in Switzerland, I use yearly data from the Swiss Labour Force Survey (SLFS) covering the years 1992 to 2018. It features extensive employment and socio-demographic information of the resident population of age 15 and older in Switzerland.[2] The SLFS is conducted annually by the Swiss Federal Statistical Office and aims to provide representative information on the socioeconomic structure and employment behavior of the employed Swiss population and those not in the labor force. Originally starting with roughly 16,000 participants, its sample has been enlarged several times and since 2010 provides information on around 70,000 respondents. The weighting procedure of the survey sample is stratified by the 24 cantons, the Swiss federal units, and follows a two-phase process: In a first step, design weights are generated as the reciprocal of the inclusion probability of the sample individuals. Then, these weights are adjusted for non-response and calibrated on major variables such as sex, age, canton of residence and nationality.

[2] The reference population for the SLFS is persons aged 15 and over of Swiss nationality who are registered in Switzerland or of foreign nationality with a residence or settlement permit of at least twelve months (B, C permit) or a short-term residence permit for a cumulative duration of stay of at least twelve months (L permit).

Between 1992 and 2009 respondents were interviewed in the second quarter for five consecutive years. From 2010 onward, they were interviewed four times within 15 months. Thus, apart from survey attrition, for every respondent there is information available for two or more consecutive years, allowing the observation of individual yearly changes in labor market state and other variables. The share of observations that can be used as yearly panel data is 87,1% in the period of the first survey setup and 81,1% from 2010 to 2018. In order to focus my analysis on the potentially active labor force, I restrict the sample to individuals of the Swiss working age population aged 15 to 65, therefore including newly retired workers who reach retirement age at 64 (women) or 65 (men).

3.1 Labor market state classification

The SLFS includes information on labor market status for every sample individual, i.e., whether they are employed, unemployed or not participating in the labor force. For employed workers, it additionally records the 4-digit ISCO-08-codes[3] associated with their current profession. The International Standard Classification of Occupations (ISCO) was designed by the International Labour Organization in order to organize occupations into clearly defined groups according to the tasks they feature.[4] In total, there are 3264 tasks attributed to 436 occupation groups[5], with the number of tasks per group varying between 2 and 14.

Following the recent literature (e.g., Acemoglu & Autor, 2011; Cortes et al., 2017; 2020), I categorize employed workers among two dimensions regarding the task profile of the their job, the first being "routine" versus "non-routine," the second being "cognitive" versus "manual." As we will see, Swiss workers categorized accordingly differ considerably both in their demographic characteristics and in their employment trends, affirming that such a categorization also makes sense in Switzerland. While cognitive tasks can be both abstractly challenging or intensive in human interaction, manual tasks are generally characterized by the use of manual labor. Like Cortes et al. (2020), I classify tasks as routine if they "can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures." On the other hand, non-routine tasks are characterized by requiring flexibility, problem-solving or social perceptiveness. Accordingly, depending on the importance of these different task types in their occupations, employed workers are grouped into four occupational groups: routine cognitive, routine manual, non-routine cognitive and non-routine manual.

In order to do this, I use task content measures by occupation group provided by Mihaylov and Tijdens (2019).[6] They calculate these task content measures as follows: First, they assign each of the 3264 tasks to one or more of five total categories: routine manual, routine cognitive, non-routine manual, non-routine abstract and non-routine interactive. I include several examples of tasks for each of these categories in Appendix Table 6. Subsequently, five task content measures are calculated for 427[7] occupation groups based on the tasks they feature:

$$T_k^j = \frac{t_k^j}{\sum_j t_k^j}, \tag{1}$$

where T_k^j, the task content measure of category $j \in$ [routine manual, routine cognitive, non-routine manual, non-routine abstract, non-routine interactive] of occupation group k, is equal to t_k^j, the number of tasks of category j in occupation group k, divided by the total number of task assignments, $\sum_j t_k^j$, of occupation group k.

With these five task content measures they calculate a single measure of routine task intensity for every occupation group:

$$RTI_k = T_k^{RC} + T_k^{RM} - T_k^{NRA} - T_k^{NRI} - T_k^{NRM}, \tag{2}$$

where RTI_k indicates the routine task intensity of occupation group k and is calculated by subtracting the occupation group's sum of non-routine task content measures, T_k^{NRA}, T_k^{NRI} and T_k^{NRM}, from the sum of its routine task content measures, T_k^{RC} and T_k^{RM}. Accordingly, the RTI index increases with higher routine intensity and ranges between -1 and 1, whereas a RTI of -1 indicates that an occupation only includes non-routine tasks, and a RTI of 1 that it contains routine tasks only.

Similarly, I calculate a measure of manual task intensity as follows:

$$MTI_k = T_k^{RM} + T_k^{NRM} - T_k^{RC} - T_k^{NRA} - T_k^{NRI}, \tag{3}$$

[3] ISCO has been revised three times, with ISCO-08 being its most recent version. For simplicity, I will write ISCO-codes referring to the ISCO-08-codes.

[4] For more information on ISCO-classification: https://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm

[5] In ISCO-classification, these are called "unit groups," for better understanding I refer to them as occupation groups.

[6] They also provide comparisons of their measures with two existing task content measures, namely by Acemoglu and Autor (2011) and Dengler et al. (2014) as well as the 'probability of computerization' by Frey and Osborne (2017). They demonstrate that their measures show higher correlation with the two other measures than those show in between each other.

[7] The authors exclude five so-called not-elsewhere-classified jobs which have no tasks classified and three military occupations.

Table 1 Shares by Labor Market State, 1992 and 2018

	1992	2018	Change (in pp.)	Change (in %)
NLF	23.56	18.84	− 4.72	− 20.0
NRC	32.88	45.01	12.13	36.9
NRM	18.48	16.58	− 1.9	− 10.3
RC	18.13	12.67	− 5.46	− 30.1
RM	4.36	2.33	− 2.03	− 46.6
UN	2.59	4.58	1.99	76.8

15–65 year old Swiss working age population

Source: Swiss Labour Force Survey, 1992–2018

Analogously, the MTI index is calculated by subtracting the occupation group's sum of non-manual task content measures, T_k^{RC}, T_k^{NRA} and T_k^{NRI}, from the sum of its manual task content measures, T_k^{RM} and T_k^{NRM}. The MTI index thus ranges from − 1 to 1, increasing with higher manual task intensity. A MTI of − 1 indicates an occupation only includes non-manual tasks and a MTI of 1 that it consists of manual tasks only.

I use both the RTI and MTI to categorize all 427 occupation groups for which Mihaylov & Tijdens (2019) provide task measures for as follows:

$$O_k = \begin{cases} RM, & \text{if } RTI_k > 0 \;\&\; MTI_k > 0 \\ RC, & \text{if } RTI_k > 0 \;\&\; MTI_k \leq 0 \\ NRM, & \text{if } RTI_k \leq 0 \;\&\; MTI_k > 0 \\ NRC, & \text{if } RTI_k \leq 0 \;\&\; MTI_k \leq 0, \end{cases} \tag{4}$$

where O_k is the occupational group of occupation group k, depending on the values of RTI_k and MRI_k, the routine task intensity and the manual task intensity of occupation group k.

According to the ISCO-codes of their current job, to each employed individual can be attributed the corresponding task content measures as well as RTI and MTI. In turn, every worker is categorized into one of the four occupational groups according to their RTI and MTI values.[8] Including unemployed and individuals not in the labor force, every sample individual i can be assigned its labor market state, S_{it}, in any given year t:

$$S_{it} \in [UN, NLF, RM, RC, NRM, NRC],$$

where UN stands for *unemployed*, NLF for *not in the labor force* and RM, RC, NRM and NRC are the occupational groups defined above, i.e., *routine manual*, *routine cognitive*, *non-routine manual* and *non-routine cognitive*.

Table 1 presents shares by labor market state of the Swiss working age population in the years from 1992 and 2018, as well as percentage point and percentage changes. It shows that RM workers make up a rather small share of the Swiss labor force but almost every fifth individual of the working age population held a RC job in 1992. However, RC employment lost almost a third of its original share by 2018, RM employment almost half. Additionally, individuals not in the labor force experienced a sharp, and NRM workers a small decline. On the other hand, the share of non-routine cognitive workers increased drastically and by 2018 45% of individuals between 15 and 65 worked in a non-routine cognitive job.

Table 2 provides some descriptive statistics on the composition of our six labor market state groups in two time periods, 1992–2001 and 2008–2018. Interestingly, in both time periods RM and NRM workers hardly differ in regards to educational backgrounds and hourly wage. Moreover, both groups are about two-thirds male and feature a disproportionately high share of immigrants. It can thus be observed that in the case of the Swiss labor market, manual intensive jobs *in general* tend to earn low wages, not non-routine manual occupations in particular.[9] In contrast, women make up almost two-thirds of individuals working in RC occupations where hourly wages are considerably higher and workers tend to be better educated than in the manual job groups. Finally, average hourly wages paid in NRC jobs are significantly higher than in all the other groups, in addition, they experienced the strongest wage increase compared to a smaller one for RC jobs.

3.2 Transition rate construction

In order to analyze flows between different labor market and occupation status on the individual-level, I construct yearly transition rates between the six labor market states. Following the approach of Cortes et al. (2020), $\rho_t^{S_t,S_{t+1}}$ is the year t transition rate between labor market states S_t and S_{t+1} computed as the number of individuals switching from S_t in year t to S_{t+1} in year $t+1$, divided by the number of individuals in state S_t between t and $t+1$.[10] This generates a 6 × 6 matrix of transition rates, ρ_t, for every year t in the sample:[11]

[8] See Table 9 for the most frequent occupations by occupational groups and their shares in the labor market.

[9] Like, e.g., in the USA, see Jaimovich and Siu (2020).

[10] Individuals leaving the sample between t and $t+1$ (survey attrition, sample rotation) or have missing labor market state information in one of the periods are excluded from the calculation of transition rates. Matched individuals are weighted using the SLFS sample weights from year t.

[11] Except for 2018, the last year in the sample (no $t+1$), and for 2009 when the survey method and sample changed.

Table 2 Descriptive statistics by labor market state

	Overall	RM	RC	NRM	NRC	UN	NLF
Panel A: 1992–2001							
Average Age	39.6	39.6	38.8	38.3	40.6	37.0	43.1
Average Hourly Wage (CHF)	36.0	32.0	36.0	31.9	44.1		
Fractions within labor market state groups							
Low Education	0.23	0.32	0.15	0.29	0.11	0.31	0.40
Medium Education	0.58	0.60	0.75	0.62	0.53	0.53	0.52
High Education	0.19	0.08	0.10	0.09	0.35	0.16	0.08
Male	0.48	0.73	0.36	0.67	0.55	0.50	0.26
Immigrants	0.20	0.33	0.14	0.26	0.17	0.41	0.19
Sample							
Number of observations	161,034	6470	28,313	26,635	59,152	4156	36,308
Weighted Shares of Sample	1.00	0.04	0.16	0.18	0.35	0.03	0.23
Panel B: 2008–2018							
Average Age	42.0	43.2	42.0	41.2	43.1	38.5	43.8
Average Hourly Wage (CHF)	37.8	31.8	38.8	32.4	48.4		
Fractions within labor market state groups							
Low Education	0.19	0.30	0.13	0.26	0.08	0.28	0.36
Medium Education	0.49	0.60	0.65	0.60	0.40	0.46	0.46
High Education	0.32	0.10	0.23	0.13	0.52	0.26	0.17
Male	0.49	0.65	0.35	0.66	0.52	0.51	0.36
Immigrants	0.25	0.36	0.18	0.30	0.22	0.45	0.27
Sample							
Number of observations	445,773	13,391	57,953	71,634	195,354	18,239	89,202
Weighted Shares of Sample	1.00	0.03	0.13	0.17	0.43	0.04	0.20

The sample excludes employed individuals with no or incomplete ISCO-code records as well as occupation groups that cannot be classified using the measurements by Mihaylov and Tijdens (2019). RM, RC, NRM and NRC stand for employment in routine manual, routine cognitive, non-routine manual and non-routine cognitive occupations; UN stands for unemployed and NLF for not in the labor force. Education groups are categorized as described in 8

$$\rho_t = \begin{bmatrix} \rho_t^{RM,RM} & \rho_t^{RM,RC} & \rho_t^{RM,NRM} & \rho_t^{RM,NRC} & \rho_t^{RM,UN} & \rho_t^{RM,NLF} \\ \rho_t^{RC,RM} & \rho_t^{RC,RC} & \rho_t^{RC,NRM} & \rho_t^{RC,NRC} & \rho_t^{RC,UN} & \rho_t^{RC,NLF} \\ \rho_t^{NRM,RM} & \rho_t^{NRM,RC} & \rho_t^{NRM,NRM} & \rho_t^{NRM,NRC} & \rho_t^{NRM,UN} & \rho_t^{NRM,NLF} \\ \rho_t^{NRC,RM} & \rho_t^{NRC,RC} & \rho_t^{NRC,NRM} & \rho_t^{NRC,NRC} & \rho_t^{NRC,UN} & \rho_t^{NRC,NLF} \\ \rho_t^{UN,RM} & \rho_t^{UN,RC} & \rho_t^{UN,NRM} & \rho_t^{UN,NRC} & \rho_t^{UN,UN} & \rho_t^{UN,NLF} \\ \rho_t^{NLF,RM} & \rho_t^{NLF,RC} & \rho_t^{NLF,NRM} & \rho_t^{NLF,NRC} & \rho_t^{NLF,UN} & \rho_t^{NLF,NLF} \end{bmatrix}$$

The resulting transition rates can be applied in a law-of-motion equation in order to trace the evolution of labor market "stocks":

$$\underbrace{Stocks_{t+1}}_{(6\text{ x }1)} = \underbrace{\rho_t}_{(6\text{ x }6)} * \underbrace{Stocks_t}_{(6\text{ x }1)} \tag{5}$$

where $Stocks_t = [RM_t\ RC_t\ NRM_t\ NRC_t\ UN_t\ NLF_t]'$ is the vector summarizing the fraction of the working age population in each labor market state. For example, the stock of RC_{t+1} depends on "inflows" of individuals from other labor market states into RC occupations between t and $t+1$, and "outflows" from RC employment into other labor market states in the same time period. In years $t = 1992$ and $t = 2010$, the first years of the two survey setups, the respective full sample labor market stocks are used as $Stocks_t$.

Ideally, Eq. (5) would trace the stocks measured cross-sectionally perfectly over time. However, the transition rates' accuracy it relies on may suffer greatly from sample rotation and survey attrition. Figure 1 plots stocks for all six labor market states as fraction of the Swiss working-age population from 1992 to 2018. The solid lines draw the stocks' evolution using the full cross section sample. The dashed lines draw the law-of-motion evolution using initial full sample stocks in years 1992 and 2010 and computed transition rates as stated in Eq. (5) based on the panel data. The gap between 2009 and 2010 is due to the changes in SLFS sample and setup as mentioned earlier in this chapter, making transition rate computation impossible between these 2 years. It shows that the law of motion tends to underestimate the fraction of individuals out of the labor force while overestimating the fraction of employed workers, particularly in the cognitive job groups. The deviation for NLF reaches a maximum of 3.1 percentage points in 2008; for NRC it lies in 2005 with

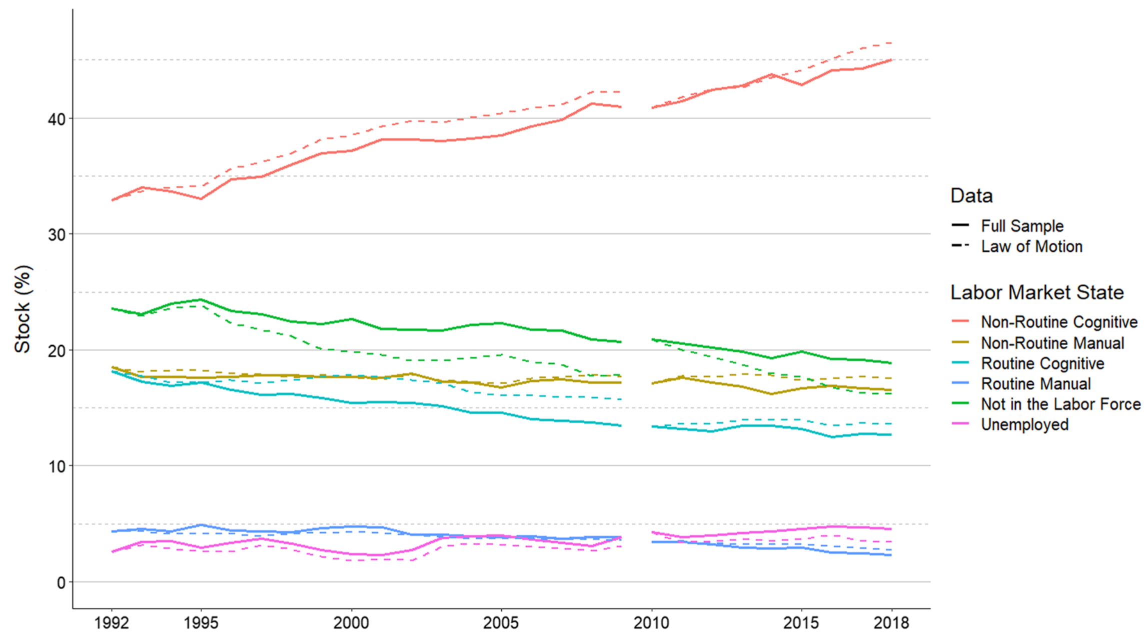

Fig. 1 Labor Market Stocks from Full Sample and based on Law of Motion. Source: Swiss Labour Force Survey, 1992–2018

1.9 and for RC in 2000 with 2.4 percentage points. Most importantly for the analysis of labor market transitions, the fact that the law of motion underestimates the decline in RC employment suggests that the panel data are net overestimating transitions into RC occupations over time.

Despite these discrepancies, my law-of-motion estimations generally follow the mid- and long-run trend of those based on the full data. Furthermore, paths for RM and NRM workers as well as for unemployed show much smaller differences between the two methods. This supports my approach of analyzing transition rates derived from labor market flows in order to better understand recent dynamics in the Swiss labor market amid ongoing occupational change.

4 The role of transitions between labor market states

Figure 1 shows that while the NRM share remained rather constant, our cross section data draw a decrease in routine jobs and a rise in NRC occupations, also, transition rates computed using the panel data track these trends quite well. However, it remains unclear which flows in and out of these labor market states are driving these trends. For example, continuing to look at the aggregate trends, a naive interpretation that NRC jobs are directly swallowing up all the losses in routine jobs and the labor market inflows from the NLF would roughly add up mathematically (see Table 1). However, labor market trends are usually not that straightforward and fortunately, our individual-level data allow us to investigate what role flows of individuals transitioning between labor market states play in these aggregate developments.

Take Figure 2, illustrating the evolution of transition rates for inflows from other labor market states into RM jobs as well as the “stayer rate” (RM → RM), i.e., the share of individuals working in RM in t and still doing so in $t+1$. Consider the transition rates from NLF to RM in the top-left corner. In 1992 and 1993, the first two data points, roughly 0.4% of individuals not in the labor force worked in routine manual occupations in the subsequent year. This rate increases to maxima of roughly 1.1% in 1999 and 2001 and shows a descending trend from the middle of the 2000s and into the 2010s. While these percentages may sound small, with the large weight of the NLF a change from 0.4% to 1.1% results in roughly 14,500 more individuals yearly flowing from NLF into RM by 2000 and 2002 than by 1993 and 1994. Furthermore, transition rates for NRC, NRM and RC workers flowing into RM jobs show a rather gradual downward trend while inflows from unemployment vary considerably across years and the share of routine manual workers remaining in their field slightly increased in the 2010s.

While these developments of transition rates show interesting dynamics in the Swiss labor market, they are likely caused not only by structural trends in the labor market but also business cycle fluctuations. In order to isolate possible structural changes from such short-term volatility, I subdivide the available data period into three

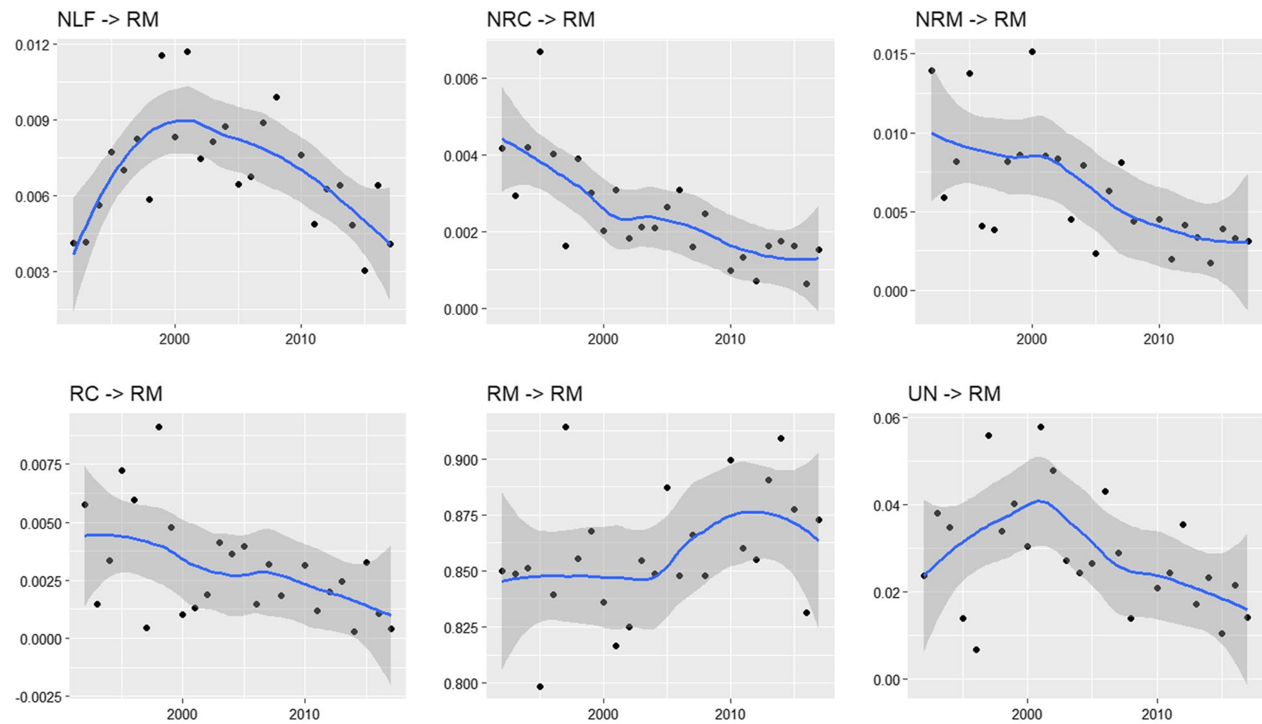

Fig. 2 Transition Rates for Inflows into Routine Manual Jobs. Notes: Transition rate computation is explained in chapter 3.2, blue lines show local regression lines, and the gray area marks the 95% confidence interval. The figure also includes the stayer rate (RM → RM), the share of routine manual workers remaining in routine manual employment. Transition rates for RC, NRM and NRC employment are provided in Appendix Figs. 5, 6 and 7. Source: Swiss Labour Force Survey, 1992–2018

phases $\tau \in [I, II, III]$, with phase I spanning 1992 to 2001, phase II 2002 to 2008 and phase II 2009 to 2018. In 2002 and 2009, Switzerland experienced negative real gross domestic product growth, marking recessions. Contrary to Cortes et al. (2020), I do not exclude recession periods in my analysis. As Jaimovich and Siu (2020) have shown for the USA, employment in routine jobs primarily experiences losses in economic downturns while failing to show recovery in the subsequent economic rebound. My aim is to take into account the potential roles of changes in both inflow rates and outflow rates in the decline of routine employment in Switzerland. Additionally, the available data period does not allow a clear distinction between a pre-polarization period and post-polarization periods as in Cortes et al. (2020): As visible in Figure 1, while routine manual employment has remained somewhat stable in the 90s before starting to decrease gradually, routine cognitive employment shows a downward trend already between 1992 and 2001.

Average aggregate transition rates for the three phases, $\bar{\rho}_\tau^{AB}$, are computed by dividing the total transitions from A to B between t_0 and $t_1 + 1$ by the sum of individuals in labor market state A in every year between t_0 and t_1.[12] In order to attribute transitions in recessions to the corresponding subsequent phase, t_0 is set to 2001 for phase II and to 2008 for phase III. In order to determine which changes in transition rates can explain the decline in routine employment, I calculate yearly flows in-between the six labor market states using the computed transition rates and the full sample estimates of the labor market state stocks:

$$Flows_t^{AB} = \rho_t^{AB} * Stocks_t^A, \tag{6}$$

where $Flows_t^{AB}$, the number of transitions from labor market state A in t to B in $t+1$, equals $Stocks_t^A$, the number of individuals in labor market state A in t as estimated by the full sample, multiplied by the transition rate between A and B in t, ρ_t^{AB}. For every phase τ, averages of yearly flows are calculated.

Table 3 presents average yearly flows in and out of routine manual and routine cognitive employment separated by origin and destination, respectively, as well as changes in phases II and III in respect to baseline phase I. Panel A shows that yearly overall inflows

[12] See Table 10 for values for t_0 and t_1 by each phase.

Table 3 Average yearly flows into and out of routine employment

	Phase I	Phase II	Phase III	II–I	III–I
Panel A: Routine Manual					
Inflows from					
NLF	6793	8191	5753	1398	− 1040
NRC	5215	4102	2903	− 1113	− 2312
NRM	6752	5185	2781	− 1567	− 3971
RC	3047	1860	1113	− 1187	− 1934
UN	4107	5280	4070	1173	− 37
Overall	25,914	24,618	16,620	− 1296	− 9294
Outflows to					
NLF	7800	9130	5688	1330	− 2112
NRC	5846	5239	4260	− 607	− 1586
NRM	7114	4940	3423	− 2174	− 3691
RC	3081	3705	1511	624	− 1570
UN	4407	4584	4198	177	− 209
Overall	28,248	27,598	19,080	− 650	− 9168
Panel B: Routine Cognitive					
Inflows from					
NLF	43,183	39,312	35,889	− 3871	− 7294
NRC	26,182	29,100	30,551	2918	4369
NRM	12,114	11,065	7162	− 1049	− 4952
RM	3081	3705	1511	624	− 1570
UN	15,083	16,589	20,161	1506	5078
Overall	99,643	99,771	95,274	128	− 4369
Outflows to					
NLF	35,405	34,081	29,963	− 1324	− 5442
NRC	34,696	33,740	34,250	− 956	− 446
NRM	8856	8349	6583	− 507	− 2273
RM	3047	1860	1113	− 1187	− 1934
UN	11,326	13,205	13,767	1879	2441
Overall	93,330	91,235	85,676	− 2095	− 7654

Averages of yearly flows computed as stated in Eq. (6)

into routine manual occupations already decreased in phase II (− 1296) before dropping significantly in phase III (− 9168). This decline in overall inflows was mainly driven by a gradual decrease in inflows from non-routine manual (− 1567 by phase II, − 3971 by phase III) and non-routine cognitive occupations (− 1113, and − 2312, respectively). Panel B shows that overall yearly inflows into routine cognitive jobs remained rather stable in phase II before decreasing in phase III, mainly driven by gradually declining inflows from non-participation and non-routine manual employment.[13] Interestingly, overall yearly outflows from both types of routine occupations decreased over time, particularly in phase III: yearly outflows from routine manual employment fell by 9168, from routine cognitive it fell by 7654. Accordingly, I conclude that routine employment decline is mostly driven by decreasing worker inflows rather than increasing outflows.

Figure 3 shows the percentage point changes in transitions rates of these inflows whose changes are mainly driving the decline in routine employment. It remains unclear what is driving these changes in inflow rates. For instance, the declining transition rate from NRM into RM could either be driven by a shrinking number of RM jobs typically filled by workers who previously worked in NRM jobs, or a smaller share of NRM workers that, given their demographic characteristics, typically tend to switch from NRM into RM occupations. Closely following (Cortes et al., 2020), I aim to disentangle to what extent the observed key inflow rate changes can be attributed to changes in (i) the demographic *composition* of the Swiss labor force and (ii) the *propensities* to make certain transitions for individuals from particular demographic groups.

5 Oaxaca-Blinder decompositions of transition rate changes

For every individual i in labor market state A in year t, let ρ_{it}^{AB} be a dummy variable equal to one if they switch to state B by the following year, and equal to zero otherwise. Average aggregate transition rates for a given phase τ, $\bar{\rho}_{\tau}^{AB}$ as introduced in Sect. 4 correspond to the averages of these ρ_{it}^{AB} with $t \in [t_0 \ldots t_1]$ for every phase $\tau \in [I, II, III]$. As mentioned above, the individual transition probability is likely driven by demographic and propensity factors; as a consequence, ρ_{it}^{AB} can thus be specified as a function of demographic characteristics:

$$\rho_{it}^{AB} = X_{it}^{A} \beta_{\tau} + \epsilon_{it}, \tag{7}$$

where X_{it}^{A} is a set of demographic variables available in the SLFS, and β_{τ} represents their phase specific coefficients. Estimating this linear probability model for the three phases allows for decomposition of changes in average aggregate transition rates $\bar{\rho}_{\tau}^{AB}$ over time as follows:

$$\begin{aligned} \bar{\rho}_{0}^{AB} - \bar{\rho}_{1}^{AB} &= (X_{0}^{A} \hat{\beta}_{0}) - (X_{1}^{A} \hat{\beta}_{1}) \\ &= \underbrace{(X_{0}^{A} - X_{1}^{A}) \hat{\beta}_{0}}_{\text{(i)}} + \underbrace{X_{1}^{A} (\hat{\beta}_{0} - \hat{\beta}_{1})}_{\text{(ii)}}. \end{aligned} \tag{8}$$

Accordingly, the change in the transition rate between phase 0 and 1 can be decomposed into two components: The first, (i), can be attributed to changes in the demographic composition of individuals in labor market state

[13] As mentioned in Sect. 3.2, the panel data are overestimating net flows into RC employment over time. As a result, the estimated decreases in inflows into RC occupations might be rather conservative.

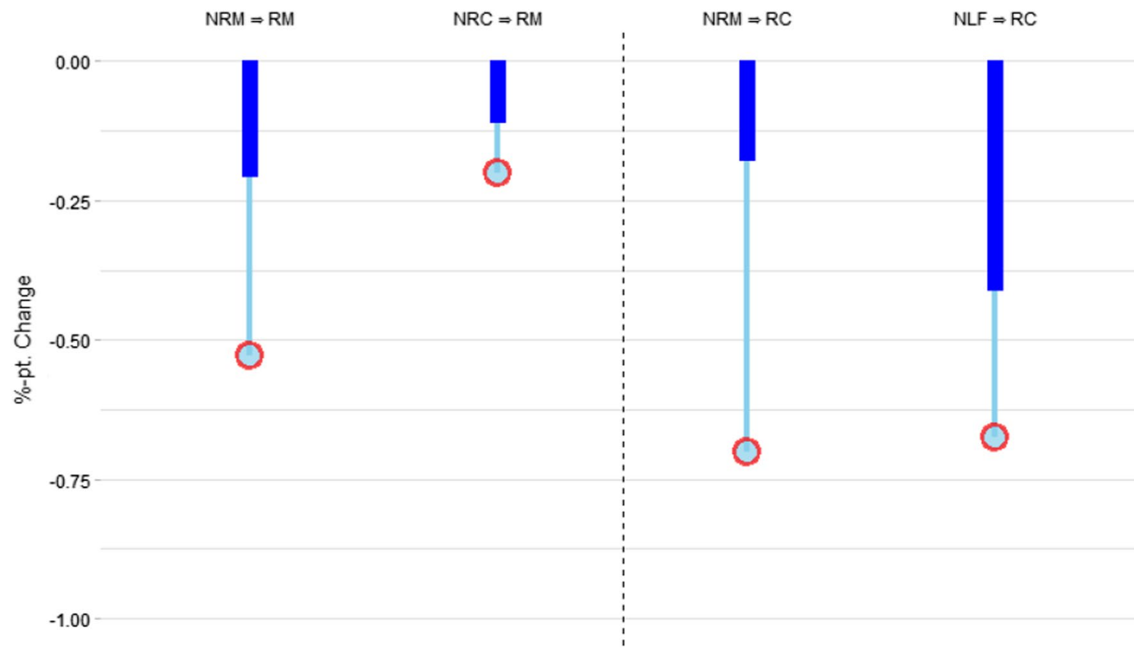

Fig. 3 Changes in Key Inflow Rates into RM and RC employment. Notes: Dark blue bars show percentage point changes in transition rates between phase I and phase II, and light blue bars show percentage point changes in transition rates between phase II and phase III. Red circles mark overall percentage point changes in transition rates between phase I and phase III.

A across phase 0 and 1. The second, (ii), accounts for changes in the corresponding coefficients, representing changes in propensities to switch from A to B conditional on demographic attributes.

I focus on the transition rates whose changes have been identified as main drivers of the decline in routine employment in Sect. 4. My vector of demographic characteristics X_{it}^{A} includes controls for age (three age groups: 15–29, 30–49, 50–65), education (nine education levels), sex (female, male), nationality (Swiss national, non-Swiss national) and greater region of residence (NUTS-2).[14]

Table 4 illustrates the Oaxaca-Blinder decomposition results for the changes in key inflow rates into routine manual and routine cognitive employment.[15] Panel A shows that the inflow rate from non-routine manual into routine manual employment decreases gradually throughout the phases. As indicated by the negative sign of the 'Composition' component in phase III, demographic changes in the NRM group appear to have played some role in this decrease. However, the negative sign and much larger size of the 'Propensities' component in both phases indicate that the rate's decline was majorly driven by a fall in propensities to switch from NRM to RM employment, conditional on demographic characteristics. Analogously, Panel B shows decomposition results for the inflow rate from non-routine cognitive occupations which also exhibits a gradual decline and more than halves by phase III. In this case, decreased propensities to switch from NRC to RM only play a slightly larger role in the drop than changes in demographic composition.

As shown in panel C, on average 1.59% of non-routine manual workers switched to routine cognitive employment in the 1990s, with this rate slightly decreasing for the period between 2001 and 2007 and falling drastically thereafter. In the post-great recession period, the aggregate decrease by 0.70 p.p. is entirely driven by a drop in transition propensities. Panel D shows that the inflow rate from non-participation, at 4.40% in the baseline phase, also decreased gradually. In phase II, it is driven by both changes in composition and propensities, however, only the former shows statistical significance. In phase III on the other hand, a fall in propensities to enter the labor market taking a routine cognitive job seems to be largely responsible for the transition rate's decline.[16]

[14] See Appendix Table 7 for detailed control variable levels.

[15] The Oaxaca-Blinder Decompositions are performed using the Stata implementation by Jann (2008).

[16] To the best of my knowledge, there is no reason to assume that the overestimation of net inflows into RC employment over time as discussed in Sect. 3.2 might bias the relative attribution of the transition rate changes to the two components. At the same time, there is no reason for such bias to be ruled out.

Table 4 Oaxaca Decompositions of Inflow Rates into Routine Employment

	Baseline (1992–2000): 0.88%	
	II: 2001–2007	**III: 2008–2018**
Panel A: Non-Routine Manual → Routine Manual		
Total Change	− 0.21*	− 0.53***
	(0.13)	(0.11)
Composition	0.00	− 0.10***
	(0.01)	(0.03)
Propensities	− 0.21*	− 0.52***
	(0.13)	(0.11)
Nr. of Obs.	37,924	41,737
	Baseline (1992–2000): 0.35%	
	II: 2001–2007	**III: 2008–2018**
Panel B: Non-Routine Cognitive → Routine Manual		
Total Change	− 0.11**	− 0.20***
	(0.05)	(0.05)
Composition	− 0.04***	− 0.11***
	(0.01)	(0.02)
Propensities	− 0.08	− 0.14***
	(0.05)	(0.05)
Nr. of Obs.	84,731	109,774
	Baseline (1992–2000): 1.59%	
	2001–2007	**2008–2018**
Panel C: Non-Routine Manual → Routine Cognitive		
Total Change	− 0.18	− 0.70***
	(0.17)	(0.16)
Composition	− 0.01	− 0.13
	(0.04)	(0.13)
Propensities	− 0.13	− 0.73***
	(0.18)	(0.16)
Nr. of Obs.	37,924	41,737
	Baseline (1992–2000): 4.40%	
	2001–2007	**2008–2018**
Panel D: Not in the Labor Force → Routine Cognitive		
Total Change	− 0.41*	− 0.68***
	(0.24)	(0.23)
Composition	− 0.25***	− 0.19**
	(0.05)	(0.09)
Propensities	− 0.13	− 0.72***
	(0.25)	(0.23)
Nr. of Obs.	50,375	51,935

The numbers represent percentage point changes. The Composition component corresponds to the change in demographic characteristics, and the Propensities component denotes changes in estimated coefficients, which represent changes in transition probabilities conditional on demographic characteristics. The differences between the sum of Composition and Propensities Component and the Total Change stem from the here omitted Interaction component

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

My decomposition results provide three learnings: First, transition rates for key inflow rates into routine employment decreased rather gradually across the three investigation phases. Second, these key inflow rates decreased more dramatically in the most recent years of the post-great recession period, and third, these decreases are primarily driven by changes in propensities conditional on demographic characteristics, namely sex, age, education level, nationality and region of residence. Importantly, robustness checks using alternative occupation classifications based on task measures by Acemoglu and Autor (2011) and Dengler et al. (2014) largely validate these findings.[17]

In a last step, I aim to examine, whether these propensities to transition into routine employment decreased generally, i.e., for all individuals in the origin labor market state irrespective of their demographic attributes, or only for some demographic groups. Therefore, I further decompose the Propensities Component into "subcomponents": (1) A *constant* subcomponent reflecting changes in overall propensities and (2) subcomponents reflecting propensity changes for *individual* demographic groups deviating from the overall change reflected in the constant.[18] I demonstrate the mathematical logic of the decomposition in regards to a constant, individual variables and coefficients in Appendix A. Table 5 provides these sub-decompositions for changes in the four key inflow rate changes between phase I and III that could be attributed to propensity changes in Table 4.

Column (1) shows sub-decomposition results for transitions from non-routine manual to routine manual employment, the constant coefficient of − 0.47 suggests that propensities generally decreased independent of demographic attributes. However, they did even more so for NRM workers with low education, while less so for those with medium or high education levels as indicated by the corresponding significant coefficients. As shown in column (2), propensities to transition into routine manual employment also seem to have generally decreased for non-routine cognitive workers, similarly, slightly more so for those with lower education and slightly less so for those with higher education. Column (3) shows that propensities to transition from non-routine manual into routine cognitive work decreased significantly and similarly for all NRM workers regardless of their demographic characteristics. In contrast, the results in column (4) suggest that propensities to transition from non-participation into routine cognitive employment have not necessarily fallen in general, but certainly for specific demographic groups, namely middle-aged individuals and those with lower or medium education levels. On the other side, propensities decreased relatively less for NLF individuals aged 50 to 65 or with higher education.

Table 5 Sub-Decomposition of Inflow Rate Changes between phase I and III

	(1) NRM → RM	(2) NRC → RM	(3) NRM → RC	(4) NLF → RC
Propensities Component	− 0.53***	− 0.15***	− 0.67***	− 0.72***
	(0.11)	(0.05)	(0.16)	(0.23)
Subcomponents				
Male	− 0.04	− 0.03	0.07	− 0.08
	(0.08)	(0.03)	(0.12)	(0.07)
Female	0.02	0.02	− 0.04	0.24
	(0.04)	(0.02)	(0.06)	(0.22)
15–29	− 0.03	0.02	− 0.07	0.14
	(0.05)	(0.02)	(0.09)	(0.15)
30–49	− 0.08	− 0.06*	0.04	− 0.28***
	(0.07)	(0.03)	(0.09)	(0.10)
50–65	0.05*	0.00	0.04	0.18**
	(0.03)	(0.02)	(0.03)	(0.08)
Low Education	− 0.20***	− 0.04*	− 0.09	− 0.29**
	(0.06)	(0.02)	(0.09)	(0.15)
Medium Education	0.14*	0.08	− 0.07	− 0.35**
	(0.08)	(0.05)	(0.14)	(0.17)
High Education	0.04***	0.07*	0.07	0.11***
	(0.02)	(0.03)	(0.03)	(0.03)
Constant	− 0.47***	− 0.19**	− 0.56*	− 0.21
	(0.12)	(0.09)	(0.29)	(0.31)
Nr. of Obs.	41,737	109,774	41,737	51,935

The numbers represent percentage point changes. The Propensities component denotes changes in estimated coefficients which represent changes in transition probabilities conditional on demographic characteristics and might slightly differ from the values in Table 4 due to different education categorizations. As in Table 4, nationality and region controls are included but omitted here. The Subcomponents denote fractions of the overall propensity change due to changes of the specific coefficients

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

6 Discussion and comparison with US results

In this section, I compare my findings with the results of the study by Cortes et al. (2020) on the decline of routine employment in the US labor market. While I follow their methodological approach in many aspects, two important differences in study design have to be considered when comparing the results: First, Cortes et al. apply an occupation-based classification into labor market states (instead of task-based classification in this study) and, second, they analyze monthly data from 1976 to 2018 (instead of yearly data from 1992 to 2018), and thus, also their baseline period for changes in transition rates is different. Apart from this, comparing the USA

[17] I used a crosswalk kindly provided by Hardy et al. (2018) to use Acemoglu and Autor (2011) SOC-measures for ISCO-occupations. Decomposition results with the two alternative classifications will be gladly provided upon request.

[18] I again use the Oaxaca-Blinder decomposition implementation for Stata by Jann (2008). The associated paper also discusses the issue that decomposition results for linear probability models using categorical predictors depend on the choice of the omitted base category and implements a solution which is also outlined in the paper.

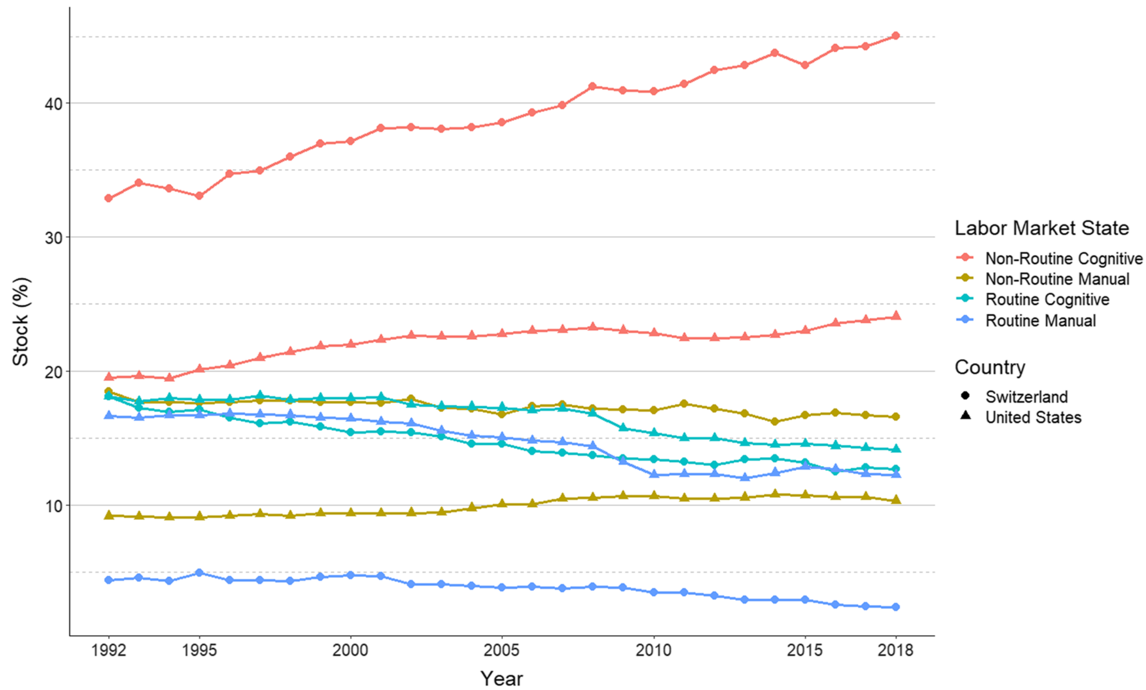

Fig. 4 Labor Market Stocks of Routine Employment, Switzerland and the USA. Source: Cortes et al. (2020), Swiss Labour Force Survey, 1992–2018

and Switzerland might give interesting insights on how advancing digital transformation affects different types of labor markets.

Most importantly, the USA features typical characteristics of a liberal market economy with extremely liberal labor market institutions and a restrained welfare state, while Switzerland is generally considered a coordinated market economy with (some) collective bargaining, more extensive social security but also rather lenient dismissal policies (Emmenegger, 2010; Hall & Soskice, 2001; Murphy & Oesch, 2017). Furthermore, while the USA has a liberal school-to-work transition regime with no structured path into skilled employment without college and significantly high youth unemployment, Switzerland's employment-centered transition regime actively allocates young people to occupational careers, and rather effectively so (Walther, 2006; Schoon and Bynner 2019).

Also, the two labor markets differ with respect to two aspects regarding employment at the lower end of the wage distribution: First, while studies for the USA locate routine manual jobs in the middle portion of the wage distribution (e.g., Jaimovich & Siu, 2020), Swiss routine manual jobs are relatively low-paid (see Table 2). Second, as visible in Figure 4, non-routine manual employment in Switzerland slightly decreased, while it increased in the USA. This might be due to relatively high wages on the lower end of the wage distribution, suppressing the growth of low-paid non-routine manual jobs (Murphy & Oesch, 2017). In contrast, non-routine cognitive employment is experiencing a persistent expansion in both economies. Given that NRC workers are relatively well educated in both countries, this goes well with the upgrading hypothesis, accompanied by educational expansion and high-skill immigration in both the USA (Borjas, 2005; Bloome et al., 2018) and Switzerland (Bonassi & Wolter, 2002; Beerli et al., 2022).

Figure 4 also shows the stocks of both types of routine employment as a fraction of the working-age population in Switzerland and the USA as measured by Cortes et al. (2020).[19] Cortes et al. observe a considerably higher share of routine manual employment in the USA. It remains unclear to what extent this difference is due to differing labor market state classifications and to what extent due to a factually higher importance of routine manual employment in the USA.[20] Though starting from distinctively different levels, in both countries employment in routine manual occupations remains rather stable throughout the 1990s before declining in the new

[19] Cortes et al. (2020) include individuals aged 16 to 75 in their working-age population, while I apply the Swiss definition for working-age population, individuals aged 15 to 65.

[20] I perform robustness checks with alternative labor market state classifications by Acemoglu and Autor (2011) and Dengler et al. (2014) which estimate higher shares of RM employment in Switzerland. Therefore, the different classifications likely play at least some role in the observed differences to the USA.

millennium. However, national recessions leave noticeably different marks on RM employment: While the global financial crisis that erupted in 2008 was accompanied by a distinct fall in RM employment in the USA, its gradual decline in Switzerland seems to have been hardly affected in 2008 and 2002, when the Swiss economy experienced negative growth.

In the case of routine cognitive employment, US and Swiss shares are virtually identical in 1992. However, while RC employment depletes rather gradually over the entire study period in Switzerland, it remains rather stable in the 1990s in the USA, before slightly decreasing after 2001 and then rapidly falling in the years of the financial crisis. It appears that while the USA experiences fierce destruction of routine jobs in recessions followed by (routine) "jobless recoveries" (Jaimovich & Siu, 2020), routine decline happens relatively gradually in Switzerland despite also rather loose Swiss dismissal protection that would allow employers quick layoffs.

As in this study, Cortes et al. identify changes in inflow rates as main drivers of the observed disappearance of routine employment. However, while I find that falling inflow rates from non-routine employment into RM and from non-routine manual and non-participation into RC employment are mainly accounting for the routine decline, shrinking inflows from non-participation and from unemployed who previously worked in routine jobs are responsible for the decreasing routine shares in the USA. These differences are likely related to the different trends visible on the aggregate: US routine workers who lose their job in recessions transition into unemployment or non-participation but reenter routine employment to a lesser extent in the subsequent years of recovery compared with previous upturns (Jaimovich & Siu, 2020). As Cortes et al. find, these decreases in transition rates are also key in accounting for the gradually increasing share of individuals not in the labor force—whose share in Switzerland, on the other hand, is gradually declining.

Nevertheless, as in Switzerland, the decreases in inflow rates into US routine employment are driven by declining propensities to transition into routine employment rather than changes in demographic composition of the labor force. Accordingly, the decline of routine employment in both countries is not so much due to a decrease in the number of individuals who would typically enter routine employment, but rather to the fact that these individuals increasingly prefer other kinds of employment or it has become more difficult for them to find employment in such occupations.

In my sub-decompositions, I find that in all key transitions apart from those from non-routine manual into routine cognitive employment, propensities decreased more for those with lower education while less for those with higher education (see Table 5). Do these less educated individuals have increasingly better alternatives to routine employment or can they no longer find a routine job? While my results do not allow to rule out the one interpretation or the other, two recent firm-level studies suggest the latter: Pusterla and Renold (2022) found that information and communication technology specialists raise employment of high-skilled workers, while reducing the share of low-skilled employees in Swiss firms, Balsmeier and Wörter (2019) found similar results for investments in such technologies. It is therefore reasonable to assume that decreased propensities to transition into routine employment reflect a decreased demand for workers, particularly with lower education, in routine jobs.

Finally, in two of the four analyzed transition rates in Switzerland, middle-aged individuals' propensities fell more sharply. In the case of labor market entry into routine cognitive jobs—which has experienced the single largest reduction in absolute transitions (see Table 3)—additional analysis shows that these mid-aged persons are mostly female. Whether these women, who probably completed their initial training some time ago and might be reentering employment after a break, e.g., parental leave, deliberately choose a different type of employment or are having a harder time finding an RC job is unclear. However, it is conceivable that digitalization has accelerated skill obsolescence in such jobs (Walter & Lee, 2022), making it more difficult for individuals to return to such jobs after prolonged work absences.

While individuals with low education and in middle-age are disproportionately driving de-routinization in Switzerland, Cortes et al. (2020) show that decreasing inflows of young and individuals with medium education account for the main share of the decline in US routine employment.[21] It appears that while low education is less and less conducive to transitioning into routine employment in Switzerland, medium education is less and less conducive to reentry into routine employment in the USA. Moreover, while little assistance is offered to young US labor market entrants, the selectively organized Swiss education system which actively seeks to train labor market entrants in ways that best meet employer's demand for workers, may explain why young individuals are not particularly suffering from occupational change in Switzerland (Walther, 2006; Schoon & Bynner, 2019).

[21] Robustness checks with occupation classifications based on task measures by Acemoglu and Autor (2011) suggest that young individuals also might be particularly affected by decreases in propensities to transition into routine employment in Switzerland. Another robustness check with task measures by Dengler et al. (2014), however, does not.

7 Conclusions

I investigate routine job dynamics in the Swiss labor market between 1992 and 2018 using individual-level panel data from the yearly Swiss Labour Force Survey. I find that routine cognitive employment has declined gradually through the entire study period and routine manual employment, though starting from a much lower initial share, started declining only after the recession in 2002. Examination of individual-level transitions between different labor market states unveils that decreasing inflow rates—rather than increasing outflow rates—are spurring these aggregate observations. Accordingly, Swiss routine work does not disappear through natural turnover. I identify decreases in inflows from non-routine manual employment, as well as from non-routine cognitive into routine manual and from non-participation into routine cognitive occupations as key drivers for the decline in routine employment. In turn, these diminishing inflow rates are predominantly driven by decreasing propensities to transition into routine employment, whereas demographic changes of the Swiss working age population play a minor role. For inflows from non-routine into routine occupations, these propensity changes appear to affect all demographic groups similarly, though workers with lower education are affected relatively more and those with higher education relatively less. However, the probability to enter the labor force by taking a routine cognitive job has specifically decreased for middle aged individuals and those with lower and medium education.

The study's findings somewhat differ from those of Cortes et al. (2020). US routine employment dropped significantly in the financial crisis and workers were decreasingly able to reenter routine employment from unemployment or non-participation in subsequent recovery years than in previous upturns, while routine decline in Switzerland happened rather gradually—and likely less individually traumatizing—through decreasing inflow rates into routine employment. In the USA, young individuals and those with medium education were particularly driving de-routinization, while in Switzerland individuals with low educational attainment were disproportionately affected. Also, my results show that non-routine manual employment decreased in Switzerland and the labor force is upgrading on the aggregate. However, with flows from routine into non-routine cognitive jobs unchanged, this upgrading is not happening 'directly'. In addition, the decreased propensities to "move up" from low-paid non-routine manual jobs to middle-wage routine cognitive occupations and the declined propensities to enter the labor force taking on a routine cognitive job for individuals with low or medium education might be worrying to policy makers.

The better understanding on how digital technology is affecting the Swiss labor market remains crucial in order to best prepare future workers for the labor market and—if necessary and sensible—retrain workers with decreasingly demanded skills. Interestingly, Pusterla and Renold (2022), who found that information and communication technology raises employment of high-skilled workers while reducing the share of low-skilled employees in Swiss firms, also observe that the possibility to aspire a high-quality tertiary vocational education and training—a rather characteristic feature of the Swiss education system—appears to allow workers that have not chosen an academic path to adjust relatively well to technological change. Certainly, the Swiss workforce has proven to be quite adaptable to the labor market effects of digital transformation so far. It remains to be seen how further technological advances will affect the demand for human labor—its heterogeneous effects thus far suggest that active policy might become increasingly appropriate to prevent undesired economic, political and societal consequences.

Appendix

Sub-decomposition

Take Eq. 8 and assume X_t^A is a set of two demographic variables, $x_{1,t}^A$ and $x_{2,t}^A$, with $\hat{\beta}_{1,t}$ and $\hat{\beta}_{2,t}$ as their respective estimated coefficients, and $\hat{\alpha}_t$ is an estimated regression constant. As in 5, we perform a Oaxaca-Blinder decomposition of the change in the aggregate transition rate between two points in time, t_0 and t_1:

$$
\begin{aligned}
\bar{\rho}_{t_0}^{AB} - \bar{\rho}_{t_1}^{AB} &= (X_{t_0}^A \hat{\beta}_{t_0}) - (X_1^A \hat{\beta}_{t_1}) \\
&= (\hat{\alpha}_{t_0} + x_{1,t_0}^A \hat{\beta}_{1,t_0} + x_{2,t_0}^A \hat{\beta}_{2,t_0}) \\
&\quad - (\hat{\alpha}_{t_1} + x_{1,t_1}^A \hat{\beta}_{1,t_1} + x_{2,t_1}^A \hat{\beta}_{2,t_1}) \\
&= \underbrace{\hat{\alpha}_{t_0} - \hat{\alpha}_{t_1}}_{\text{(i)}} \\
&\quad + \underbrace{(x_{1,t_0}^A - x_{1,t_1}^A)\hat{\beta}_{1,t_0}}_{\text{(ii)}} + \underbrace{(x_{2,t_0}^A - x_{2,t_1}^A)\hat{\beta}_{2,t_0}}_{\text{(iii)}} \\
&\quad + \underbrace{(\hat{\beta}_{1,t_0} - \hat{\beta}_{1,t_1})x_{1,t_1}^A}_{\text{(iv)}} + \underbrace{(\hat{\beta}_{2,t_0} - \hat{\beta}_{2,t_1})x_{2,t_1}^A}_{\text{(v)}}.
\end{aligned}
\tag{9}
$$

We see that the decomposition actually allows to distinguish between *individual* composition components, terms (ii) and (iii), and *individual* propensity components, terms (i), (iv) and (v), of the total change. Accordingly, term (i) reflects propensity changes irrespective of (available) demographic characteristics and terms (iv) and (v) reflect propensity changes of groups with specific attributes, x_1^A and x_2^A, respectively. Similarly, terms (ii) and (iii) are the components attributed to changes in the composition of individuals in labor market state A in regards to attributes x_1^A and x_2^A, respectively.

Additional tables and figures

See Tables 6, 7, 8, 9, 10 and Figs. 5, 6, 7.

Table 6 Task Examples by Task Category

Task category	Work tasks
Routine Cognitive	Controlling balance sheets, operating cash registers, operating office computer equipment, scanning, photocopying and faxing documents, secretarial works, correcting data, compiling inventories, changing money, entering data into databases
Routine Manual	Operating stationary machinery, making standardized products, assembling prefabricated parts and components, sorting and storing produce, processing of agricultural produce
Non-Routine Abstract	Researching, designing, planning, providing medical treatment and care, using advanced software, creating art, investing, studying
Non-Routine Interactive	Advising, consulting, teaching, training, negotiating, entertaining, acting, preaching, interviewing, representing organizations, recruiting
Non-Routine Manual	Making involving craft and handwork (e.g., jewelry, carpentry, musical instruments), operating cranes or excavation machines, driving, painting buildings, cooking, serving drinks and food, cleaning, hair styling, patrolling, providing personal care and assistance

Examples taken from Mihaylov and Tijdens (2019).

Table 7 Control Variables and Levels

Variable	Levels
Age Group	15–29; 30–49; 50–65
Education	Compulsory School; 'Anlehre' (basic apprenticeship); Household apprenticeship, commercial school 1–2 years; Secondary school, general education School; Vocational apprenticeship; Full-time vocational school; Matura, teacher training college; Higher vocational training; University
Sex	Female; Male
Nationality	Swiss citizen; foreign citizen
Greater Region of Residence (NUTS-2)	Lake Geneva Region; Espace Mittelland; Northwestern Switzerland; Zurich; Eastern Switzerland; Central Switzerland; Ticino

Table 8 Education Level Categorization

Education Level	1992–2009: SLFS-classification	2010–2013: ISCED-97-codes	2014–2018: ISCED– 11-codes
Low	Mandatory school or pre-vocational education	10, 11, 21: Primary education, basic education, lower secondary education	1, 2: Primary and lower secondary education
Medium	Commercial school, diploma secondary school, general education school, vocational apprenticeship, full-time vocational school, high-school diploma, teacher training school	31, 32, 33, 34, 35, 41: Upper secondary education, Post-secondary non-tertiary education	3: Upper secondary education
High	Higher vocational training, graduates of universities or universities of applied science	51, 52, 61: Tertiary education	6 and above: Bachelor's degree or equivalent, Master's degree or equivalent, Doctorate, Habilitation or equivalent

I used the most recent ISCED-codes where available. For 1992–2009 data the SLFS's own education classification was used, in 2010 the ISCED-07 classification was introduced, in 2014 the ISCED-11 classification. "No education" was not recorded before 2014 and I therefore refrain from assigning it to any of the education categories

Table 9 Most frequent occupations by Labor Market State

Labor market state	ISCO-Code	Occupation title	Share 2018 (in %)	Share 1992 (in %)
Routine Cognitive	4110	General office clerks	3.92	9.65
	4120	Secretaries (general)	2.18	5.22
	3313	Accounting associate professionals	1.41	1.07
	5222	Shop supervisors	1.29	0.36
	3343	Administrative and executive secretaries	1.00	0.53
	8332	Heavy truck and lorry drivers	0.85	0.40
	4321	Stock clerks	0.62	0.98
	5230	Cashiers and ticket clerks	0.42	0.33
	4312	Statistical, finance and insurance clerks	0.39	0.25
	3111	Chemical and physical science technicians	0.37	0.69
Routine Manual	7512	Bakers, pastry-cooks and confectionery makers	0.40	0.51
	7511	Butchers, fishmongers and related food preparers	0.27	0.40
	4412	Mail carriers and sorting clerks	0.24	0.45
	8160	Food and related products machine operators	0.24	0.32
	7322	Printers	0.19	0.60
	7549	Craft and related workers not elsewhere classified	0.18	0.20
	8131	Chemical products plant and machine operators	0.14	0.30
	8183	Packing, bottling and labeling machine operators	0.14	0.17
	7223	Metal working machine tool setters and operators	0.13	0.40
	7222	Toolmakers and related workers	0.12	0.69
Non-Routine Cognitive	5223	Shop sales assistants	4.19	5.02
	3221	Nursing associate professionals	2.54	2.77
	2330	Secondary education teachers	2.37	2.16
	2512	Software developers	1.89	0.23
	5120	Cooks	1.87	1.06
	2422	Policy administration professionals	1.74	0.32
	3324	Trade brokers	1.56	0.99
	1221	Sales and marketing managers	1.41	0.36
	2341	Primary school teachers	1.40	2.13
	1120	Managing directors and chief executives	1.28	1.60
Non-Routine Manual	5131	Waiters	1.46	1.76
	5153	Building caretakers	1.15	0.97
	7231	Motor vehicle mechanics and repairers	0.98	0.95
	7115	Carpenters and joiners	0.95	0.90
	7412	Electrical mechanics and fitters	0.93	1.39
	5322	Home-based personal care workers	0.85	0.61
	7411	Building and related electricians	0.85	0.37
	7126	Plumbers and pipe fitters	0.83	1.11
	5321	Health care assistants	0.80	1.05
	6113	Gardeners, horticultural and nursery growers	0.71	0.79

Shares of employed workers in the respective years.

Source: Swiss Labour Force Survey, 1992–2018

Table 10 Comparison Phases

Phase τ	t_0	t_1
I: 1992–2001	1992	2000
II: 2002–2008	2001	2007
III: 2009–2018	2008	2017

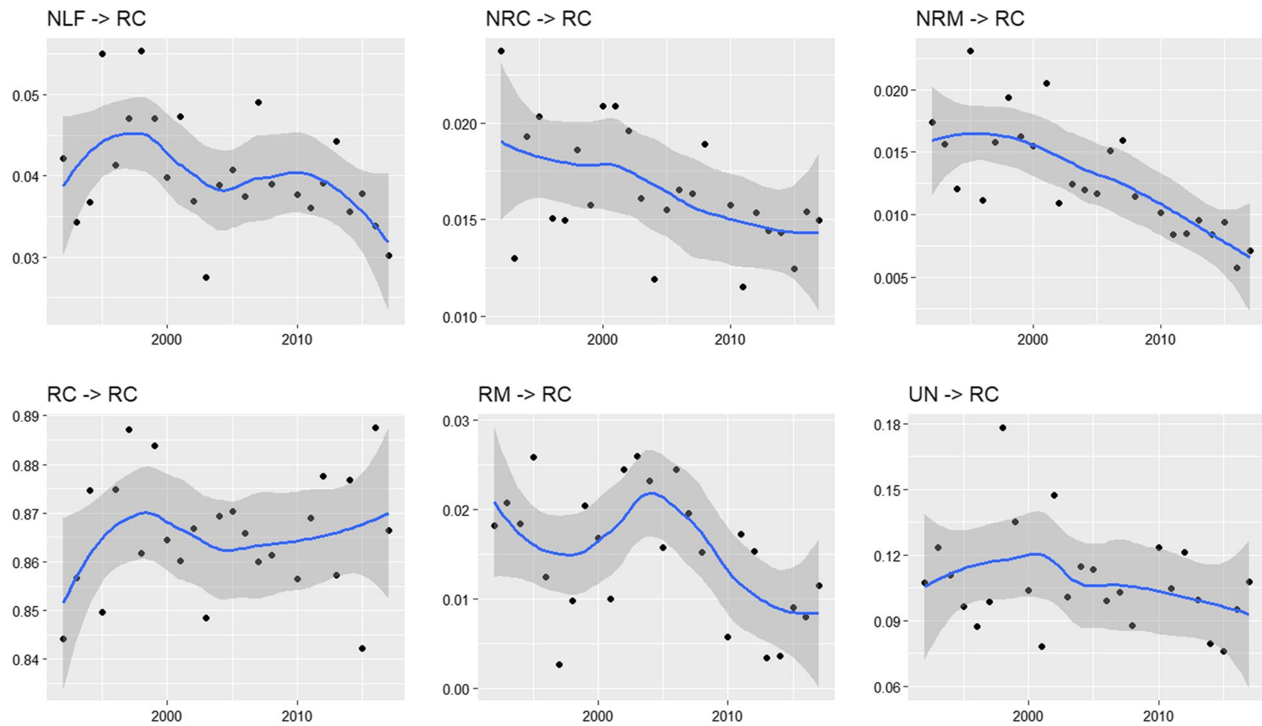

Fig. 5 Transition Rates for Inflows into Routine Cognitive Jobs. Notes: Transition rate computation is explained in chapter 3.2, blue lines show local regression lines, and the gray area marks the 95% confidence interval. The figure also includes the stayer rate (RC → RC), the share of routine cognitive workers remaining in routine cognitive employment. Source: Swiss Labour Force Survey, 1992–2018

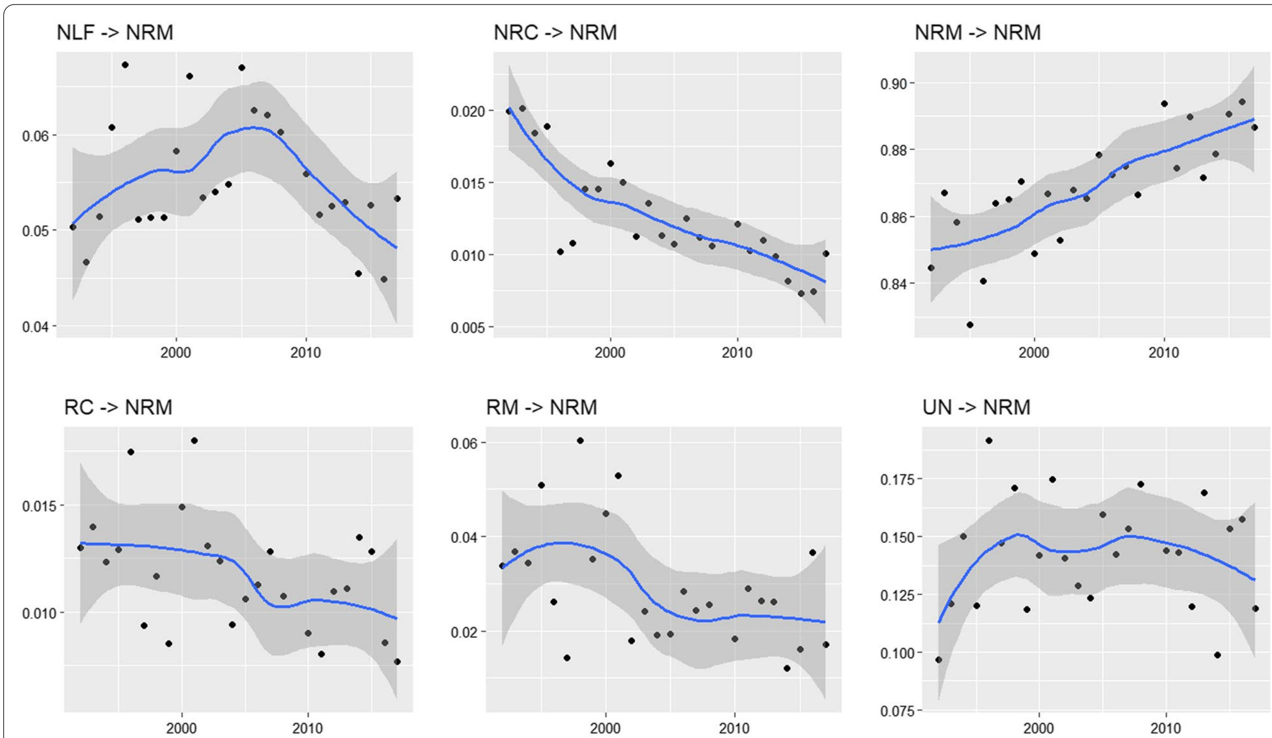

Fig. 6 Transition Rates for Inflows into Non-Routine Manual Jobs. Notes: Transition rate computation is explained in chapter 3.2, blue lines show local regression lines, and the gray area marks the 95% confidence interval. The figure also includes the stayer rate (NRM → NRM), the share of non-routine manual workers remaining in non-routine manual employment. Source: Swiss Labour Force Survey, 1992–2018

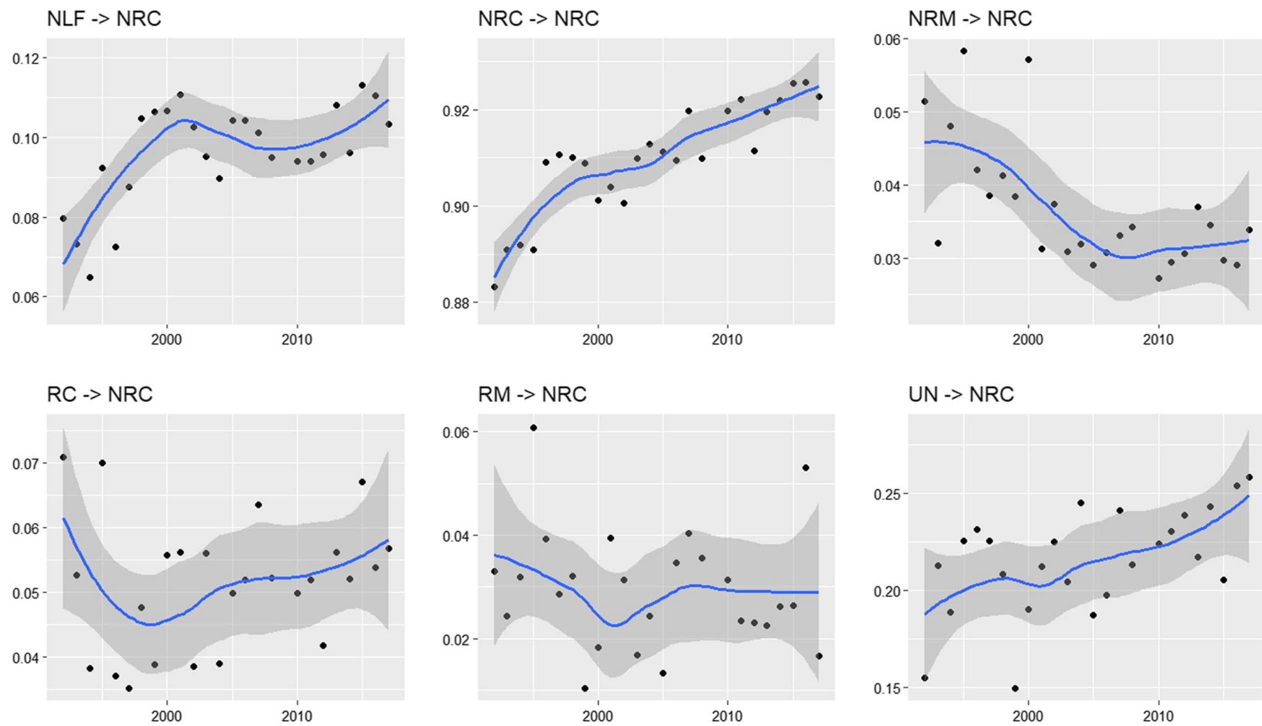

Fig. 7 Transition Rates for Inflows into Non-Routine Cognitive Jobs. Notes: Transition rate computation is explained in chapter 3.2, blue lines show local regression lines, and the gray area marks the 95% confidence interval. The figure also includes the stayer rate (NRC → NRC), the share of non-routine cognitive workers remaining in non-routine cognitive employment. Source: Swiss Labour Force Survey, 1992–2018

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Availability of data and materials
The data used in this study, namely the Swiss Labour Force Survey, are available upon request from the Swiss Federal Statistical Office (http://www.slfs.bfs.admin.ch).

Declarations

Competing interests
The author declares that he has no competing interests.

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