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Task content routinisation, technological change and labour turnover: Evidence from China

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Abstract

This article addresses the unresolved question of whether recent technological change causes job instability in a non-western context. China is now the world's largest user of industrial robots. A Lewis turning point has been predicted, involving a transition from a plentiful supply of rural low-cost workers to a labour shortage economy in which rising labour costs drive labour-technology substitution. The routine-biased technological change hypothesis suggests that technology-induced routinisation in job task content has a profound impact on employment structure. This study captures the extent of routinisation of jobs in the transitional context of China and examines the incidence and impact of routinisation on labour turnover in the labour market. Using rotating panel data from the China Labour-force Dynamics Survey 2012, 2014 and 2016, this study, based on individual information with regard to flexibility in work schedules and degree of autonomy in workload and task content on the job, follows a recently developed measure to construct a routine intensity index and indicates a division into three routine intensity groups. The empirical findings show that the probability of job mobility is significantly increased with the magnitude of routine task intensity, suggesting that the process of technology-induced routinisation is strongly associated with labour turnover.

JEL Codes: J63, J20

Keywords

Chinese labour market, labour turnover, Lewis turning point, routine intensity index, routine-biased technological change, routinisation, skill-based technological change

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Introduction

The previous literature on measuring the employment impact of technological change mainly involves rich countries (Piva and Vivarelli, 2018). There is, however, relatively less on developing countries and particularly little on China. As the largest user of industrial robots in the world, China's leading role in artificial intelligence (AI) application areas has drawn worldwide attention, and the central government is providing all-round support to digital technology and AI development, which will provide more convenience and opportunities for firms to complete the labour-technology substitution. In the meantime, in the process of China's economic transition with the arrival of a Lewis turning point, the serious labour shortage and the continuous rise of labour costs also give a direct and strong motivation to firms to implement labour-saving technology for cost minimisation. Thus, a question which is worthy of study naturally arises: whether the recent technological change causes job instability in a non-western context. This study attempts to answer this question and to investigate technology-induced job losses in China.

The nexus between technology and employment is a 'classical' and still inconclusive controversy. The major worries about unemployment stress stem from the direct impact of labour-saving process innovation. Virtually, there are different market compensation mechanisms exerting a labour augmenting effect and indirectly counterbalancing the initial job losses via various channels, such as the 'introduction of new machines' (Say, 1964 [1803]), the 'decrease in prices (Steuart, 1966 [1767]) and the 'increase in incomes' (Boyer, 1988; Pasinetti, 1981). However, the actual effectiveness of these compensation mechanisms is much affected by different parameters and the different institutional and economic contexts (Van Roy et al., 2018; Vivarelli, 2013).

In addition, although product innovation has a positive impact on employment growth due to its labour-friendly nature, this impact may not be assuredly effective because the introduction of new products may cause the displacement of old products (Barbieri et al., 2019; Vivarelli, 2013) and the decrease in employment will occur if the innovating firm has a monopoly power (Lachenmaier and Rottmann, 2011). Theoretical work cannot give a clear-cut answer about the overall employment effect of technological change, which calls for more empirical assessments. Interestingly enough, the existing empirical analyses (at the country, sectoral or firm levels) with consideration of different conceptual coverage, methods as well as specifications, also present inconsistent findings.

Technological change may show a skill-biased nature, leading to a shift in the market demand for workers with specific skills to varying extents. In the context of the skill-biased technological change (SBTC) hypothesis, labour demand shifted away from the unskilled towards the skilled (Katz and Murphy, 1992), which explains the changes in the employment structure in many developed countries during the 1980s (Berman et al., 1998). The routinisation or routine-biased technological change (RBTC) hypothesis proposed by Autor et al. (2003) which is seen as a nuanced version of the SBTC hypothesis describes that unemployment stress and the substitution effect induced by technological progress are greater for routine jobs or occupations with a high concentration of medium-skilled workers. Thus, employment shares expand at both the top and the bottom of the skill distribution and contract in the middle in the meantime, presenting a polarising pattern instead of the monotonic skill upgrade predicted by the SBTC.

The focus of the RBTC hypothesis is the task content of jobs or occupations: non-routine versus routine. The former can be further divided into two categories, namely, abstract and manual task contents. Workers in abstract tasks, such as managers and professionals, similar to the definition of skilled workers in SBTC, are complementary with technological changes. Workers in manual tasks, such as waiters and personal service workers at the lower tail of both the skill and wage distributions, are required to have interpersonal skills and adaptability, both of which can hardly be performed by machines. The direct technology-induced displacement of workers in abstract and manual tasks is quite limited. By contrast, workers in routine task-intensive jobs/occupations – that is, ones involving a high level of tasks that can be accomplished by a set of codable instructions or repeatedly performed without thinking – would be relatively easily replaced by well-designed computer programmes or automatic machines. Indeed, technological deepening will accelerate to reduce the cost of new technology adoption and to increase the likelihood of transitioning to unemployment or job mobility.

The contributions of the current study are twofold. First, this study constructed a routine intensity index (RII) following a recently developed measure proposed by Marcolin et al. (2019) to capture the extent of the routinisation of jobs in the transitional context of China. Most of the extant literature regarding the routinisation of job content mainly examines such issues in the context of developed countries and follows out the taxonomies of routinisation based on scores assigned by occupational analysts or experts according to the US labour market; however, due to various phases of economic as well as technological development, among others, this taxonomy, which is suitable for US occupations, may not apply to other countries (Marcolin et al., 2019; World Bank, 2019), especially developing countries. Thus, this study was based on individual information concerning flexibility in work schedules and the degree of autonomy in workload and on-the-job task content, provided a relatively more accurate routinisation index suitable for China's labour market and contributed to the existing literature concerning routinisation by providing evidence from the world's largest developing country.

Second, this study contributes to the empirical literature on the employment effect of technological change through using the recent survey data to capture the impact of technology-induced routinisation on labour turnover. Prior literature empirically checks the employment effect of technological change mainly through adopting the model in which the employment rate at the country or sector level, or the number of employees at the firm level is regressed on the innovation variables (such as, R&D (research and development) expenditures or patent counting), among others. The current study, from the perspective of the 'victims' of technological change, utilises the aforementioned method to identify the group of workers whose task contents on the job have the highest likelihood of being routinised by technological progress and further measures the likelihood of leaving his or her job over a certain period of time. To the best of the authors' knowledge, this study is the first to investigate the connection between the routinisation of job content and labour turnover in China's labour market.

The remainder of this article is organised as follows. Section 'Previous literature evidence' reviews previous empirical work. Section ' Methods' describes the dataset, the measurement of the routine intensity indicator and the empirical methodology. Section 'Analytical approach' presents the descriptive statistics about the variables considered as well as the routine intensity groups consisting of different two-digit occupations. Section 'Results' presents the empirical findings, and section 'Discussion and conclusion' concludes the present paper.

Previous literature evidence

In view of the discussion in the prior section, much empirical work concerning the relationship between employment and technological change can be broadly divided into two strands.

The first strand involves analysing the effects of technology on overall employment levels. Country-level studies have mainly involved testing the efficacy of compensation mechanisms (e.g., Layard and Nickell, 1985; Simonetti et al., 2000; Sinclair, 1981; Vivarelli, 1995). Studies at the sectoral level largely consider the heterogeneity in the labour-saving (augmenting) nature of process (product) innovation between the sectors and between the high-tech (the knowledge-intensive) and the low-tech (the traditional) within the sector (see, for example, Bogliacino and Pianta, 2010; Bogliacino and Vivarelli, 2012; Coad and Rao, 2011; Mastrostefano and Pianta, 2009; Piva and Vivarelli, 2018). The empirical analyses, based on firm-level data recording the specific innovative activities for the firm-level mapping of innovation variables, provide consistent evidence of the labour-friendly impact of product innovation while the effects of process innovation vary across methods and countries (Greenan and Guellec, 2000; Harrison et al., 2014; Lachenmaier and Rottmann, 2011; Piva and Vivarelli, 2004, 2005; Van Roy et al., 2018).

The second strand of literature is more about exhibiting the skill-biased nature of technological change, measuring the impact on the employment structure and mapping the changing pattern of employment (from upgrading to polarisation). As the seminal paper of empirically checking the SBTC hypothesis, Berman et al. (1994) present an increase in skilled labour demand in the 450 US manufacturing sectors during the 1980s and find evidence of a positive relationship between R&D and the increasing share of skilled labour. Autor et al. (2006) find the similar results including nonproduction sectors in the US and present a skill upgrading pattern of employment change over the period 1940–1996 with rapid diffusion of computers. By the same token, a substantial body of empirical literature presents consistent evidence for the pervasive SBTC hypothesis in developed countries, such as Betts (1997) and Gera et al. (2001) for Canada; Machin (1996) and Haskel and Heden (1999) for the UK; Falk and Koebel (2004) for Germany; Goux and Maurin (2000) and Mairesse et al. (2001) for France; and Casavola et al. (1996) and Piva and Vivarelli (2002) for Italy.

Differently from the SBTC hypothesis in which technological progress is unfavourable to workers with low human capital, the emphasis of the recent RBTC hypothesis is more on the substitutability between technological change and routine tasks. In the seminal paper on this issue, Autor et al. (2003) define different task contents of occupations based on the variables in the US Department of Labor's Dictionary of Occupational Titles (DOT) and provide evidence that the falling cost of computerising routine tasks is the crucial driving force behind declined labour input in routine tasks. Similar employment phenomenon has been widely documented in developed countries (see, for example, Acemoglu and Autor (2011) and Autor and Dorn (2013) for the US; Montresor

(2019) and Salvatori (2018) for the UK; Fonseca et al. (2018) for Portugal; Kampelmann and Rycx (2011) and Spitz-Oener (2006) for Germany; and Goos and Manning (2007) and Michaels et al. (2014) for Europe). Furthermore, combining with world input-output tables, Reijnders and de Vries (2017) use the new harmonised cross-country occupation database to provide evidence of the hollowed-out structure of employment in many developing countries.

The technology-induced detrimental effect or displacement effect may bring back the fear of the Luddite riots. Manyika et al. (2011) indicated that approximately 44% of firms in the US had reduced headcounts due to automation. Frey and Osborne (2017) estimated that approximately 47% of jobs in the US are at risk of being automatable, and the World Bank (2016) gave a similar conclusion, indicating that approximately 60% of jobs would suffer the same fate in Organisation for Economic Cooperation and Development (OECD) countries before long. In addition, with continuous technological advancements, such as the digitalisation revolution and AI, technological deepening will widen the scope of being routinised along with the occurrence of technological breakthrough. Manyika et al. (2017) further predict that more than 30% of task content will be automatable within approximately 60% of occupations in the US by 2055. Frey and Osborne (2017) predict that many occupations would be wiped out. Although many studies argue that this displacement effect could be counterbalanced by different forces. However, for laid-off workers, retooling is costly to be competent to carry out the new job or task (World Bank, 2019), and these counteracting forces seem to take effect in the long term. Thus, job instability seems to be inevitable, at least in the short term.

Methods

Data

The data used in this study are from the China Labour-force Dynamics Survey (CLDS), which is a nationally representative dataset that covers 29 provinces distributed across eastern, central and western China. The CLDS started in 2012 and was then biennially conducted by Sun Yat-sen University with the probability proportional to size sampling strategy. Data collection of the CLDS follows a rotating panel design. Targeted respondents are tracked and interviewed for four consecutive waves (6 years in total) of the survey and are permanently retired from the sample afterwards. The CLDS records the dynamic information about individuals' social and economic behaviours, employment status and labour mobility, among others, if individuals are followed in at least two consecutive waves of the survey. The targeted respondents who are unable to be tracked will be replaced by new ones from the same stratum in the follow-up. Taking the new samples added in each wave of the survey into account to minimise losses in the samples of the original rotation group, this study built a database of individuals who were interviewed in two consecutive waves of the survey. Currently, except for the baseline survey, data are also available for 2014 and 2016, which formed two groups of samples, namely, the 2012–2014 group and the 2014–2016 group.

Because this study focuses on whether workers who perform a high degree of routine tasks on the job have an increased likelihood of being unemployed or changing jobs relative to those whose jobs are non-routine or less routine-intensive during a given period, the dependent variables are self-reported employment status[1] (dummy variable, which is 1 if a person in a paid job in 2012 (2014) still worked in 2014 (2016) and 0 otherwise) and job status (categorical variable, which is 1 if a person stayed in his or her job in the 2012–2014 and 2014–2016 periods, 2 if a person in a paid job in 2012 (2014) became unemployed in 2014 (2016) and 3 if a person was a job-to-job mover in the same time intervals). Thus, this study is restricted to full-time workers who had been recorded in a wave of the survey, who were aged between 15 and 60, who were receiving wages, who were employed in non-agricultural as well as in non-military jobs, and who reported their employment status and job information in the follow-up wave. Those whose self-reported reasons of being unemployed in the follow-up wave are family roles, retirement, bad health condition and returning to school are excluded. Following the extant literature, the variables include individual characteristics (age, gender, marital status, occupation, residential registration status (Hukou), education and foreign language proficiency) and employer characteristics (industry, ownership and location (province)). Any samples with missing information concerning the aforementioned factors are excluded as well.

RII measurement

To investigate the changes in routine and non-routine employment, that is, the impact of the RTBC on the labour market outcomes, the task measure proposed by Autor et al. (2003) is widely used. However, this measure depends on ad hoc choices of variables featuring the task content of each occupation which may lead to imprecision due to the time-invariant setting of task content (Marcolin et al., 2019; Salvatori, 2018). Another way of measuring routine and non-routine occupations is to directly categorise occupations into different task groups without calculating the level of different tasks performed in occupations. Salvatori (2018) argued that such coarse categorisation may miss some information related to the automated 'ability' of work content.

A recently developed measure proposed by Marcolin et al. (2019) known as the RII could help to alleviate the time-invariant relevance of ad hoc choices of task variables and coarse categorisation. The measure constructs a new index depending on the pointed questions and individual reports in the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey rather than on scores assigned by occupational analysts or experts in the DOT. These questions are, namely, the extent to which workers can decide on the sequence and the type of tasks on the job, as well as the frequency of planning their own activities and organising their own time on the job. The individuals' answers, on the one hand, reflect the flexibility of the tasks and the degree of autonomy that correspond to the nature of automation and other labour-saving technologies – that is, to replace human work with more and simpler options following the specified procedures but less space for workers to determine in the process. On the other hand, the individuals' answers capture the most recent trend of potential automation of current task content. In addition, Marcolin et al. (2019) indicated that using individual information of such questions can take into account the latent unobserved phenomenon, that is, the unobserved task contents, and thereby obtain a relatively more precise proxy for the routine intensity group.

Following Marcolin et al. (2019), this study will make use of similar questions in the CLDS survey to derive the RII. In CLDS, the workers were asked about the degree of autonomy they possessed on the job to determine their workload, work schedule and task contents. Three questions are based on a 3-point scale. The higher the score is, the lower the degree of freedom possessed by workers. Thus, according to variables of interest in this study, equation (1) can be rewritten as follows

$$RII_{io} = w_{load}Workload_{io} + w_{sch}Schedule_{io} + w_{con}Content_{io} \tag{1}$$

where Workload, Schedule and Content correspond to the three variables mentioned above for the individual i in occupation o. The correlation between the sum of these three questions and an underlying latent variable that is an indicator of routine intensity in the worker's job is 87.5%, indicating that the three questions have relatively high internal consistency and strong power in explaining the underlying factor.[2] For the selection of weight and the functional form, this study is in line with previous studies (see, for example, Autor et al., 2003; Goos et al., 2014; Heyman, 2016), assigning weights derived from the principal component analysis (PCA) and setting an additive functional form.[3] The obtained RII value ranges from 1 to 3, and higher RII values correspond to a higher level of routine intensive tasks performed by the worker on the job. Each worker will be given a unique RII value. The level of occupational routine intensity could be derived from averaging the individual RII values at the two-digit occupational level, which can then be used to rank and map these occupations into different routine quartiles. Specifically, occupations falling into the top 25% of routine intensity are characterised as high-routine occupations (HR), and correspondingly, those occupations would be considered non-routine occupations (NR) if they were allocated into the bottom quartile. The remaining occupations in the middle represent medium-routine occupations (MR).

Analytical approach

This study aims to analyse the relationship between labour turnover and technological changes, particularly for technology-induced routinisation in task content. To fulfil the objective and observe the dynamics of the labour market, this study first adopted a probit regression in which labour turnover is regressed on a set of demographic characteristics and other control variables for worker i. The probit model estimated in the current study is of the following reduced form

$$Prob\left(Turnover_i^t\right) = \Phi\left(\alpha^t + \sum_j T_{ij}^t \theta_j^t + X_i^t \xi + Z_i^t \beta\right) \tag{2}$$

where $Turnover_i^t$, a binary variable, is equal to 1 if the workers stayed at the same job between two adjacent waves of the survey and 0 if the workers changed jobs as well as remained unemployed after leaving in the follow-up wave, which corresponds to the mutually exclusive state of 'job-to-job' and 'job-to-unemployment' transitions, relative to the base of 'staying' in the same job with the same employer of the individual worker

i. As aforementioned, by the time of this study, only three waves of the CLDS (2012 for the baseline, 2014 and 2016) have been finalised and issued. Thus, the subscript t means the period interval 2012–2014 and 2014–2016, respectively. T_{ij}^{t} is the occupation selection indicator on the basis of routine quartile, which is equal to 1 if the workers were in the occupation $j \in \{NR, MR, HR\}$ at one period interval and 0 otherwise. X_i^t is a vector of demographic variables and Z_i^t is a vector of employer characteristics. Furthermore, there would be a difference between the propensities of workers who stayed unemployed and those who changed their jobs relative to those who worked for the same employer consistently throughout the period. To further investigate the routinisation-induced job losses, this study ran a multinomial logit (MNL) regression. The linear model can be expressed as follows

$$log\left(\frac{Pr\left\{Y_i = k|T_{ij}, X_i, Z_i\right\}}{Pr\left\{Y_i = reference|T_{ij}, X_i, Z_i\right\}}\right) = \gamma_{0k}^{t} + \sum_j T_{ijk}\vartheta_{jk} + X_{ik}\zeta_k + Z_{ik}\rho_k \tag{3}$$

where $Pr\{Y_i = k \mid T_{ij}, X_i, Z_i\}$ means the probability of the ith individual entering into the kth state, conditional on considered explanatory variables; and $Y_i = reference$ means that one of the employment states is regarded as the reference group. The explanatory variables here are identical to those in equation (3). The subscript t is omitted for simplicity.

Results

Descriptive analysis

In this section, the current study lists occupational classification by routine quartiles based on the method introduced in the previous section, illustrates the descriptive facts about their employment shares over time and distributions with regard to considered variables, and then presents the summary statistics of characteristics of employers and workers.

In Table 1, the RII values of occupations are ranked in ascending order. Occupations are categorised into three routine intensity groups, namely NR, MR and HR, depending on which of the routine quartiles their RII values fall into. The results are similar to the reports in the previous research. The NR intensity group, as expected, contains occupations that involve advanced cognitive skills and the creative ability required to perform on the job; these occupations are closely related to the high degree of autonomy. MR-intensive occupations are more diversified relative to NR and HR. In particular, service-related occupations are classified into this group due mainly to the job requirement of social skills that endow workers with a certain degree of autonomy. By contrast, assemblers, operators and production workers are mainly allocated into the HR-intensive group.

Figure 1 shows the educational composition of employment in each occupational routine group. According to the mechanism of job polarisation, the shrinking employment share in the middle of the skill distribution is attributable to the strong relationship between middle-skill jobs and routine intensity. As shown in Figure 1, the majority of

Table 1. Occupational classifications by routine quartiles.

Classification	Occupations	RII	Percent
Non-routine intensity	Leaders of GPPS and enterprises	1.8975	3.96
	Sales and purchasing personnel	1.9305	8.98
	Business/finance personnel	2.0457	5.57
	Engineers, technicians and science researchers	2.0619	2.42
	Other professionals	2.0905	1.46
	Teaching personnel	2.1007	5.90
	RFT personnel, art designers	2.1143	1.17
	Technical workers	2.1333	0.51
	Other business service personnel	2.1601	2.37
Medium routine intensity	Medical technicians	2.1627	2.12
	Office clerks	2.1825	7.44
	Occupation not elsewhere classified	2.1920	1.47
	Catering service personnel	2.1980	4.28
	Construction workers	2.2042	7.53
	Glass and ceramics plant operators	2.2077	0.94
	Social service and residential service personnel	2.2167	5.59
	Garment and related workers	2.2466	3.06
High routine intensity	Warehouse staffs	2.2488	1.58
	Other production workers	2.2518	0.86
	Postal and telecommunication services personnel	2.2685	1.26
	Building material production and processing workers	2.2762	1.88
	Mechanical process operators	2.2797	1.73
	Transportation services staffs	2.2934	3.18
	Auxiliary workers	2.2996	4.49
	Rubber/plastic product workers	2.2997	0.56
	Electromechanical assemblers	2.3139	2.65
	Metal casting operators	2.3431	0.91
	Knitting, dyeing and textile-related workers	2.3466	0.95
	Electrical equipment operators	2.3480	1.32
	Transportation equipment operators	2.3558	7.36
	Electronic components and related workers	2.3983	1.36
	Personal and protective workers	2.4445	3.46
	Chemical plant operators	2.4688	0.58
	Labourers in mining	2.5201	1.07

RII: routine intensity index; GPPS: Party organisations, Public institutions, Government and Social organisation; RFT: radios, films and television.
Percent means the employment share of each occupation and percentages add up to 100. Two-digit occupational codes of NSOCC are used.

workers with tertiary education dealt with NR-intensive tasks on the job throughout the period; however, the tertiary education employment share in the NR group slightly decreased. Workers with primary education who were evenly distributed into the MR and HR groups in 2012 became relatively more concentrated in the MR group than in the

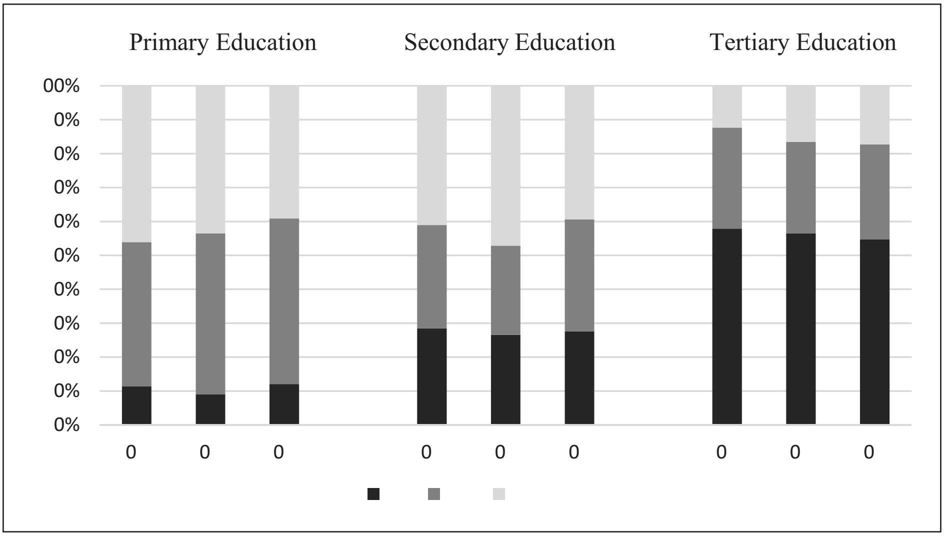

Figure 1. Routine employment share by education level, CLDS 2012, 2014 and 2016.
NR: non-routine employment; MR: medium-routine; HR: high-routine.

HR group in 2016. Likewise, although certain percentages of employees with secondary educational attainment undertake NR- and MR-intensive jobs, most of them are concentrated in the HR intensity group. Figure 2 plots the changes in the employment share by routine quartiles between 2012 and 2014. The HR-intensive employment share increased slightly until 2014, after which it dropped rapidly, while the share of MR jobs had a reverse change. The share of NR jobs, in contrast, consistently increased throughout the period.

Table 2 (columns 1–3) presents the summary statistics of some key variables considered in the analysis for each sample year. Variables are available in all CLDS in 2012, 2014 and 2016. The exclusions mentioned in the previous section yielded a sample of 4061, 5640 and 5515 individuals for 2012, 2014 and 2016, respectively. The sample was composed of workers with a mean age of approximately 38 years. A majority of these wage earners were males (approximately 57%) through the period, and more than 70% of workers lacked foreign language skills. As a form of human capital, those with a strong written and verbal command of a foreign language were seen as reflecting relatively higher personal abilities. Another important form of human capital is education. Workers had an average of 10.1 years of schooling in 2012, and this figure became slightly higher in 2014 as well as in 2016. In addition, there was a gradual decline in employment in the manufacturing sector over time. Columns 4 and 5 report the statistics of samples that were continuously tracked in 2014 and 2016, respectively, and fit the present analysis. In total, 3761 workers were followed in two consecutive waves of the survey (1782 from the 2012–2014 sample and 1979 from the 2014–2016 sample). Table 3 further provides another perspective, presenting the means of individual characteristics and sample distributions of RII groups, ownerships and other factors,

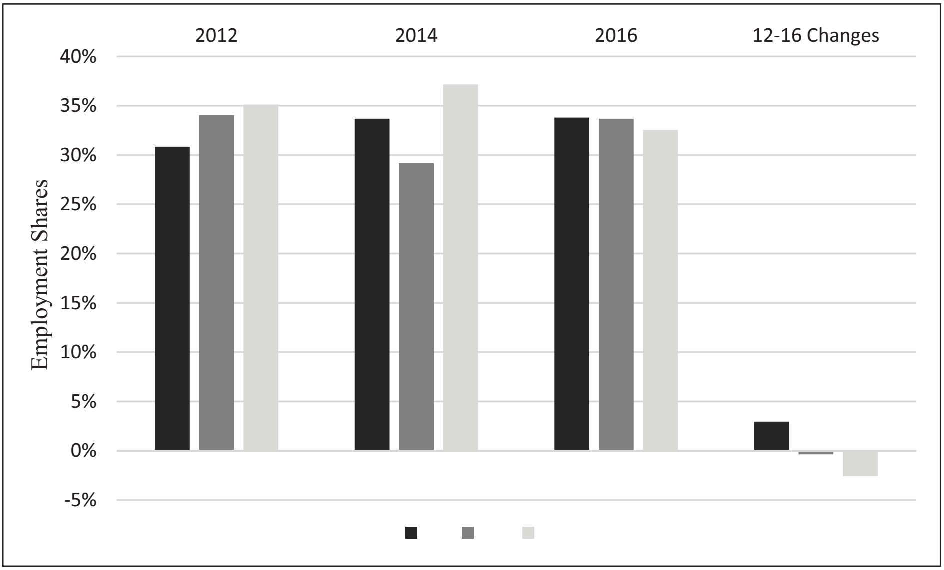

Figure 2. Trends and changes in employment based on routine intensive groups, CLDS 2012, 2014 and 2016.

considering the situations in which all individuals were actively employed in the initial wave of the survey, and then may turn into three different statuses in the follow-up: job stayers, job-to-job movers and job-to-unemployment movers. The follow-up wave will proceed for the targeted respondents after 2 years, which can record the dynamics in the labour market and the transition behaviours of tracked workers.

In Table 3, more than three-quarters of workers stayed in the same job with the same employer between two adjacent waves of the survey. The proportions of those who became unemployed in the second wave were twice as high as those of workers who changed the jobs in both sample intervals. For the 2012–2014 sample, most job stayers and job-to-unemployment movers were workers who mainly performed MR-intensive tasks on the job, while workers in the HR-intensive group dominated the three statuses in the 2014–2016 sample. This finding probably shows that routinisation-driven structural changes were just beginning to challenge the stability of the labour market of China via aggravated labour turnover, which reinforces the importance of the current study in investigating the relationship between routinisation and future job turnover.

Empirical analysis

In this section, the empirical results present the impact of technology-induced routinisation on labour turnover, specifically job-to-job and job-to-nonemployment transitions. In addition, this analysis is extended to investigate changes in labour participation for different routine intensity groups over time.

Table 2. Descriptive statistics of individual and employer characteristics.

Variable (years)	2012	2014	2016	2012–2014	2014–2016
Age	38.039	38.732	39.089	40.401	40.762
	(10.409)	(10.456)	(10.644)	(9.683)	(10.005)
Age^2/100	15.553	16.094	16.412	17.260	17.616
	(8.089)	(8.190)	(8.323)	(7.780)	(8.094)
Male	0.567	0.565	0.565	0.566	0.562
	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)
Language skill	0.281	0.243	0.234	0.252	0.215
	(0.450)	(0.429)	(0.423)	(0.434)	(0.411)
Urban	0.478	0.524	0.440	0.497	0.502
	(0.500)	(0.499)	(0.496)	(0.500)	(0.500)
Education	10.126	11.496	11.068	9.967	11.164
	(4.612)	(3.717)	(3.666)	(4.617)	(3.692)
Tenure	16.205	9.280	9.872	11.596	10.008
	(10.709)	(9.413)	(9.614)	(10.481)	(9.778)
Manufacture	0.289	0.248	0.227	0.269	0.266
	(0.454)	(0.432)	(0.419)	(0.444)	(0.442)
Service	0.544	0.528	0.543	0.544	0.505
	(0.498)	(0.499)	(0.498)	(0.498)	(0.500)
Others	0.166	0.224	0.230	0.186	0.228
	(0.373)	(0.417)	(0.421)	(0.389)	(0.420)
State-owned	0.199	0.220	0.169	0.241	0.224
	(0.399)	(0.414)	(0.375)	(0.428)	(0.417)
Collective	0.184	0.134	0.105	0.199	0.140
	(0.387)	(0.340)	(0.306)	(0.400)	(0.347)
Private	0.403	0.421	0.406	0.355	0.398
	(0.491)	(0.494)	(0.491)	(0.479)	(0.490)
Foreign	0.058	0.054	0.039	0.049	0.044
	(0.234)	(0.226)	(0.193)	(0.217)	(0.206)
Others	0.156	0.171	0.281	0.155	0.194
	(0.363)	(0.377)	(0.450)	(0.362)	(0.395)
No. obs.	4061	5640	5519	1782	1979

Labour turnover. As presented in equation (3), this study adopted probit models in which labour turnover was regressed on the degrees of routine task intensity and a series of control variables. Table 4 displays the estimated marginal effects of the probit model. The first column for the 2012–2014 interval indicates that the probability of labour turnover significantly increases with the magnitude of routine task intensity, particularly for employees who perform HR-intensive tasks on the job. More specifically, controlling for other variables, workers in MR- and HR-intensive jobs are 3.7% and 5.9%, respectively, more likely to leave their jobs than are those in NR-intensive jobs, suggesting that routinisation of job content has, as expected, a negative effect on labour stability. Reinforcing evidence can be found in the third column for the 2014–2016 interval. The likelihood of

Table 3. Descriptive statistics of job stayers, job-to-nonemployment movers and job-to-job movers for the period interval 2012–2014 and 2014–2016.

	$T_0 - T_1$ Job stayers		$T_0 - T_1$ Job-to-unemployment		$T_0 - T_1$ Job-to-job	
	2012–2014	2014–2016	2012–2014	2014–2016	2012–2014	2014–2016
Non-routine	0.298	0.321	0.222	0.276	0.288	0.300
Medium routine	0.353	0.317	0.423	0.302	0.345	0.263
High routine	0.349	0.361	0.355	0.422	0.367	0.438
Age	39.945	40.502	42.673	45.262	37.548	35.538
$Age^2/100$	17.313	17.279	20.124	21.780	15.169	13.713
Male	0.593	0.589	0.473	0.436	0.480	0.519
Language skill	0.248	0.225	0.172	0.138	0.271	0.256
Urban	0.474	0.504	0.438	0.549	0.339	0.406
Education	9.878	11.368	7.970	10.156	9.354	10.931
Tenure	11.503	10.514	13.809	10.360	7.717	4.519
Manufacture	0.271	0.259	0.246	0.236	0.318	0.388
Service	0.529	0.516	0.540	0.516	0.540	0.388
Others	0.200	0.225	0.214	0.247	0.142	0.225
State-owned	0.239	0.249	0.142	0.164	0.120	0.081
Collective	0.196	0.144	0.154	0.138	0.109	0.100
Private	0.359	0.386	0.388	0.385	0.549	0.537
Foreign	0.050	0.044	0.031	0.033	0.051	0.069
Others	0.157	0.176	0.286	0.280	0.171	0.212
Obs. (average).	76.94	78.02	15.14	13.90	7.89	8.08

leaving one's job if he or she undertakes the highest routine-intensive jobs is approximately 5% higher than for one whose job is categorised into the NR- and MR-intensive groups. More importantly, the effect of medium-routine intensity on the likelihood of labour turnover becomes negative. Although the effect is not significant, it still indicates that there is at least no difference in the propensity towards turnover between employees in NR- and MR-intensive jobs. The results reflect job stability within the MR intensity group. The reason may be that service-related jobs/occupations concentrating in the MR intensity group are, as described above, hard to overtake by automation and routinisation. As such, to some extent, this finding also signals the emergence of RBTC in China's labour market.

To further distinguish the impact of technology-induced routinisation on job-to-job transitions from job-to-nonemployment movement, the standard multinomial logit estimations are employed, and the dependent variables are job stayers, job-to-nonemployment movers and job-to-job movers. Table 5 presents the marginal effects of variables by employment status over two period intervals. Employees who perform HR-intensive tasks on the job are 6.2% and 5.9% less likely to work for the same employers in the 2012–2014 and 2014–2016 interval, respectively, relative to those in NR-intensive jobs. Similar to the results reported in Table 4, workers are 3.7% less likely to stay in their MR-intensive jobs in the 2012–2014 interval and become 2.6% more likely to work for

Table 4. The marginal effects of the probit model for labour turnover 2012–2016.

	2012–2014		2014–2016	
	Coef.		Coef.	
Medium routine	0.037*	(0.022)	−0.027	(0.024)
High routine	0.059**	(0.024)	0.053**	(0.023)
Age	−0.032***	(0.006)	−0.065***	(0.006)
$Age^2/100$	−0.000***	(0.000)	0.001***	(0.000)
Education	−0.001	(0.002)	−0.007**	(0.003)
Male	−0.101***	(0.018)	−0.120***	(0.019)
Language skill	0.012	(0.023)	−0.021	(0.026)
Urban	0.053**	(0.023)	0.079***	(0.022)
Collective	0.041	(0.027)	0.049	(0.032)
Private	0.118***	(0.027)	0.080***	(0.029)
Foreign	0.045	(0.047)	0.074	(0.049)
Others	0.153***	(0.032)	0.134***	(0.030)
Tenure	0.001	(0.001)	−0.003***	(0.001)
Service sector	0.053**	(0.023)	−0.008	(0.025)
Others	0.015	(0.027)	0.010	(0.026)
Central	−0.012	(0.022)	0.045*	(0.023)
Western	−0.001	(0.022)	−0.003	(0.024)

Data source: 2012, 2014 and 2016 CLDS survey.
CLDS: China Labour-force Dynamics Survey.
Robust standard errors in parentheses. All independent variables are based on the same wave of the survey, while the dependent variable is the employment status based on the follow-up wave: job stayers = 0; job-to-job movers or job-to-unemployment movers = 1. Non-routine intensity group, state-owned firms and eastern region are omitted groups.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

the same employer in the 2014–2016 interval, compared to those in NR-intensive jobs. A similar analysis can be performed with respect to the estimations of job-to-nonemployment movers. Again, there is no significant difference in the propensity towards turnover among workers in NR- and MR-intensive jobs over time, indicating that workers in MR-intensive jobs may not necessarily face unemployment risk in the process of technology-induced routinisation which is in line with the RBTC hypothesis. The probability of becoming unemployed for HR-intensive jobs is approximately 4.8% in the 2012–2014 interval and increased by 5.2% in the 2014–2016 interval relative to NR-intensive jobs, suggesting that workers in HR-intensive jobs would suffer from more unemployment stress with routinisation deepening and widening. For the regressions of job-to-job movers, there is no strong relationship between the magnitude of routinisation and job mobility. Perhaps due to the limited sample size of job-to-job movers, most coefficients are consistently insignificant in both sample intervals. This finding may also reveal that labour market instability would be mainly attributable to routinisation-induced unemployment (at least, this is the case in the short run) and show that laid-off employees might suffer from considerable adjustment or retooling costs.

Table 5. The marginal effects of the multinomial logit model for labour turnover 2012–2016.

	Job stayers				Job-to-nonemployment movers				Job-to-job movers			
	2012–2014		2014–2016		2012–2014		2014–2016		2012–2014		2014–2016	
Medium routine	−0.037*	0.022	0.026	0.024	0.030	0.020	−0.016	0.020	0.006	0.010	−0.010	0.016
High routine	−0.062**	0.024	−0.059**	0.023	0.048**	0.022	0.052***	0.019	0.014	0.011	0.007	0.016
Age	0.027***	0.007	0.056***	0.006	−0.035***	0.005	−0.047***	0.005	0.008*	0.005	−0.008*	0.005
$Age^2/100$	0.000***	0.000	−0.001***	0.000	0.000***	0.000	0.001***	0.000	0.000	0.000	0.000	0.000
Education	0.001	0.002	0.007**	0.003	−0.002	0.002	−0.006**	0.003	0.001	0.001	−0.001	0.002
Male	0.109***	0.018	0.129***	0.020	−0.107***	0.017	−0.125***	0.017	−0.002	0.008	−0.005	0.013
Language skill	−0.006	0.023	0.022	0.027	0.004	0.022	−0.026	0.023	0.002	0.010	0.004	0.017
Urban	−0.061**	0.024	−0.083***	0.022	0.070***	0.022	0.067***	0.018	−0.009	0.009	0.015	0.014
Collective	−0.038	0.027	−0.056	0.034	0.042*	0.024	0.021	0.025	−0.004	0.014	0.036	0.028
Private	−0.118***	0.027	−0.080**	0.031	0.105***	0.025	0.031	0.024	0.013	0.011	0.049*	0.024
Foreign	−0.031	0.051	−0.061	0.053	0.029	0.048	0.013	0.046	0.002	0.019	0.049	0.033
Others	−0.156***	0.032	−0.137***	0.032	0.145***	0.030	0.086***	0.024	0.011	0.013	0.051	0.024
Tenure	−0.001	0.001	0.005***	0.001	0.002**	0.001	0.000	0.001	−0.001*	0.001	−0.005***	0.001
Service sector	−0.051*	0.024	0.002	0.025	0.028	0.022	0.012	0.022	0.023**	0.010	−0.015	0.016
Others	−0.013	0.028	−0.023	0.026	0.003	0.026	0.020	0.022	0.010	0.013	0.003	0.017
Central	0.012	0.022	−0.046*	0.023	−0.001	0.021	0.088***	0.020	−0.011	0.009	−0.042***	0.014
Western	0.000	0.022	0.009	0.024	0.013	0.021	0.000	0.019	−0.013	0.008	−0.009	0.018
Pseudo R^2	0.102		0.137		0.102		0.137		0.102		0.137	

Data source: 2012, 2014 and 2016 CLDS survey.
CLDS: China Labour-force Dynamics Surveys.
Robust standard errors in parentheses. All independent variables are based on the same wave of the survey, while the dependent variable is the employment status based on the follow-up wave: job stayers = 0; job-to-job movers or job-to-unemployment movers = 1. Non-routine intensity group, state-owned firms and eastern region are omitted groups.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Turning to the other controls, most variables have consistent and expected effects on individual turnover behaviours (Job-to-Nonemployment) through the period. As expected, age has a statistically significant negative effect on labour turnover, indicating that young people are more likely to make turnover decisions than their older counterparts. Because young employees are more likely to feel dissatisfied with their working conditions or other aspects relative to older workers, and the relatively lower cost of switching employers in the meantime would increase their turnover intentions (Aguiar do Monte, 2012).

Furthermore, there seems to be a difference in the effect of task-routinisation on labour turnover between males and females. Female employees have a higher probability of becoming unemployed relative to male employees, which is similar to that observed by Souza-Poza and Souza-Poza (2007). The marginal effects decrease with education[4] and language skills, indicating that higher human capital is more conducive to employment stability. In addition, relying on more fringe benefits and the far-reaching cradle-to-grave regime, those who work in state-owned enterprises are much less likely to leave compared to those working in firms with other ownership.

The choice of routine and non-routine jobs. The analysis above concentrated on the discussion concerning the relationship between the dynamics of the labour market in China and the deepening and widening routinisation in the perspective of labour turnover or job mobility from the labour demand side. Economic theory confirms that different workers have various working capabilities and career preferences for the varieties of utility and disutility in the labour supply. As a consequence, these differences, among others, are expected to be factors affecting individuals' job (occupational) expectations and choices. In response to substitution risks and external unemployment stress induced by the de-routinisation process, employees may have different preferences for different routine intensity groups to maximise their utilities when entering the labour market during different times. Thus, following prior research that examines factors influencing occupational choice (e.g. Hinks and Watson, 2001; Klimova, 2012; Tran et al., 2018), the next analysis is extended to carry out the similar estimation strategies and simply investigate, on average, the changes in preference for routine and non-routine jobs over time.

Table 6 presents the results obtained by the standard MNL regression and logit estimation, both of which estimate the probability of being in one status relative to the base group. MNL (1) and (2) (columns 1 and 2) report the estimated marginal effects, respectively, based on 2012–2014 and 2014–2016 CLDS stacked data which are consistent with the settings for two period intervals considered in the previous subsection. MNL (1) (the reference year is 2012) indicates that, on average, the likelihood of choosing HR-intensive jobs in 2014 is approximately 5% higher than in 2012, while individuals have a 3.5% lower probability of undertaking MR-intensive jobs in the 2012–2014 interval. Interestingly but not surprisingly, MNL (2) (the reference year is 2014) demonstrates that workers' willingness to choose MR- and HR-intensive jobs had a reverse change in the 2014–2016 interval. A plausible reason for this transition might be the influence of entering the stage where robot adoption and development were supported and promoted by the government after 2013. Furthermore, stacking all CLDS data, the results of MNL (3) (the reference year is 2012) show that compared to HR-intensive jobs, MR-intensive jobs are

Table 6. The marginal effects of the multinomial logit model and the logit model for the choice of routine and non-routine jobs.

	MNL (1) 2012–2014	MNL (2) 2014–2016	MNL (3) 2012–2014–2016		Logit (1) 2012–2014	Logit (2) 2014–2016	Logit (3) 2012–2014–2016	
			2014	2016			2014	2016
Pr(NR)	−0.014	0.008	−0.011	−0.003				
	(0.010)	(0.008)	(0.009)	(0.009)				
Pr(MR)	−0.035***	0.038***	−0.037***	0.002				
	(0.010)	(0.008)	(0.009)	(0.009)				
Pr(HR)	0.049***	−0.047***	0.048***	0.002				
	(0.009)	(0.008)	(0.009)	(0.009)				
Pr(NR + MR)					−0.050***	0.048***	0.470***	0.000
					(0.009)	(0.008)	(0.009)	(0.009)
Pseudo R^2	0.101	0.094	0.095		0.101	0.089	0.090	
Obs.	9701	11,159	15,220		9701	11,159	15,220	

Data source: 2012, 2014 and 2016 CLDS survey.
MNL: multinomial logit; NR: non-routine; MR: medium-routine; HR: high-routine; CLDS: China Labour-force Dynamics Survey.
Robust standard errors in parentheses. The dependent variable is the routine intensity groups: NR = 1, MR = 2 and HR = 3 for multinomial logistic regressions; NR and MR = 1, and HR = 3 for logistic regressions. The independent variables in all model specifications include age, gender, education, language skills, Hukou and regions.
***$p < 0.01$.

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relatively less attractive for employees in 2014 than they are in 2012. However, in 2016, the probabilities of being in either NR- or MR-intensity groups obviously increased. The results also reflect that the ongoing process of routinisation in job content may be not given sufficient attention among employees in the workplace. Employees' delay in responding to the dynamics of the labour market may intensify labour market instability.

Discussion and conclusion

This study captures the extent of the routinisation of jobs in the transitional context of China and examines the incidence and impact of routinisation on labour turnover in the labour market. Using rotating panel data from the CLDS 2012, 2014 and 2016, the current study follows a recently developed measure proposed by Marcolin et al. (2019) to construct an RII. The approach is a refinement of measures of routine task intensity in extant studies that rely on a coarse categorisation based on broad occupational groups or on classification based on scores assigned by occupational analysts or experts according to the US labour market, both of which are subject to certain limitations or are not proper for China's labour market. Thus, this study, based on individual information with regard to flexibility in work schedules, degree of autonomy in workload and task content on the job, considers three routine intensity groups, namely the NR-, MR- and HR-intensive groups. The results are consistent with the classifications of Marcolin et al. (2019). The NR-intensive group contains managerial and professional occupations, while most manufacturing and production occupations are allocated into the HR-intensive group. Service-related workers can be found in the MR group.

The main econometric results shown in this study are as follows. The process of technology-induced routinisation is strongly associated with labour turnover. The probability of job mobility is significantly increased with the magnitude of routine task intensity. In particular, employees who undertake HR-intensive jobs are most likely to leave their jobs over time. The probability of employees keeping the job if they mainly handle MR-intensive tasks has shown a change over time. Employment in the MR intensity group is identical to that in the NR intensity group and tends to be stable, suggesting the emergence of the RBTC in China's labour market. Furthermore, through the use of multinomial logit estimations, this study found that the impact of routinisation on labour turnover is mainly attributable to job-to-nonemployment movements. No relationship between the process of routinisation and job-to-job transition indicates that the adjustment or retooling cost may be the barrier preventing employees from easily switching their employers. Finally, considering changes in preference for different routine intensive jobs, this study found that individuals are more likely to choose HR-intensive jobs and refuse MR-intensive jobs when entering the labour market in the 2012–2014 interval, while there is a reverse change in the 2014–2016 interval. However, the ongoing process of routinisation in job content may be not given sufficient attention among employees in the workplace and that such a lack of awareness may intensify labour market instability.

One shortcoming of the current study is that the estimation approach is unable to account for unobserved individual heterogeneity. Although three-quarters of the sample overlapped in two consecutive waves of the survey due to the rotating panel design of the CLDS, exploiting the panel nature of the data over the whole survey period is impossibly difficult due to attrition. This may be worse when certain exclusions apply. In addition, the previous literature concerning the RBTC hypothesis provides evidence that workers undertaking routine jobs experience a decline in wages compared to those performing non-routine-task on the job. Future research will concentrate on capturing the wage effect of technology-induced routinisation in context of China.

The empirical evidence of this study raises policy challenges with regard to labour market stability in China. The government is currently accelerating the introduction of robots into the workplace and society. Several national programmes and plans launched in recent years set targets to aggressively promote robot adoption and development for grasping the strategic opportunities and the competitive edge in the digital era. Technological deepening and widening through promotion of the process of routinisation or automation of job content are occurring at an unprecedented pace. Policymakers should beware of labour market instability and put more emphasis on building a lifelong learning platform or system, updated according to the changing demand for job-content skills. On the one hand, such initiatives will enable laid-off workers to develop necessary skills and abilities required for different jobs with relatively low adjustment or retooling costs. On the other hand, such lifelong learning initiatives will allow the current workforce to upgrade its own skills in order to meet new digital skill requirements. Policy efforts should be concentrating on incorporating basic digital knowledge into initial education, on translating the needs of current job-specific skills into school curricula and on cultivating digital literacy in order to enhance young people's adaptability in the digital era.

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Notes

1. The question I3.1 in the China Labour-force Dynamics Survey (CLDS) 2014 (the question code for CLDS 2016 is I3.7) which is used to define job turnover asked the respondent that 'Which of the following categories best describes your employment status?' The respondent only has two items to choose, namely employed and unemployed. The 'employed' includes wage earners, farmers, part-time workers and paid family workers. Only wage earners

reported the job information which can be used to calculate the routine intensity index (RII), and others will be automatically omitted. The 'unemployed' does not distinguish different types of departure from the labour market. The question I3c.3 in the CLDS 2014 (the code for 2016 is same) which asked the reason of being unemployed is used to further exclude those who are unemployed because of family roles, retirement and bad health conditions.
2. Cronbach's (1951) alphas were used to examine the performance of the factor construct based on these three questions. The alphas were 86.1%, 80.4% and 80.3% when calculated without any one question, and showing the underlying construct based on the sum of all questions is the most appropriate.
3. The authors admit that such selection is an ad hoc choice, which can be regarded as the reference index. According to Marcolin et al. (2019), its robustness was also confirmed after considering multiple selections on weights and functional forms. The Kaiser–Meyer–Olkin (KMO) measure is 0.733. In the principal component analysis (PCA), the first component explained most of the variability of the data (80%), and its eigenvalue is 2.400.
4. Individuals are expected to mitigate the influence of routinisation-induced labour turnover relying on enhancing their capabilities through education and learning-by-doing in the workplace. However, the estimated effects of education (and tenure) for two period intervals are not consistent, indicating that there may be a problem of endogeneity. We simply exclude education and tenure, respectively, from the estimation model, and find that, as expected, there is a significant increase in the likelihood of labour turnover for high-routine (HR) intensity jobs when both tenure and education are omitted in the 2014–2016 interval, while there is still no change in the likelihood for the 2012–2014 interval. This means that the results and conclusion will not be influenced much in the absence or presence of these two control variables. Results are available upon request.

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