Routine Biased Technological Change, Principal-Agent Model and Non-Standard Employment: Evidence from PIAAC

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Article

Routine Biased Technological Change, Principal-Agent Model and Non-Standard Employment: Evidence from PIAAC

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Abstract: This study applied the principal-agent model to interpret the impact of routine biased technological change (RBTC) on the structure of employment relations. RBTC increases the proportion of routine tasks in work activities, due to their fixed procedural nature, routine tasks reduce uncertainties in the principal-agent problem. Employers, being able to predict work contingencies and to verify employee efforts, find the benefit of offering standard labor contracts is reduced, thereby increasing the ratio of non-standard employment. This study applied logistic regression based on the Program for the International Assessment of Adult Competencies (PIAAC) survey data to verify this framework. The results indicated that with each standard deviation increased in routine task intensity, the odds ratio of non-standard employment increased by 13.6%. This effect was heterogeneous in various institutional contexts. This study expends the toolkit for analyzing employment relations problems, and extends the scope of RBTC to employment relations.

Keywords: routine biased technological change; principal-agent model; non-standard employment; routine task

Introduction

From the late 20th to the early 21st century, developed countries experienced a labor market polarization, which was characterized by a dual decline in both the job opportunities and income of the middle-income group (Autor et al., 2006; Goos and Manning, 2007). A rising theoretical framework, RBTC, interprets this trend through the lens of the biased nature of technological change (Autor, 2010; Goos et al., 2014; Cortes, 2016). During the same period, the structure of employment relations has been changed as well. The ratio of standard employment decreased sharply, and the proportion of various forms of non-standard employments increased (Kalleberg, 2000, 2003). Although foundings of RBTC effectively explained the mechanisms behind the labor market polarization, literature so far falls short in discussing changes in the structure of employment relations. Considering that the employment and wage structure have been changed dramatically, the structure of employment relations is hardly remaining unchanged. Since the middle-income group such as accountants, bank tellers, and blue-collar workers constitutes the core of standard employment, it could be inferred that if RBTC has impact on middle-income group's employment and wage structure, the structure of employment relations should be also affected by RBTC. Has the RBTC was one of the reason of shifting of non-standard employment? This study is trying to answer this question.

We built a framework through the principal-agent model to explain the rise of non-standard employment based on RBTC. We proposed that for work dominated by routine tasks, employers are well-prepared with protocols for emergency responses and effort assessments even before the beginning of work. This preparedness diminishes uncertainties, reducing the cost happened with employees' morality hazard, therefore lessening the necessities of motivating and constraining employees through standard labor contract. The technological change increased the proportion of routine tasks, therefore, it leads to a reluctance among employers to offer standard labor contracts, and the ratio of non-standard employment was rising.

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The marginal contributions of the study are:

1. Through the principal-agent model, this study constructed a framework to illustrate the impact of technological change on employment relations, and using quantitative method to check it, which expend the toolkit for employment relations analyzing.

2. While RBTC researches have an outstanding achievement to illustrate the impact of technological change on job and wage structures, this study is the first one that extending the scope of RBTC's impact on employment relations.

The remainder of this study is structured as follows. Section two provides literature review and Hypothesis, discussing how RBTC and non-standard employment are interconnected under the principal-agent model. Section three describes the data and methods. Section four presents the regression results and robustness check. Section five offers conclusions, implications and future directions.

Literature Review and Hypothesis

Task Approach and RBTC

It is widely accepted that a job can be viewed as a bundle of tasks (Wong and Campion, 1991; Lazear, 1995; Autor et al., 2003; Acemoglu and Restrepo, 2018). By definition, a task is "the smallest unit of work activity" (Acemoglu and Autor, 2011)(pp. 19). Autor et al. (2003) introduced the task approach, categorizing tasks into routine/non-routine and cognitive/manual. They suggested that "a task is 'routine' if it can be accomplished by machines following explicit programmed rules (pp.1283)." Based on the task approach, RBTC posits that technological progress has transformed more tasks into routine tasks, which are predominant in the jobs of middle-income groups. Routine tasks are more easily to handle by machine or off-shored to cheaper foreign workers, leading to a reduction in job opportunities and wages for these groups, resulting in labor market polarization (Autor et al., 2006; Ebenstein et al., 2014; Cortes, 2016; Bárány and Siegel, 2018; Acemoglu and Restrepo, 2022). Economists have described and explained labor market polarization in various countries based on the logic of RBTC (Goos et al., 2014; Akcomak et al., 2015; Fernández-Macías and Hurley, 2017; Fonseca et al., 2018; Reijnders and de Vries, 2018).

However, these studies focused primarily on job and income structures, but did not discuss the impact of technological change on employment relations. While the job and income structures have dramatically changed, the structure of employment relations is expected to be reconstructed as well.

Technological Change and Non-Standard Employment

Since the late 20th century, the proportion of non-standard employment had increased sharply in developed countries (Kalleberg, 2000; Connelly and Gallagher, 2004; Harvey et al., 2017). Technological change is also considered a key impetus. Non-standard employment primarily refers to those employees with limited attachment to their employers in terms of time, space, and subordination (Pfeffer and Baron, 1988). These limited attachments makes non-standard employment more flexible than traditional standard employment. Technological change has accelerated the deindustrialization process, and the work in the third industry, e.g. the service industry, is more flexible and fragmented, which has led to an increase in requirement of non-standard employment (Lee, 2005; Barbieri and Scherer, 2009; Kollmeyer, 2018). Even within industrial sectors, the growing demand for flexible production has similarly driven the increase in non-standard employment (Taplin, 1995; Blair, 2001; Kalleberg, 2003).

These research findings are substantial, but mainly focusing on observing the fact of changing flexibility, overlooking the changing nature of work activities, which should be the origin of changing flexibility. It leads to fall in digging out the mechanism between technological change and employment relations. Routine tasks, due to their lower uncertainty, reduce instances of moral hazard behavior in the workplace. Even with minimal connection between employees and employers, employer's interests could be ensured. Although Taplin (1995) interviewed managers of textile firms in North Carolina, identifying the routinization of work due to technological change as one of the reasons for the rise in non-standard employment (pp.432), the mechanism was not illustrated clearly.

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The Principal-Agent Model, Routine Tasks, and Research Design

The principal-agent model provides a framework for understanding the interactions between routine tasks and non-standard employment. The model suggests that the uncertainties during the work activities may give employees an informational advantage over employers. Since the interests of employers and employees often do not align, employees with an informational advantage may intentionally or unintentionally harm the employer's interests, leading to moral hazard and incurring additional costs (Cahuc et al., 2014) (pp. 328). Therefore, employers (principals) often choose to offer long term or fixed term contracts - which is a standard labor contract - to employees (agents). These contracts emphasize a subordinate relationship between employer and employee. When uncertainties arise, such as unexpected events or unverifiable work efforts, the advantage of labor contracts lies in their ability to motivate and regulate employees to align their actions with the employer's interests, thereby reducing the costs associated with moral hazard.

However, the concept of routine task challenges the assumption that all works involve uncertainties. The procedural and systematic nature of routine tasks implies that any unexpected event during the work process has predetermined solutions. These solutions should explicitly enough to be executed by machines following fixed procedures. The outcomes of routine tasks should be necessarily explicit enough to be identified and calculated by fixed procedures; otherwise, any uncertainties that require human intervention may break the fixed procedure executed by machines. The content of routine task could be complicated, but has to be extremely logical and explicit for computer comprehension. It means that for routine tasks, employers are fully aware of the context, handling methods, and results of all the activities in the work before it even begins. Therefore, Assumption 1 was raised :

Assumption 1: The routine task intensity (RTI) measure the uncertainties during the work (inverse).

In the scenario of high RTI, the uncertainty in work significantly decreases, reducing the necessities of offering standard labor contract, leading to a increasing of non-standard employment. Research has found that RBTC reduces employees' discretion in their work, and various institutional contexts play a significant role (Holman and Rafferty, 2018). From the perspective of the task approach, lower discretion is equivalent to a higher proportion of routine tasks. Therefore, Hypothesis 1 was proposed :

Hypothesis 1: An increase in the RTI would raises the ratio of non-standard employment.

It would be more straightforward if employment is just an economic agreement between employers and employees. Under ideal conditions, the employer would package routine tasks and allocate them to non-standard employees, while assigning all non-routine tasks to standard employees. As the RTI increase, more non-standard employees would be hired. However, the prevailing labor laws and institutional settings predominantly hinge on the paradigm of standard employment (Barley et al., 2017). In many countries, a formal labor contract is closely linked to a range of labor market policies such as labor protection, labor union threshold, social welfare, or employment subsidies (Holman and Rafferty, 2018). It means that the institutional social significantly influences how employers hire, which may affect non-standard employment ratio and the impact of RTI on non-standard employment. Therefore, Hypothesis 2 and 3 were raised :

Hypothesis 2: The non-standard employment ratio is different in various social contexts.

Hypothesis 3: the social contexts have a heterogeneous effect of the impact of RTI on the ratio of non-standard employment. [1]

Data and Methods

Data

PIAAC is a large-scale international survey conducted by the OECD in 2012. The advantages of using the PIAAC database are: 1. The PIAAC database includes multiple questions about the task

[1] To illustrate this intuition clearly, a simple formula derivation of Assumptions and Hypothesis was raised in Appendix A in the end of the text.

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characteristics. Economists have used this database to construct an effective cross-national RTI (Marcolin et al., 2019; Rica et al., 2020), which facilitates this study[2]; 2. PIAAC datasets collect information from various countries, which is beneficial for testing Hypothesis 2 and 3.[3]

The study constructed a dummy variable as the response variable: workers who have not had a long-term or fixed-term labor contract, are considered to be non-standard employees. In total of 73,993 employee (gets a salary or wage from an employer or a temporary employment agency) samples of 24 countries were gathered from PIAAC datasets. The RTI was constructed as the core independent variables. As shown in Table 1:

Table 1. Components of RTI .

Components of routine tasks	Describe	N	mean	std.	min	max
Teaching People (inverse)	How often Does your Job usually involve instructing, training or teaching people, individually or in groups?	73,993	3.437	1.529	1	5
Presentations (inverse)	How often Does your Job usually involve making speeches or giving presentations in front of five or more people?	73,993	4.163	1.244	1	5
Advising People (inverse)	How often Does your Job usually involve advising people?	73,993	2.561	1.589	1	5
Planning Own Activities (inverse)	How often Does your Job usually involve planning your own activities?	73,993	2.109	1.563	1	5
Organizing Own Time (inverse)	How often Does your Job usually involve organizing your own time?	73,993	1.976	1.548	1	5
Sequence Tasks (inverse)	To what extent can you choose or change the sequence of your tasks?	73,993	2.701	1.285	1	5
Flexibility (inverse)	To what extent can you choose or change how you do your work?	73,993	2.663	1.255	1	5

[2] Some studies applied U.S. datasets O*NET to calculate RTI (Autor and Dorn, 2013; Cortes, 2016). However, task data from O*NET was gathered from few incumbents or experts (around 20-50) based on working information merely in U.S.. Further more, O*NET RTI was hinged on U.S. occupation code SOC, while PIAAC data used ISCO occupation code. There might be loss of accuracy when transforming occupation code if applying O*NET RTI. Since the study aims to test a universal impact of RTI on employment relations and to test heterogeneous effect of various social contexts, the author decided not to use O*NET and to use PIAAC to calculate RTI.

[3] PIAAC also has datasets in 2014 and 2017. However, numbers of survey countries are much lower: 9 in 2014 and 6 in 2017, compare to 24 in 2012. Though the data is relatively old, recent studies used it for it high quality (Hämäläinen et al., 2021; Van Nieuwenhove and De Wever, 2022). Therefore, the study uses 2012 datasets to test Hypothesis.

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The study controlled a series controls to avoid omitted variable bias. The control variables are in three level: individual, organizational and country. Individual control variables include gender (Casey and Alach, 2004; Booth and van Ours, 2013), education (Biemann et al., 2012), age (Loughlin and Barling, 2001; Macdonald and Giazitzoglu, 2019), income (Uzzi and Barsness, 1998; Kalleberg, 2000), marital and offspring status (Horemans, 2016), migrant and native speaker (Anderson, 2010), parents education background (Caro et al., 2015), education and skill mismatch (Esposito and Scicchitano, 2022, 2023), and other task information from PIAAC, 23 individual controls in total. Table 2 presents descriptive statistics of dependent variable, RTI and individual control variables：

Table 2. Descriptive statistics[a.]

VARIABLES	N	Mean	Std.	Min	Max
non-standard employment	73,993	0.102	0.302	0	1
RTI	73,993	2.849	1.039	1	5
male	73,993	0.513	0.500	0	1
living_with_partner	73,993	0.756	0.429	0	1
child	73,993	0.669	0.471	0	1
less_than_high_school	73,993	0.109	0.311	0	1
above_high_school	73,993	0.489	0.500	0	1
high_school	73,993	0.402	0.490	0	1
working_hours_40less	73,993	0.373	0.484	0	1
working_hours_40_50	73,993	0.498	0.500	0	1
working_hours_50_60	73,993	0.085	0.279	0	1
working_hours_60more	73,993	0.043	0.204	0	1
age_25less	73,993	0.095	0.293	0	1
age_25_54	73,993	0.749	0.434	0	1
age_55_65	73,993	0.156	0.363	0	1
income_less10	73,993	0.093	0.291	0	1
income_10_25	73,993	0.150	0.357	0	1
income_25_50	73,993	0.304	0.460	0	1
income_50_75	73,993	0.217	0.412	0	1
income_75_90	73,993	0.133	0.340	0	1
income_90more	73,993	0.103	0.304	0	1
father_edu	73,993	1.718	0.746	1	3
mother_edu	73,993	1.619	0.725	1	3
numeracy	73,993	1.577	1.217	0	6.050
reading	73,993	1.914	1.054	0	7.021
migrant	73,993	0.099	0.299	0	1
native_speaker	73,993	0.918	0.275	0	1
overskilled	73,993	0.838	0.369	0	1
underskilled	73,993	0.339	0.473	0	1
overeducated	73,993	0.197	0.397	0	1
undereducated	73,993	0.106	0.307	0	1
shareinfo	73,993	4.312	1.164	1	5
problemsolv	73,993	3.867	1.308	1	5

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complex	73,993	2.796	1.305	1	5
physical	73,993	3.038	1.811	1	5
finger	73,993	3.780	1.709	1	5
cooperate	73,993	3.454	1.417	1	5

a:the definition of all variables are shown in appendix Table B1. b: Marital status may affect employment status. The datasets have no marital status, "living with partner" was applied as a proxy.

The sample has a nearly balanced gender distribution, with a slight male majority (51.3%). Education levels indicate a fairly educated sample with a tilt towards high school and over. The predominant age group is 25-54 years, which corresponds to prime working age. Most samples are living with partner (75.6%), two third of samples are having child (66.9%). Samples work between 40 and 50 hours per week, and the income distribution suggests moderate economic diversity.

For organizational controls, the study uses 4 variables, which are the firm size (Uzzi and Barsness, 1998; Kalleberg and Marsden, 2005), the ownership of the firm (Olsen and Kalleberg, 2004), part time job (Busilacchi et al., 2024) and manage status. For country level controls, the study uses 9 controls that may affect labor relations: strictness of labor protection, union density, social expenditure and whether the country is developed country (Holman and Rafferty, 2018), GDP per-capita, CPI, unemployment rate, unemployment duration, internet permeability. The descriptive statistics of organizational and country controls are shown in appendix Table B2 and B3. Furthermore, different industry may have different characters that impact the ratio of non-standard employment (such as flexibility which was mentioned before), the study controls the two-digit industry fixed effect.

To test Hypothesis 2 and 3, the study categorizes all countries into five groups - Anglo Saxon, South West Europe, Middle East Europe, East Asia, and Nordic. Each of them has its unique institutional, economy, cultural and social context. Given the variation in the structure of routine tasks among different EU countries (Hardy et al., 2018), EU countries was separated into South West Europe and Middle East Europe. Table 3 shows the country groups:

Table 3. Country groups[a.]

Group	Countries	Group	Countries
Anglo Saxon	New Zealand	Nordic	Denmark
	United Kingdom		Norway
	United States		Sweden
Middle East EU	Czech Republic	South West EU	Austria
	Estonia		Belgium
	Hungary		Germany
	Lithuania		France
	Poland		Greece
	Slovak Republic		Ireland
	Slovenia		Italy
East Asia	Japan		Netherlands
	Korea Republic		Spain

a: Detail statistics of non-standard employment and RTI of each groups are shown in Appendix Table B4.

Methods

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The logistic model is suitable for analyzing dummy response variable:

$$Logit\ (NSE) = \beta_0 + \beta_1 z\_RTI_i + \beta_2 \boldsymbol{X_i} + \beta_3 \boldsymbol{O_i} + \beta_4 \boldsymbol{C_i} + \beta_5 \boldsymbol{Industry_i} \quad (1)$$

In equation (1), $NSE = ln(\frac{P_i(NSE)}{1-P_i(NSE)})$where $P_i(NSE)$ indicating that the probability of an employee has no long-term or fixed-term labor contract. z_RTI_i represents the standardized form of the RTI of individual i. $\boldsymbol{X_i}$ represents individual controls, $\boldsymbol{O_i}$ represents organizational controls, C_i represents country controls, $\boldsymbol{Industry_i}$ represents industry fixed effects. According to Hypothesis 1, it could be expected a significant positive value of β_1, meaning the RTI is positively correlated with the odds-ratio of non-standard employment.

$$Logit\ (NSE) = \beta_0 + \beta_1 z\_RTI_i + \beta_2 \boldsymbol{X_i} + \beta_3 \boldsymbol{O_i} + \beta_4 \boldsymbol{C_i} + \beta_5 \boldsymbol{Industry_i} + \beta_6 \boldsymbol{G_i} + \beta_7 \boldsymbol{G_i} \cdot z\_RTI_i + \varepsilon_i \quad (2)$$

In equation (2), $\boldsymbol{G_i}$ represents the country group. We interact $\boldsymbol{G_i}$ and RTI to analyze the heterogeneous of the impact of RTI on the ratio of non-standard employment. According to Hypothesis 2 and 3, it could be expected a significant β_6 and β_7, but the direction is not assure.

Results and Robustness Check

Regression Results

Table 4 represents the regression results of equation (1). Columns 1-5 respectively represent results by one independent variable RTI, controlling individual variables, controlling organizational variables, controlling country variables, and controlling industry fixed effect. For ease of reading, the results are displayed in the form of indices, which interpret the odds ratio of non-standard employment (the probability of the individual is a non-standard employee over standard employee). For ease of reading, the results of control variables was omitted, the complete results are shown in Appendix Table B5. The regression results of control variables are constant with the findings of related literature, indirectly validate the effectiveness of regression.

Table 4. Regression results (Eq.1).

VARIABLES	(1)	(2)	(3)	(4)	(5)
z_RTI	1.264***	1.144***	1.124***	1.133***	1.124***
	(0.015)	(0.019)	(0.020)	(0.024)	(0.025)
Constant	0.111***	0.049***	0.037***	1,598.894***	821.78***
	(0.001)	(0.005)	(0.004)	(567.486)	(316.595)
Individual Controls		√	√	√	√
Organizational Controls			√	√	√
Country Controls				√	√
Industry Fixed Effect					√
Observations	73,993	73,993	73,993	73,993	73,993
Pseudo R2	0.008	0.064	0.085	0.398	0.408
LL	-24112.1	-22735.72	-22239.47	-14634.66	-14380.49
AIC	48228.19	45537.44	44560.93	29371.33	29038.97

seEform in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the VIF of all independent variables are less than 10. In the e-form of coefficient, the result minus 1 is the changing odds-ratio of dependent variable for every change of independent variable.

The findings of Table 4 are：

(1) With the increase in the number of control variables (especially country control variables), the Pseudo R2 increases, the log likelihood (LL) increases (the base number is -24298.36), the AIC indicator decreases, indicating that the effectiveness of the regression equation is improving. After

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controlling industry fixed effects, the Pseudo R2 is 0.408, means that 40.8% of the variation of non-standard employment could be explained by the equation.

(2) RTI has a significant positive impact on the odds ratio of non-standard employment. The regression results are positively significant in Columns 1-5, the RTI increases one standard deviation, the odds ratio of non-standard employment increases by 12.4%-26.4%. In column 5, after controlling for all control variables, the odds ratio of non-standard employment increases by 12.40%. The result is consistent with Hypothesis 1.

Table 5 represents the regression results of equation (2).

Table 5. Regression results (Eq.2).

VARIABLES	(1)	(2)	(3)	(4)
z_RTI	1.145***	1.428***	1.136***	1.435***
	(0.025)	(0.096)	(0.026)	(0.098)
Anglo_Saxon	0.017***	0.017***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Middle_East_EU	0.01***	0.01***	0.01***	0.01***
	(0.003)	(0.003)	(0.003)	(0.003)
East_Asia	0.016***	0.017***	0.013***	0.014***
	(0.004)	(0.005)	(0.003)	(0.004)
South_West_EU	0.01***	0.011***	0.013***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Nordic (referee group)	-	-	-	-
	-	-	-	-
Anglo_Saxon_z_RTI		0.764***		0.765***
		(0.057)		(0.057)
Middle_East_EU_z_RTI		0.818***		0.787***
		(0.063)		(0.061)
East_Asia_z_RTI		0.781***		0.767***
		(0.060)		(0.060)
South_West_EU_z_RTI		0.797***		0.788***
		(0.057)		(0.057)
Constant	918,833.084***	870,234.058***	1825478.453***	1740741.184***
	(635,962.156)	(604,061.379)	(1287979.406)	(1231838.829)
Individual Controls	√	√	√	√
Organizational Controls	√	√	√	√
Country Controls	√	√	√	√
Industry Fixed Effect			√	√
Observations	73,993	73,993	73,993	73,993
Pseudo R2	0.41	0.411	0.419	0.419
LL	-14329.11	-14322.05	-14120.41	-14113.36
AIC	28768.21	28762.09	28526.81	28520.71

seEform in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The findings of Table 5 are：

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(1) By adding country group variables, the pseudo R2 and LL keep increase, and AIC indicator keep decrease. The explanation power of regression are keeping rising. The column 3 shows that after controlling social context controls, every increase of the standard deviation of RTI may lead to the odds-ratio of non-standard employment increase by 13.6%, which is still constant with Hypothesis 1.

(2) In Column 1-4, compared to Nordic countries, the odds ratio of employees in other groups are significant lower. In column 4, it shows that Anglo Saxon is about 98.4% lower; Middle East Europe is about 99.1% lower; East Asia is about 98.7% lower ; and South West EU is about 98.66% lower. This huge gap may coming from the Nordic countries' typical social, institutional and even geographic context. The result is consistent with Hypothesis 2.

(3) In Column 4, the impact of the RTI on non-standard employment is heterogeneous in various groups. In Nordic countries, every standard deviation increase in the RTI raises the odds ratio of non-standard employment by 43.5% (first row), in Anglo Saxon countries by 9.9% (calculated by 1.4354×0.7654), in Middle East EU countries by 13%, in East Asian countries by 10.1%, in South West EU countries by 13.2%. Compared to the results in Column 3 (13.6%), Nordic countries have a positive heterogeneous effect, Anglo Saxon and East Asia countries have a negative heterogeneous effect, while South West EU and Middle East EU countries have a slightly negative heterogeneous effect. The result is consistent with Hypothesis 3.

Robustness Check

Employers would always prefer non-standard employment for it's lower cost, but non-standard employment could generate more cost in non-routine task. Employers offer different types of contracts based on the characteristics of various tasks. Workers may accept or reject these offers. However, regardless of what the workers' personal preferences are, they will ultimately choose a contract that maximizes their utility, thereby becoming employees. The employees' choices reflect the relationship between task characteristics and the employment relations. Therefore, the self-selection bias has limited effects in the model.

Firstly, Marcolin et al. (2019) built another equation to calculate routine task intensity based on PIAAC data. The study changed the method of calculating the RTI followed Marcolin et al. (2019), with everything else remaining unchanged. The results changed very little, as shown in appendix Table B6. Secondly, the study applied the binary probit regression instead of logit regression to run the model. The results are shown in Table B7, which are constant with Hypothesis 1, 2 and 3. Lastly, the study used liner probability model (LPM), and Oster test to check the endogenous of omitted variables (Oster, 2019). The results of LPM are shown in Table B8, which are still constant with Hypothesis 1, 2 and 3. The result of Oster check is shown as Table 6:

Table 6. The result of Oster test.

Bound Estimate	Inputs from Regressions			Other Inputs	
delta		Coeff.	R2	R_max	Beta
1.07815	Uncontrolled	0.02186	0.005	0.8	0.1
	Controlled	0.00498	0.357		

Table 6 shows that after controlling all the controls in LPM, the explanation power of model is increased (R2 increased from 0.005 to 0.357). In the assumption of the model could explain 80% of the variation of the dependent variable at most (input R-max=0.8), and under the premise that the adjustment coefficient is 0.1 (input beta=0.1), the estimation results are still robust even if the potential omitted variables are considered (delta>1), which means that the model is robust after considering the endogenous of omitted variables.

Conclusions, Implications and Future Directions

Conclusions

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This study suggests that there is a positive correlation between routine task intensity and non-standard employment. This impact is heterogeneous in various institutional contexts. This study builds a framework to illustrate this correlation based on the principle-agent model, and applying the PIAAC database to test it. Regression results explain the trend of non-standard employment from the perspective of RBTC, which expending the toolkit for analyzing employment relations problem. And this study is the first one that illustrates the changing structure of employment relations by the RBTC framework, expending the scope of RBTC into employment relations.

Implications

The implications of this study include two aspects: 1. From a micro perspective, firms should choose employment relationships properly based on the level of routine task intensities. Although non-standard employment is prevalent, non-routine tasks without the constraints of standard labor contracts may incur potential moral hazard costs that exceed the savings from not offering a standard labor contract. 2. From a macro perspective, the government should not force companies to complete routine tasks in the form of standard employment. It would lose efficiency and reduce the competitiveness of domestic firms. To better protect employees, the government should incorporate the density of routine tasks in major jobs in society into its decision-making process, and develop corresponding regulations based on the different types of tasks that employees engage in.

Future Directions

Directions for future studies include: 1. This study found that institutional contexts have a heterogeneous effect on the relationship between routine task intensity and non-standard employment, but did not clarify the underlying mechanisms. Future analyses could reveal how the specific contextual factors, such as culture or labor law regulations, affect the costs associated with moral hazard. 2. RBTC literature provides a method to measure the potential impact of AI techniques on the labor market (Frey and Osborne, 2017; Eloundou et al., 2023; Korinek, 2023). Analyzing and predicting how the application of AI technologies, such as ChatGPT, affects standard and non-standard employment by changing the routine task intensity, could outline how AI technologies will influence employment relations in the future.

Appendix A: The Formula Derivation of Intuition

Denoting the uncertainties inherent in the work process is ε_j, which could only be addressed by labor. The cost associated with managing uncertainties of standard employment and non-standard employment are denoted by $C_{SE}(\varepsilon_j)$ and $C_{NSE}(\varepsilon_j)$, which are the monotonically increasing function of ε_j. The fixed costs of contracts are $F_j(SE)$ and $F_j(NSE)$. Therefore, Assumption A1 was raised:

Assumption A1: $F_j(SE) > F_j(NSE)$.

Assumption A1 illustrates that the legal, textual, and social costs of offering standard employment contracts are usually higher than non-standard employment contracts (Tilly, 1991; George and Chattopadhyay, 2015). Therefore,

Assumption A2: $\frac{\partial C_{SE}(\varepsilon_j)}{\partial \varepsilon_j} < \frac{\partial C_{NSE}(\varepsilon_j)}{\partial \varepsilon_j}$.

Assumption A2 illustrate that when uncertainties arise, the cost of morality hazard are different between various employment relations. By emphasizing the employer's control over employees during unexpected events, standard employment has an advantage in reducing costs associated with moral hazard compared to non-standard employment.

Therefore, the probability of non-standard employment, $P_j(NSE)$, hinges on the trade-off between the costs of uncertainties and the fixed costs associated with each type of contract. As shown in Figure A1:

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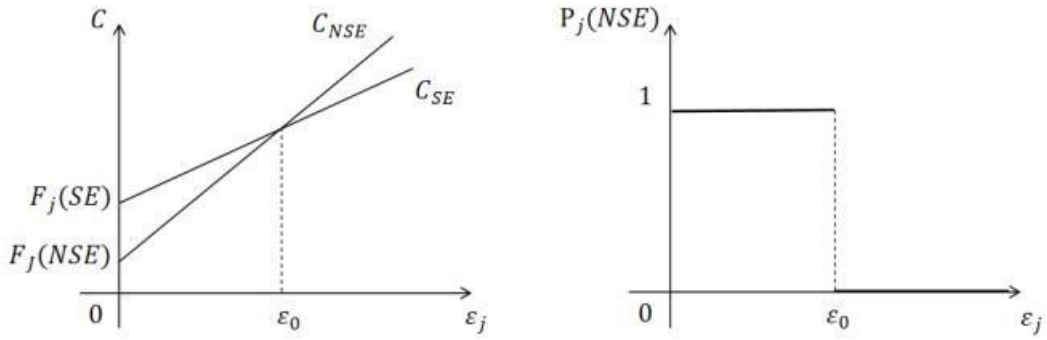

Figure A1. The probability of non-standard employment and uncertainties.

From 0 to ε_0, it is shown that when the cost of drafting a labor contract is higher than the advantages it brings in dealing with uncertainties. In this scenario, non-standard employment has a cost advantage relative to standard employment. When $\varepsilon > \varepsilon_0$, offering a labor contract reduces the cost of uncertainties to a greater extent than it of drafting the contract, giving standard employment a cost advantage relative to non-standard employment. Figure A1 illustrate the logic of trading-off between standard and non-standard employment.

From 0 to ε_0 shows when the cost of drafting a standard labor contract is higher than the advantages it brings in. In this scenario, non-standard employment has a cost advantage relative to standard employment, $P_j(NSE)$=1. When $\varepsilon_j > \varepsilon_0$, offering a standard labor contract reduces the cost of uncertainties to a greater extent than it of drafting the contract, giving standard employment a cost advantage relative to non-standard employment, $P_j(NSE)$=0. Figure A1 illustrate the logic of trading-off between standard and non-standard employment.

Assuming occupation A has two different tasks, j_1 and j_2. These two tasks have different fixed costs and moral hazard costs, therefore $\varepsilon_{0,j_1} \neq \varepsilon_{0,j_2}$. Denoting $\varepsilon_A = \varepsilon_{j_1} + \varepsilon_{j_2}$ as the sum of uncertainties of the occupation A, $\varepsilon_{0,A} = min[\varepsilon_{j_1}, \varepsilon_{j_2}]$. Whether offering a standard labor contract or not is depended on the gap between total fixed costs and moral hazard costs.Therefore:

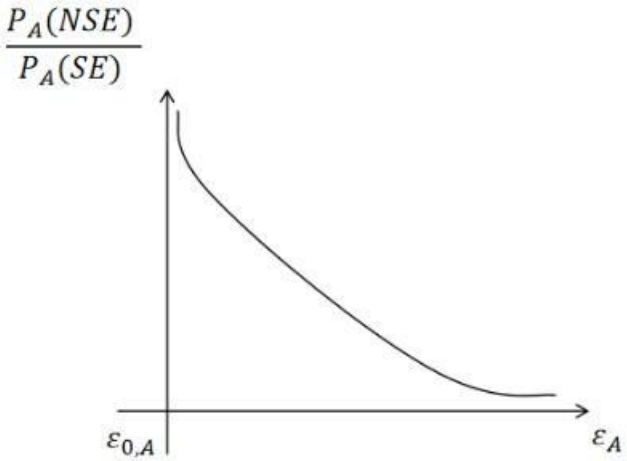

Figure A2. The odds-ratio of non-standard employment of an occupation.

The relationship of the odds-ratio of non-standard employment (the probability of non-standard employment over standard employment) of the occupation A, $\frac{P_A(NSE)}{P_A(SE)}$, and uncertainties of the occupation A was shown as Figure A2. Employers consider the sum of uncertainties of each task in the occupation A, weight the cost and benefit of each type of employment. As the uncertainties rising, the costs of moral hazard increases, heightening the need for standard employment to reduce these costs, thereby reducing the odds-ratio of non-standard employment. If all the uncertainties converge to $\varepsilon_{0,A}$, there are almost no uncertainties the odds-ratio of non-standard employment would be extremely high.

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As assumed in the main study, the concept of routine task indicating that routine task has no uncertainties, the RTI could measure the uncertainties in the work (inverse). Therefore, Hypothesis 1 was raised:

Hypothesis 1: An increase in the RTI would raises the ratio of non-standard employment.

As shown in Figure A3:

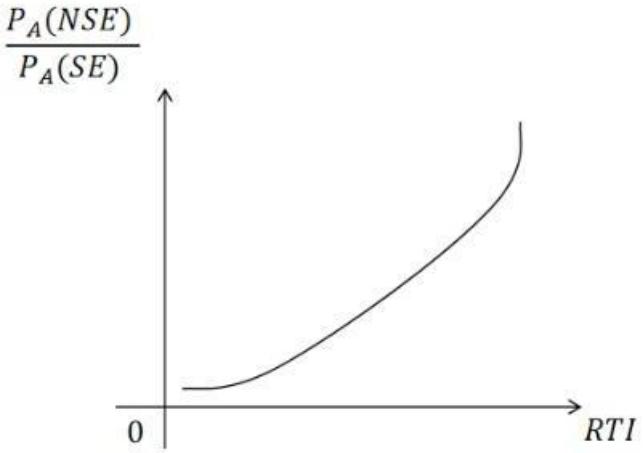

Figure A3. The odds-ratio of non-standard employment of an occupation and RTI.

The institutional context significantly influences how employers hire, which may affect non-employment ratio through changing fixed labor contract costs, leading to a intercept effect. As shown in Figure A4:

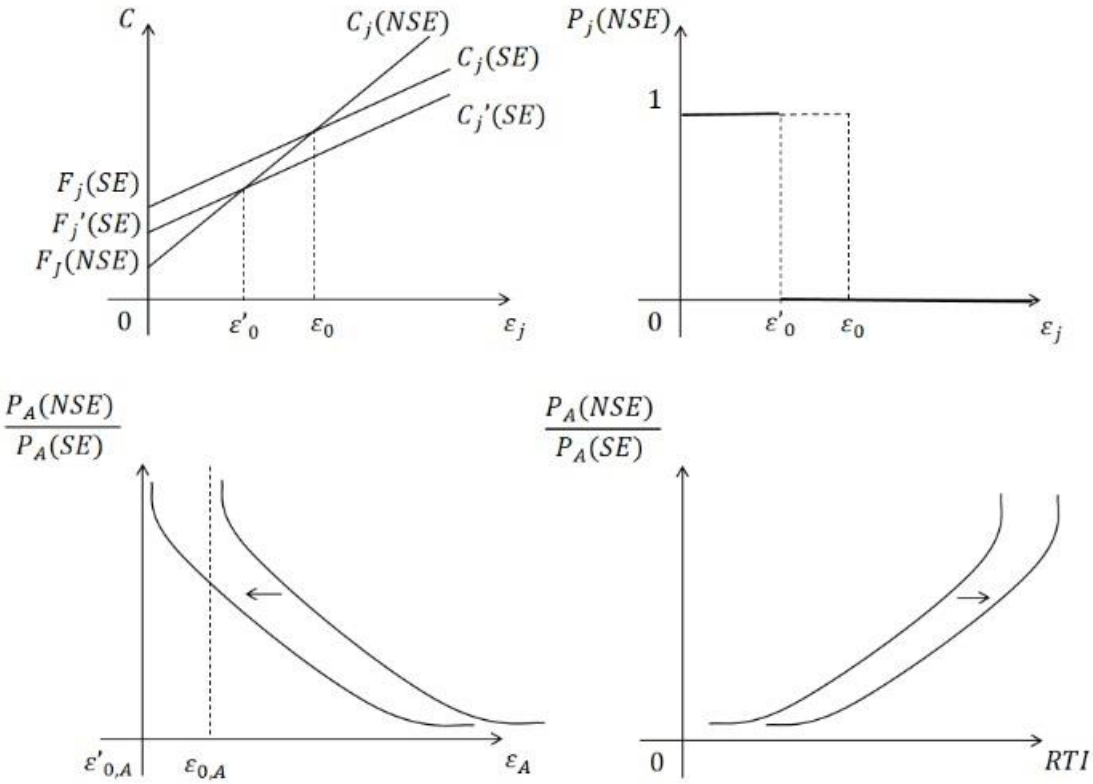

Figure A4. Changing fixed costs of standard employment.

In Figure A4 it denoted as $F_j(SE)$ and $F_j'(SE)$. Then the cost curve $C_j(SE)$ moves to $C_j'(SE)$, leads to $\varepsilon_{0,A}$ move to $\varepsilon'_{0,A}$. It brings more cost advantages of standard employment, then the odds-ratio of non-standard employment is decreased. Therefore, Hypothesis 2 was proposed.

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Hypothesis 2: The non-standard employment ratio is different in various social contexts.

Similarly, different institutional contexts may affect the $\frac{\partial C_j(SE)}{\partial \varepsilon_j}$ and $\frac{\partial C_j(NSE)}{\partial \varepsilon_j}$ through various task discretion (Minardi et al., 2023), attitude towards new technologies (Holman and Rafferty, 2018) or labor law execution (Barbieri and Scherer, 2009). The impact of RTI on odds-ratio of non-standard employment may heterogeneously between different contexts, leading to a slop effect. As shown in Figure A5:

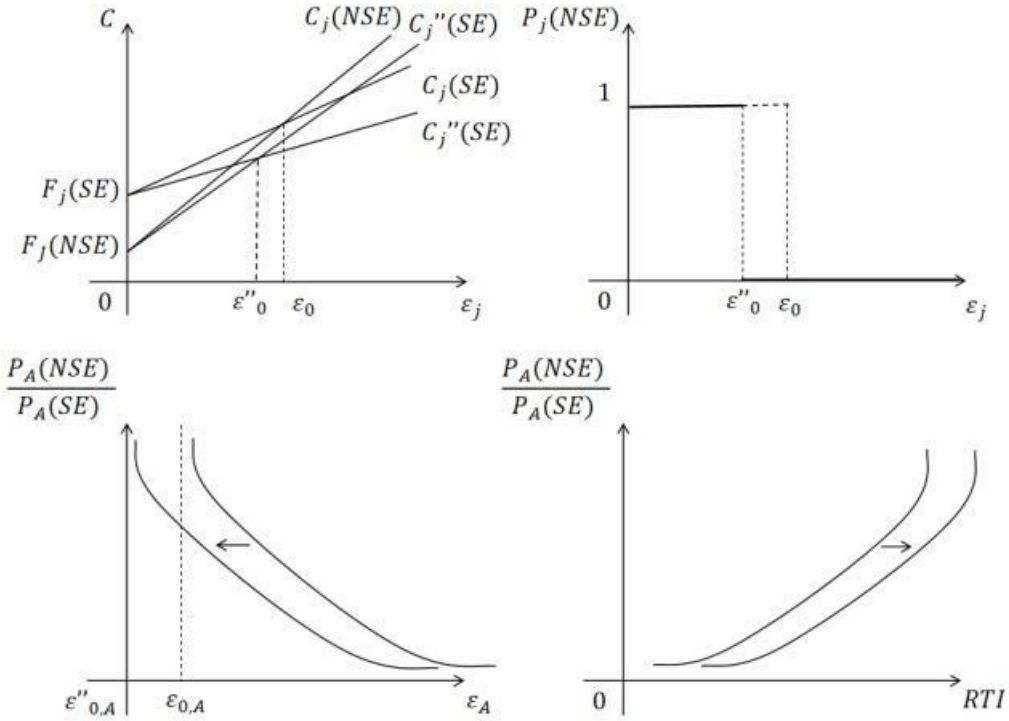

Figure A5. Changing cost saving of standard employment.

In some countries, the cost saving of standard employment may lower than other countries. In Figure A5 it denoted as $C_j(SE)$ and $C_j''(SE)$, $C_j(NSE)$ and $C_j''(NSE)$. The different between $\frac{\partial C_j''(SE)}{\partial \varepsilon_j}$ and $\frac{\partial C_j''(NSE)}{\partial \varepsilon_j}$ determines the moving direction of $\varepsilon''_{0,A}$ compare to $\varepsilon_{0,A}$, then changes the odds-ratio of non-standard employment. Therefore, Hypothesis 3 was proposed.

Hypothesis 3: the social contexts have a heterogeneous effect of the impact of RTI on the ratio of non-standard employment.

References

1. Acemoglu D and D H Autor. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labor Economics* (1043-1171). Elsevier Science Ltd.
2. Acemoglu D and P Restrepo. (2018). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 6(108), 1488-1542.
3. Acemoglu D and P Restrepo. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica*, 90(5), 1973-2016.
4. Akcomak S, S Kok and H Rojas-Romagosa. (2015). Technology Offshoring and the Task Content of Occupations in the United Kingdom. *International Labour Review*, 155(2), 201-230.
5. Anderson B. (2010). Migration, Immigration Controls and the Fashioning of Precarious Workers. *Work Employment and Society*, 24(2), 300-317.
6. Autor D H and D Dorn. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the Us Labor Market. *American Economic Review*, 5(103), 1553-1597.
7. Autor D H, F Levy and R J Murnane. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4), 1279-1333.

8. Autor D H, L F Katz and M S Kearney. (2006). The Polarization of the U.S. Labor Market. *American Economic Review*, 2(96), 189-194.
9. Autor D. (2010). The Polarization of Job Opportunities in the U.S. Labor Market: Implications for Employment and Earnings. *Center for American Progress and the Hamilton Project*, 6, 11-19.
10. Bárány Z L and C Siegel. (2018). Job Polarization and Structural Change. *American Economic Journal. Macroeconomics*, 10(1), 57-89.
11. Barbieri P and S Scherer. (2009). Labour Market Flexibilization and its Consequences in Italy. *European Sociological Review*, 25(6), 677-692.
12. Barley S R, B A Bechky and F J Milliken. (2017). The Changing Nature of Work: Careers, Identities, and Work Lives in the 21St Century. *Academy of Management Discoveries*, 2(3), 111-115.
13. Biemann T, H Zacher and D C Feldman. (2012). Career Patterns: A Twenty-Year Panel Study. *Journal of Vocational Behavior*, 81(2), 159-170.
14. Blair H. (2001). 'You're Only as Good as Your Last Job': The Labour Process and Labour Market in the British Film Industry. *Work Employment and Society*, 15(1), 149-169.
15. Booth A L and J C van Ours. (2013). Part-Time Jobs: What Women Want? *Journal of Population Economics*, 26(1), 263-283.
16. Busilacchi G, G Gallo and M Luppi. (2024). I would Like to but I Cannot: What Influences the Involuntariness of Part-Time Employment in Italy. *Social Indicators Research*, 1-35.
17. Cahuc P, S Carcillo and A Zylberberg. (2014). *Labor Economics*. The MIT Press.
18. Caro D H, K S Cortina and J S Eccles. (2015). Socioeconomic Background, Education, and Labor Force Outcomes: Evidence From a Regional U.S. Sample. *British Journal of Sociology of Education*, 36(6), 934-957.
19. Casey C and P Alach. (2004). 'Just a Temp?' - Women, Temporary Employment and Lifestyle. *Work Employment and Society*, 18(3), 459-480.
20. Connelly C E and D G Gallagher. (2004). Emerging Trends in Contingent Work Research. *Journal of Management*, 30, 959-983.
21. Cortes G M. (2016). Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data. *Journal of Labor Economics*, 34(1), 63-105.
22. Ebenstein A, A Harrison, M McMillan and S Phillips. (2014). Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys. *Review of Economics and Statistics*, 96(4), 581-595.
23. Eloundou T, S Manning, P Mishkin and D Rock. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. *Arxiv Preprint Arxiv:2303.10130*
24. Esposito P and S Scicchitano. (2022). Educational Mismatch and Labour Market Transitions in Italy: Is there an Unemployment Trap? *Structural Change and Economic Dynamics*, 61, 138-155.
25. Esposito P and S Scicchitano. (2023). Drivers of Skill Mismatch Among Italian Graduates: The Role of Personality Traits. *Applied Economics*, 55(40), 4642-4663.
26. Fantom N J and U Serajuddin. (2016). The World Bank's Classification of Countries by Income. *World Bank Policy Research Working Paper Series*.
27. Fernández-Macías E and J Hurley. (2017). Routine-Biased Technical Change and Job Polarization in Europe. *Socio-Economic Review*, 3(15), 563-585.
28. Fonseca T, F Lima and S C Pereira. (2018). Job Polarization, Technological Change and Routinization: Evidence for Portugal. *Labour Economics*, 51, 317-339.
29. Frey C B and M A Osborne. (2017). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114, 254-280.
30. George E and P Chattopadhyay. (2015). *Non-Standard Work and Workers: Organizational Implications*. ILO Geneva, Switzerland.
31. Goos M and A Manning. (2007). Lousy and Lovely Jobs：the Rising Polarization of Work in Britain. *Review of Economics and Statistics*, 89(1), 118-133.
32. Goos M, A Manning and A Salomons. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104(8), 2509-2526.
33. Hämäläinen R, K Nissinen, J Mannonen, J Lämsä, K Leino and M Taajamo. (2021). Understanding Teaching Professionals' Digital Competence: What Do PIAAC and TALIS Reveal About Technology-Related Skills, Attitudes, and Knowledge? *Computers in Human Behavior*, 117
34. Hardy W, R Keister and P Lewandowski. (2018). Educational Upgrading, Structural Change and the Task Composition of Jobs in Europe. *Economics of Transition*, 26(2), 201-231.
35. Harvey G, C Rhodes, S J Vachhani and K Williams. (2017). Neo-Villeiny and the Service Sector: The Case of Hyper Flexible and Precarious Work in Fitness Centres. *Work, Employment and Society*, 31(1), 19-35.
36. Holman D and A Rafferty. (2018). The Convergence and Divergence of Job Discretion Between Occupations and Institutional Regimes in Europe From 1995 to 2010. *Journal of Management Studies*, 55(4), 619-647.
37. Horemans J. (2016). Polarisation of Non-Standard Employment in Europe: Exploring a Missing Piece of the Inequality Puzzle. *Social Indicators Research*, 125(1), 171-189.

38. Kalleberg A L. (2000). Nonstandard Employment Relations: Part-Time, Temporary and Contract Work. *Review of Sociology*, 26(1), 341-365.
39. Kalleberg A L. (2003). Flexible Firms and Labor Market Segmentation: Effects of Workplace Restructuring on Jobs and Workers. *Work and Occupations*, 30(2), 154-175.
40. Kalleberg A L and P V Marsden. (2005). Externalizing Organizational Activities: Where and How U.S. Establishments Use Employment Intermediaries. *Socio-Economic Review*, 3(3), 389-416.
41. Kollmeyer C. (2018). Trade Union Decline, Deindustrialization, and Rising Income Inequality in the United States, 1947 to 2015. *Research in Social Stratification and Mobility*, 57, 1-10.
42. Korinek A. (2023). Language Models and Cognitive Automation for Economic Research: National Bureau of Economic Research No. w30957.
43. Lazear E P. (1995). *Personnel Economics*. MIT press.
44. Lee C. (2005). International Migration, Deindustrialization and Union Decline in 16 Affluent OECD Countries, 1962-1997. *Social Forces*, 84(1), 71-88.
45. Loughlin C and J Barling. (2001). Young Workers' Work Values, Attitudes, and Behaviours. *Journal of Occupational and Organizational Psychology*, 74, 543-558.
46. Macdonald R and A Giazitzoglu. (2019). Youth, Enterprise and Precarity: Or, What is, and What is Wrong with, the 'Gig Economy'? *Journal of Sociology*, 55, 724-740.
47. Marcolin L, S Miroudot and M Squicciarini. (2019). To be (Routine) Or Not to be (Routine), that is the Question: A Cross-Country Task-Based Answer. *Industrial and Corporate Change*, 28(3), 477-501.
48. Minardi S, C Hornberg, P Barbieri and H Solga. (2023). The Link Between Computer Use and Job Satisfaction: The Mediating Role of Job Tasks and Task Discretion. *British Journal of Industrial Relations*
49. Olsen K M and A L Kalleberg. (2004). Non-Standard Work in Two Different Employment Regimes: Norway and the United States. *Work Employment and Society*, 18(2), 321-348.
50. Oster E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, 37(2), 187-204.
51. Pfeffer J and J N Baron. (1988). Taking the Workers Back Out: Recent Trends in the Structuring of Employment. *Research in Organizational Behavior*, 10(1988), 257-303.
52. Reijnders L S and G J de Vries. (2018). Technology, Offshoring and the Rise of Non-Routine Jobs. *Journal of Development Economics*, 135, 412-432.
53. Rica S D L, L Gortazar and P Lewandowski. (2020). Job Tasks and Wages in Developed Countries: Evidence From PIAAC. *Labour Economics*, 65, 101845.
54. Taplin I M. (1995). Flexible Production, Rigid Jobs: Lessons From the Clothing Industry. *Work and Occupations*, 22(4), 412-438.
55. Tilly C. (1991). Reasons for the Continuing Growth of Part-Time Employment. *Monthly Lab. Rev.*, 114, 10.
56. Uzzi B and Z I Barsness. (1998). Contingent Employment in British Establishments: Organizational Determinants of the Use of Fixed-Term Hires and Part-Time Workers. *Social Forces*, 76(3), 967-1005.
57. Van Nieuwenhove L and B De Wever. (2022). Why are Low-Educated Adults Underrepresented in Adult Education? Studying the Role of Educational Background in Expressing Learning Needs and Barriers. *Studies in Continuing Education*, 44(1), 189-206.
58. Wong C and M A Campion. (1991). Development and Test of a Task Level Model of Motivational Job Design. *Journal of Applied Psychology*, 76(6), 825-837.